

Sell-Side Debt Analysts and Debt Market Efficiency

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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, which is consistent with debt analysts facilitating the process by which available information is impounded in debt prices. The effect of debt research on the debt market's lag 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, which is 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, which is consistent with new information being provided despite the absence of a debt market reaction. Finally, there is a 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, whereas 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.

Keywords: analyst; equity markets; debt markets; market efficiency

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1. Introduction

Sell-side investment research is generally partitioned into debt and equity, mirroring the debt and equity segmentation of capital markets. Although 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, Womack 1996, Hong et al. 2000, Gleason and Lee 2003), 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 because the public debt market is on average larger than the equity market (Bessembinder and Maxwell 2008), but it is also less liquid and less efficient (Kwan 1996, Gebhardt et al. 2005, Downing et al. 2009). This study answers the Beyer et al. (2010) and Berger (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 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 research 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 with credit rating agencies having 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 the finding of Ronen and Zhou's (2013) that institutional bond trades impound information more efficiently than retail bond trades because 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% 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% of its time-series standard deviation suggests that debt reports on average address cash flow news rather than debt-equity conflict events. Furthermore, we find that 37% of the reports have no immediate effect on the debt market but have an economically large effect on absolute equity returns, equivalent to 32% of their time-series standard deviation. We suggest that because of 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%, respectively, and the time-to-first trade is shortened by half a day or more. Timely reports 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.

Our evidence on the immediate effects of debt research complements and extends prior work on sell-side debt analysts (Johnston et al. 2009, 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. Furthermore, our finding that debt reports increase the probability of a 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

¹ We describe the endogeneity problem and how we alleviate it in §§3.1 and 4.2.

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 and/or 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 §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 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 Securities in

New York and the leader of the top-ranked team in healthcare. Bland says BofA’s fixed-income research department, with 40 publishing analysts in the United States, 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, p. 152). Furthermore, 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 eighth, 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, nondeal road shows, field trips, and management meetings (see Maber et al. 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, whereas our hypothesis concerns the relationship between debt analyst following and the speed with which the debt market impounds available information.

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, and Downing et al. 2009 for evidence that bond returns lag equity returns).⁴

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.

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.

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).

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 as well as 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 evidence from De Franco et al. (2009) of a volume response indicates a change in individual investors' expectations, not a change in the market's expectation, a distinction first made in the Beaver (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 to the magnitudes of the price changes" (p. 833). Evidence of a return response thus makes us more confident that debt research provides new information to capital markets.⁶

⁵ The De Franco et al. (2009) findings hold in our sample.

⁶ Johnston et al. (2009) show a Day 0 equity return reaction but do not control for the activities of equity analysts.

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 debt-holder and equity-holder 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 debt-holder and equity-holder 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 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

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

where Ret_{it}^B 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_{it}^E is contemporaneous equity return; $Ret_{i,t+1}^E$ and $Ret_{i,t-1}^E$ are the lead and lagged equity returns, respectively; and ϵ_{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 β_3 is zero. If the equity market is efficient with respect to the debt market, then β_1 is zero.

⁷ See De Franco et al. (2014) for evidence on debt analysts' views of this conflict.

⁸ We use the Center for Research in Security Prices (CRSP) daily treasuries database, Fixed Term Indices, and match to the closest maturity.

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 information impounded in the equity market.⁹ Our prediction is that the coefficient β_3 will be lower when sell-side debt coverage is present, implying that the debt market impounds public information relatively faster as a result of 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, $DF_{it} \times Ret_{i,t-1}^E$. If company i has had at least one debt report over a one-year period ending on day t , DF_{it} is equal to one 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.

Although Kwan (1996) did not find that debt returns lead equity returns, we interact leading stock returns with a dummy variable representing high equity analyst coverage, $EF_{it} \times Ret_{i,t+1}^E$.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 EF_{it} is equal to one and zero otherwise. We partition equity coverage based on the median rather than zero 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 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} , a dummy variable equal to one when the number of equity analysts exceeds the 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 four; *Hedge Fund Ownership*, a dummy variable equal to one when hedge funds' percentage equity ownership 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

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.

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 and Kelley (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 et al. (2012). We thank the authors of the study for sharing these data.

models the debt analyst coverage choice, the second includes the inverse Mills ratio. Second, we perform the analysis on subsamples 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

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 the day of publication and day of first trade) by estimating

$$\begin{aligned} & \text{Day 0 Trade}_i \text{ (Time to Trade}_i\text{)} \\ &= \beta_0 + \beta_1 \text{High Reputation}_i + \beta_2 \text{Timely Report}_i \\ & \quad + \beta_3 \text{EquityAbsRet}_i + \beta_4 \text{Bond Volume}_i + \beta_5 \mathbf{Z}_i + \varphi_i. \end{aligned} \quad (2)$$

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. The following control variables are included in \mathbf{Z} : Junk equals one if one of the bonds of the firm is rated below BBB (S&P Rating) and zero otherwise, Convertible equals one 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.

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

$$\begin{aligned} & \text{BondAbsRet}_i = \beta_0 + \beta_1 \text{High Reputation}_i \\ & \quad + \beta_2 \text{Timely Report}_i + \beta_3 \mathbf{Z}_i + \omega_i. \end{aligned} \quad (3)$$

BondAbsRet is the absolute value of BondRet , which is equal-weighted bond portfolio returns minus the corresponding maturity-matched U.S. Treasury security.

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; 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.¹⁹ In the case of nonmatches, we also examine whether

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.

¹⁷ These firms were ranked by *Institutional Investor* in the top 10 firms for fixed income research. Approximately 54% 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, Data25 \times Data199: Market value of equity, Data9: Long-term liabilities, Data6: Total assets.

¹⁹ The CUSIP identifier is given by the Committee on Uniform Securities and Identification Procedures.

Table 1 Sample Statistics

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		
<i>Equity Capitalization</i>	14,416	5,133	6,705	1,944		
<i>Total Assets</i>	39,592	8,985	11,254	2,492		
<i>Market to Book</i>	2.78	1.98	7.15	1.96		
<i>Leverage</i>	0.32	0.28	0.26	0.24		
<i>Credit Rating</i>	14.36	15.00	13.70	15.00		
<i>Credit Rating Agency Coverage</i>	0.79	1.00	0.52	1.00		
<i>Hedge Fund Ownership %</i>	0.049	0.024	0.037	0.021		
<i>Disclosure</i>	12.27	11.00	8.74	7.00		
<i>Media Coverage</i>	27.55	13.00	14.70	8.00		
Panel C: Frequency 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 100 million	711	14	Less than 1 year	102	2	
From 100 million to 500 million	2,691	53	From 1 year to 5 years	914	18	
From 500 million to 900 million	711	14	From 5 years to 10 years	2,945	58	
More than 900 million	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					

Notes. Panel A describes how the sample companies are identified. Panel B reports mean and median *Equity Capitalization* (the number of shares times share price), *Total Assets* (the book value of assets), *Market to Book* (the market value of equity divided by book value of equity), *Leverage* (the book value of debt divided by book value of assets at year end), *Credit Rating* (at year end, source: FISD, converted to an ordinal scale, best 23 through worst 1), and *Credit Rating Agency Coverage* (*NRaters*: 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 four), *Hedge Fund Ownership* (end of year, percentage ownership), *Disclosure* (the number of 8 K and management forecasts), and *Media Coverage* (the 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 the frequency 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.

or not the bond issuer is a subsidiary of a parent with publicly traded equity; we use the Fixed Income Securities Database (FISD) 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 10 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.²⁰

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% 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% of the time, respectively). Equity reports commonly follow (days 2 to 10) debt reports as well (23% 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% of our sample. The remaining years to maturity is most commonly five to 10 years (58%). 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

Panel A of Table 2 presents descriptive statistics for the primary variables in our lead-lag return analysis,

²⁰ The Johnston et al. (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.

and panel B of Table 2 presents the regression results. 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 report parameter estimates and p -values in parentheses; standard errors are adjusted to account for daily cross-correlations in bond returns.²¹

The first column of panel B of Table 2 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 predict debt returns. The coefficients on the contemporaneous and lagged equity returns are 0.09 and 0.049; both are statistically significant at the 1% level. Unlike Kwan (1996), 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% 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.²²

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% 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% 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, which is consistent with credit rating agencies having weaker incentives for quick information processing and dissemination than sell-side debt analysts.²³ Hedge fund ownership

²¹ 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.

²² Kwan (1996) did find that bond returns predict equity returns for companies rated BB, but those results were explained by nonsynchronous trading.

²³ The slope coefficient on $NRaters_{it} \times Ret_{i,t-1}^E$ can be compared with the slope coefficient on $DF_{it} \times Ret_{i,t-1}^E$ because $NRaters$ is divided by

Table 2 Debt Analyst Following and the Lag with Which Debt Prices Incorporate Information

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
SD	1.201	2.138	0.424	0.474	0.474	0.46	4.27	7.91
P50	-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			
	Ret_{it}^B	Ret_{it}^B	Ret_{it}^B
$Ret_{it}^B = \beta_0 + \beta_1 Ret_{i,t+1}^E + \beta_2 Ret_{it}^E + \beta_3 Ret_{i,t-1}^E + \beta_4 DF_{it} + \beta_5 EF_{it} + \beta_6 NRaters_{it} + \beta_7 Hedge\ Fund\ Ownership_{it} + \beta_8 Media\ Coverage_{it} + \beta_9 Firm\ Disclosure_{it}$ $+ \beta_{10} DF_{it} \times Ret_{i,t+1}^E + \beta_{11} EF_{it} \times Ret_{i,t+1}^E + \beta_{12} DF_{it} \times Ret_{i,t-1}^E + \beta_{13} EF_{it} \times Ret_{i,t-1}^E + \beta_{14} NRaters_{it} \times Ret_{i,t-1}^E + \beta_{15} Hedge\ Fund\ Owners_{it} \times Ret_{i,t-1}^E$ $+ \beta_{16} Media\ Coverage_{it} \times Ret_{i,t-1}^E + \beta_{17} Firm\ Disclosure_{it} \times Ret_{i,t-1}^E + \beta_{18} Inverse\ Mills\ Ratio_{i,t} + v_{it}$			
$Ret_{i,t+1}^E$	0.008** [0.023]	0.013** [0.037]	-0.001 [0.939]
$Ret_{i,t}^E$	0.090*** [0.000]	0.089*** [0.000]	0.096*** [0.000]
$Ret_{i,t-1}^E$	0.049*** [0.000]	0.047*** [0.000]	0.036** [0.034]
$DF_{it} \times Ret_{i,t+1}^E$		-0.002 [0.679]	0.006 [0.387]
$EF_{it} \times Ret_{i,t+1}^E$		-0.004 [0.423]	0.005 [0.525]
$DF_{it} \times Ret_{i,t-1}^E$		-0.032*** [0.000]	-0.043*** [0.000]
$EF_{it} \times Ret_{i,t-1}^E$		0.017*** [0.005]	0.027*** [0.000]
$NRaters_{it} \times Ret_{i,t-1}^E$		-0.007* [0.074]	-0.006 [0.108]
$Hedge\ Fund\ Ownership_{it} \times Ret_{i,t-1}^E$		-0.029*** [0.000]	-0.044*** [0.000]
$Media\ Coverage_{it} \times Ret_{i,t-1}^E (\times 100)$		0.05 [0.751]	-0.182 [0.365]
$Firm\ Disclosure_{it} \times Ret_{i,t-1}^E (\times 100)$		-1.134*** [0.000]	-1.540*** [0.004]
$Inverse\ Mills\ Ratio$			0.012 [0.672]
Observations	107,812	107,812	74,388
Adjusted R^2	0.034	0.036	0.040

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 -0.032 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.²⁴ 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 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.

four and, similar to DF , ranges from zero to one. In untabulated analysis, we find an even larger coefficient on $DF_{it} \times Ret_{i,t-1}^E$ when $NRaters = 0$, consistent with a greater role for sell-side debt analysts when credit rating agency coverage is absent.

²⁴ Including lagged bond returns in Equation (3) does not alter this result. Results are similar for a subsample of firms with no credit rating.

Table 2 (Continued)

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
$Ret_{i,t+1}^E$	0.019*** [0.004]	0.018* [0.052]	-0.017 [0.650]	0.015 [0.145]	0.014* [0.082]	0.005 [0.214]
$Ret_{i,t}^E$	0.065*** [0.000]	0.109*** [0.000]	0.094*** [0.000]	0.103*** [0.000]	0.110*** [0.000]	0.072*** [0.000]
$Ret_{i,t-1}^E$	0.029 [0.154]	0.017 [0.552]	0.052 [0.197]	0.053** [0.013]	-0.003 [0.892]	0.052 [0.140]
$DF_{it} \times Ret_{i,t+1}^E$	-0.004 [0.717]	0.002 [0.864]	0.019 [0.261]	0.005 [0.581]	0.004 [0.710]	0.012 [0.397]
$EF_{it} \times Ret_{i,t+1}^E$	0.002 [0.821]	-0.016 [0.215]	0.022 [0.149]	0.002 [0.795]	0.005 [0.667]	-0.002 [0.912]
$DF_{it} \times Ret_{i,t-1}^E$	-0.066*** [0.000]	-0.047*** [0.000]	0.005 [0.569]	-0.013 [0.182]	-0.035*** [0.002]	-0.064*** [0.000]
$EF_{it} \times Ret_{i,t-1}^E$	0.027** [0.019]	0.036*** [0.005]	0.034** [0.026]	0.000 [0.992]	0.027** [0.015]	0.044*** [0.003]
$NRaters_{it} \times Ret_{i,t-1}^E$	-0.002 [0.596]	-0.001 [0.908]	-0.009 [0.230]	0.001 [0.865]	-0.006 [0.237]	-0.006 [0.381]
$Hedge\ Fund\ Ownership_{it} \times Ret_{i,t-1}^E$	-0.054*** [0.000]	-0.035*** [0.001]	-0.038** [0.014]	-0.045*** [0.000]	-0.039*** [0.000]	-0.042*** [0.002]
$Media\ Coverage_{it} \times Ret_{i,t-1}^E (\times 100)$	-0.056 [0.754]	-0.251 [0.458]	-0.022 [0.970]	-0.107 [0.583]	-0.187 [0.559]	-0.105 [0.827]
$Firm\ Disclosure_{it} \times Ret_{i,t-1}^E (\times 100)$	-1.094* [0.050]	-2.174** [0.010]	-1.385 [0.297]	-0.633 [0.278]	-3.038*** [0.000]	-0.803 [0.493]
Observations	35,364	34,565	37,883	40,115	33,837	25,335
Adjusted R^2	0.037	0.053	0.047	0.047	0.052	0.044

Notes. 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, and 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; and 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 four. $Hedge\ Fund\ Ownership$ is a dummy variable that takes a value of one if the percentage of ownership by hedge funds (as defined in Ben-David et al. 2012) 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 a firm's 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 1994).

***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

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 R^2 of 0.23.²⁵ 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 it 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 *Inverse Mills Ratio* increases confidence in the hypothesis that sell-side debt analysts enhance debt market efficiency.²⁶

²⁶ 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

²⁵ A model with only the instruments has a pseudo R^2 of 0.15.

Although the Heckman approach is widely used in accounting, finance, and economics, it is not without limitations (e.g., Tucker 2010, 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 Table A.1 in Appendix A. The coefficient of interest, $PostInit_{it} \times InitFirms_{it} \times Ret_{i,t-1}^E$, 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.

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 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

$DF_{it} \times Ret_{i,t-1}^E$ 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% 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 .²⁷ We split the sample based on this ex ante measure of liquidity to mitigate endogeneity concerns; all observations are classified into low, medium, and high liquidity groups using the 33% and 66% 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 $DF_{it} \times Ret_{i,t-1}^E$ is negative and statistically significant in the medium and high groups but not in the low liquidity group, which is 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 \$100,000, 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.

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

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.

²⁷ 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.

Table 3 Information Events

Panel A: Number of information events and market data availability					
Information event	Sample period	TRACE coverage	<i>BondAbsRet</i>	<i>EquityAbsRet</i>	<i>COV</i>
<i>Debt Report Publication</i>	2,758	1,737	1,103	2,726	1,100
<i>Equity Recommendation</i>	26,749	13,123	7,154	26,728	7,154
Δ <i>Credit Rating</i>	3,817	2,417	1,676	3,583	1,578
<i>Earnings Announcement</i>	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				
	<i>Debt Report</i>	<i>Equity Recommendation</i>	Δ <i>Credit Rating</i>	<i>Earnings Announcement</i>
Mean	2.99	29.04	4.14	8.75
Median	0.00	27.00	2.00	10.00
SD	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

Notes. 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 days for which we have nonmissing *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*, and *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 (SD), and the 25th and the 75th percentiles.

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.²⁸ We compare debt reports with 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 panel A in Table 3 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 the second column 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. As a result of infrequent bond trading, we observe *BondAbsRet* for 64% of the debt report publication days, 55% of the equity recommendation days, 65% of the credit rating changes days, and 47% of the earnings announcement days (calculated as the ratio of the third column to the second column). 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%. On days when debt market information intermediaries such as credit rating agencies and sell-side debt analysts release information, there is a greater probability that a trade will take place (65% and 64%, respectively), relative to days on which earnings are announced or equity recommendations are released (47% and 55%). This means that debt analysts and credit rating agencies play an important role in making debt markets more liquid.

Although 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

²⁸ 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. (2012) for analyses of credit watches.

Table 4 Event Time Analysis of Equity and Debt Returns

Panel A: Cross-sectional distribution of select parameters of the distributions of market return variables—Prior to standardization					
	<i>BondRet</i>	<i>EquityRet</i>	<i>BondAbsRet</i>	<i>EquityAbsRet</i>	<i>COV</i>
Mean					
Mean	0.0867	0.0336	0.9719	1.6183	0.0076
Median	0.0470	0.0356	0.7847	1.3086	0.0009
SD	0.4632	0.1210	0.7050	0.9497	0.0469
SD					
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					
	<i>BondAbsRet</i>	<i>EquityAbsRet</i>	<i>COV</i>		
Mean	−0.010	−0.035	−0.004		
Median	−0.273	−0.287	−0.043		
SD	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					
Event day	<i>BondAbsRet</i>	Debt trading <i>EquityAbsRet</i>	No debt trading <i>EquityAbsRet</i>	<i>COV</i>	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	

Notes. 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 nonmissing observations. We report cross-sectional means and standard deviations of these company-specific parameters, the number of companies, and nonmissing observations used in the estimations. *BondRet* is the 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*, and *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 nonmissing sample observations. The reported medians, standard deviations (SD), 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 significance at the 5% level. Standard errors are heteroscedasticity-consistent and adjusted to account for cross-correlation in contemporaneous daily returns and volume (Rogers 1994).

mean and the 75th percentile are equal to three. The median of zero suggests that the majority of the sample companies do not have any debt coverage.²⁹

²⁹ 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 10 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 Footnote 3 as well. As a result, published

4.3.2. Cross-Sectional Distributions of Market Reaction Variables. Panel A of Table 4 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 (*BondAbsRet*, *EquityAbsRet*), 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,

information for a debt analyst would understate analyst-generated and disseminated information.

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%. The cross-sectional mean of mean absolute equity returns (*EquityAbsRet*) is higher at 1.61%, 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 dividing by the company-specific standard deviation. Panel B of Table 4 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.³⁰ 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% 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% 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% 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% versus 51% of its standard deviation. We conclude that debt reports that do not trigger a debt market reaction are still informative. However, because 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.³¹

In an untabulated analysis, we replicate the analysis of panel C in Table 4 with two changes: we (1) adopt Beaver's (1968) statistical approach and (2) exclude debt report observations likely to be contaminated by the effects of competing information events. We identify contaminated observations as debt reports occurring within one 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 panel A in Table 5 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% (9.2%).³² As a reference, the unconditional probability of Day 0 trading is 23.3%. 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%. 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% marginal probability effect.

The last three columns of panel A in Table 5 report the results from the estimation of Equation (2) as a

³⁰ We exclude debt reports occurring within 21 days of another debt report.

³¹ We replicated panel C of Table 4 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.

³² In calculating marginal effects, we hold continuous variables at their sample means and dummy variables at zero.

Table 5 Cross-Sectional Analysis of Debt Market Reaction

Panel A: Bond trade analysis						
<i>Day 0 Trade_i or Time to Trade_i = $\beta_0 + \beta_1 High\ Reputation_i + \beta_2 Timely\ Report_i + \beta_3 EquityAbsRet_i + \beta_4 Bond\ Volume_i + \varphi_i$.</i>						
	Day 0 trade incidence (probit model)			Time to first trade (Weibull hazard model)		
	(1)	(2)	(3)	(1)	(2)	(3)
<i>EquityAbsRet</i>		0.103*** [0.000]	0.121*** [0.000]		−0.333*** [0.002]	−0.291** [0.013]
<i>High Reputation</i>	0.533* [0.090]	0.832** [0.017]	0.754** [0.035]	−0.358*** [0.000]	−0.357*** [0.000]	−0.352*** [0.000]
<i>Timely Report</i>	0.316*** [0.000]	0.311*** [0.000]	0.394** [0.027]	−0.844* [0.046]	−0.668** [0.011]	−0.662*** [0.011]
<i>Bond Volume</i>	0.645*** [0.000]	0.655*** [0.000]	0.651*** [0.000]	−0.646*** [0.000]	−0.648*** [0.000]	−0.647*** [0.000]
<i>Junk</i>			0.150** [0.042]			−0.291* [0.052]
<i>Convertible</i>			0.052 [0.374]			−0.060 [0.441]
<i>Book to Market</i>			0.126** [0.012]			0.117 [0.129]
<i>Maturity</i>			0.004 [0.106]			0.000 [0.984]
<i>Leverage</i>			0.013 [0.990]			−0.001 [0.970]
<i>Intercept</i>	0.095 [0.266]	0.132 [0.128]	0.149 [0.142]	−2.329*** [0.000]	−2.354*** [0.000]	−2.298*** [0.000]
Shape parameter <i>p</i>				0.978	0.975	0.931
Log likelihood				−2,427	2,438	2,513
Number of observations	1,725	1,725	1,725	1,725	1,725	1,725
Pseudo <i>R</i> ²	0.317	0.343	0.393			

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% ($e^{-0.352} - 1$). 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 one 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% ($e^{-0.291 \times 0.913} - 1$). The shape parameter of the Weibull hazard model is less than one, 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.

Panel B of Table 5 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% level and economically large, representing 24% of the standard deviation of *BondAbsRet*. We do not find that reports by brokers with high reputation affect debt returns.³³ 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.

³³ 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).

Table 5 (Continued)

Panel B: Absolute day 0 return analysis	
$BondAbsRet_i = \beta_0 + \beta_1 High\ Reputation_i + \beta_2 Timely\ Report_i + \beta_3 Z_i + \omega_i$	
	<i>BondAbsRet</i>
<i>High Reputation</i>	0.081 [0.278]
<i>Timely Report</i>	0.781** [0.033]
<i>Junk</i>	0.127 [0.112]
<i>Convertible</i>	0.059 [0.555]
<i>Book to Market</i>	0.148*** [0.004]
<i>Maturity</i>	0.006 [0.180]
<i>Leverage</i>	−0.091 [0.761]
<i>Intercept</i>	0.102** [0.024]
Number of observations	1,100
Adjusted R^2	0.003

Notes. Panel A explores determinants of a bond trade on a report publication day as well as 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 is zero otherwise. *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 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. The 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 the following: *Junk* equals one if one of the bonds of the firm is rated below BBB (S&P Rating). *Convertible* equals one 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 (Data199 × Data25). *Maturity* is the average of outstanding bonds' number of years to maturity. *Leverage* is long-term liabilities scaled by total assets (Data9/Data6). The p -values are provided in brackets.

***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

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 equation

$$\begin{aligned}
 REACT_{it} = & \beta_0 + \beta_1 DR_{it} + \beta_2 ER_{it} + \beta_3 \Delta CR_{it} \\
 & + \beta_4 EA_{it} + \epsilon_{it}, \quad (4)
 \end{aligned}$$

where $REACT_{it}$ is the market reaction for company i on day t ($BondAbsRet_{it}$, $EquityAbsRet_{it}$, and COV_{it}) and where DR_{it} , ER_{it} , ΔCR_{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 (ΔCR_{it}), or earnings announcement (EA_{it}), respectively). The error term is ϵ_{it} .³⁴

³⁴ All standard errors are heteroskedasticity consistent and adjusted to account for cross-correlation in contemporaneous absolute returns and volume (Rogers 1994). Clustering by day and firm does not change the results from our tests.

The slope coefficients signify the average increase in the respective $REACT$ variable surrounding information events relative to noninformation event days (the intercept). For example, when $BondAbsRet$ is the dependent variable, β_0 is the mean absolute debt return in the absence of any information events, β_1 is the increase in the mean absolute debt returns induced by the occurrence of a debt report, and β_2 , β_3 , and β_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% 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

Table 6 Debt Analysts as a Source of New Information: A Comparative Analysis

Panel A: Regression analysis				
$REACT_{it} = \beta_0 + \beta_1 DR_{it} + \beta_2 ER_{it} + \beta_3 \Delta CR_{it} + \beta_4 EA_{it} + \mu_{it}$				
	<i>BondAbsRet</i>	<i>EquityAbsRet</i>	<i>COV</i>	
<i>Debt Report</i>	0.055** [0.020]	0.261*** [0.000]	0.072** [0.014]	
<i>Equity Recommendation</i>	0.042*** [0.000]	0.280*** [0.000]	0.047*** [0.000]	
Δ <i>Credit Rating</i>	0.046** [0.016]	0.151*** [0.000]	0.037** [0.045]	
<i>Earnings Announcement</i>	0.041** [0.015]	0.523*** [0.000]	0.089*** [0.000]	
<i>Intercept</i>	-0.018** [0.024]	-0.086*** [0.000]	-0.015*** [0.000]	
<i>F</i> -statistics				
<i>Debt Report</i> = <i>Equity Recommendation</i>	0.28	1.78	1.24	
<i>Debt Report</i> = Δ <i>Credit Rating</i>	0.08	37.84***	2.68**	
<i>Debt Report</i> = <i>Earnings Announcement</i>	0.22	267.08***	0.43	
Number of observations	113,591	549,515	108,681	
Adjusted R^2	0.001	0.019	0.001	
Panel B: Mean annual information ratios (%)				
	<i>Debt Report</i>	<i>Equity Recommendation</i>	Δ <i>Credit Rating</i>	<i>Earnings Announcement</i>
<i>BondAbsRet</i>	1.03	7.88	1.66	1.96
<i>EquityAbsRet</i>	2.47	15.59	2.48	5.99

Notes. 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} , ΔCR_{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. The p -values are provided in brackets. 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 1994). 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 $IR_{sit} = \sum_1^K MktReaction_{sik} / \sum_1^N MktReaction_{in}$, where $MktReaction_{eik}$ occurs on event days (-1 to $+1$). We report means.

*** and ** represent statistical significance at the 1% and 5% levels, respectively.

announcement days (52% of the standard deviation of equity absolute returns), 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 only the equity market results are statistically significant.³⁵ 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% 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

³⁵ 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.

the covariation results, debt reports and earnings announcements again are not statistically different and have the largest reaction.³⁶

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, $IR_{sit} = \sum_1^K MktReaction_{sik} / \sum_1^N MktReaction_{in}$, 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 .³⁷ 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.

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 of Table 6). 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. Because sell-side debt research is predominantly institutional, whereas equity research is typically both institutional and retail, it is 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.

³⁶ We replicated Table 6 by inserting zero for bond returns if the bond of a firm is not traded on the day of debt report, and the results are similar.

³⁷ See Francis et al. (2002) and Frankel et al. (2006) for similar approaches.

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 as well as 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, which is 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, whereas 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.

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Appendix A. Endogeneity Concerns

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

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

We calculate the *Inverse Mills Ratio* using the probit model estimates; i.e., for each observation used in the first stage model reported in panel B of Table 2, 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, *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 one 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 one 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 four. *Institutional 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 et al. (2012) is greater than median hedge fund ownership in that year.³⁸ *Media Coverage* is the number of articles written on firms in the *Wall Street Journal*, *New York Times*, and *Washington Post* in a given year.³⁹ *Firm Disclosure* is the total number of firm's 8K filings and earnings management forecasts in a given year.⁴⁰

The demand for debt reports may also be influenced by the features of the 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 bond transaction volume. We take the average of the 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, where higher indicates 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. Descriptive statistics of these variables are presented in Table A.1, panel A. The probit model results are reported in Table A.1, panel B. The *p*-values are provided in brackets, and ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

³⁸ Specifically, Ben-David et al. (2012) use a proprietary list of hedge funds provided by Thompson Reuters to identify which 13F filers are hedge funds. Prior literature on hedge funds relies on self-reported industry lists and as such subject to survival bias.

³⁹ 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.

⁴⁰ We obtain 8K filings from the SEC Edgar website and management forecast data from the First Call database.

Table A.1 Debt Analyst Following and the Lag with Which Debt Prices Incorporate Information: Endogeneity Concerns

Panel A: Descriptive statistics								
	<i>Debt Following (DF)</i>	<i>NRaters</i>	<i>Day Since Last Bond Issue</i>	<i>Maturity</i>	<i>Debt Outstanding</i>	<i>Bond Liquidity</i>	<i>Junk</i>	<i>Convertible</i>
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
SD	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

	<i>Institutional Ownership</i>	<i>Market Value</i>	<i>Leverage</i>	<i>Book to Market</i>	<i>Volatility</i>	<i>Hedge Fund Ownership</i>	<i>Media Coverage</i>	<i>Firm Disclosure</i>
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
SD	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		Panel C: Difference in difference (with a propensity score matched control sample):	
	Debt following = 1		Ret_{it}^B
<i>NRaters</i>	0.1575*** [0.000]	<i>PostInit_{it}</i>	0.000 [0.574]
<i>Day Since Last Bond Issue</i>	-0.1831*** [0.000]	<i>InitFirms_{it}</i>	-0.387 [0.624]
<i>Junk</i>	-0.1089*** [0.000]	$Ret_{i,t+1}^E$	0.007 [0.535]
<i>Maturity</i>	0.0346*** [0.000]	$Ret_{i,t}^E$	0.146*** [0.000]
<i>Debt Outstanding</i>	0.2897*** [0.000]	$Ret_{i,t-1}^E$	0.056 [0.110]
<i>Bond Liquidity</i>	-0.2470*** [0.000]	$NRaters_{it} \times Ret_{i,t-1}^E$	-0.021*** [0.001]
<i>Market Value</i>	0.2083*** [0.000]	$Firm Disclosure_{it} \times Ret_{i,t-1}^E$	-0.364 [0.756]
<i>Leverage</i>	3.6897*** [0.000]	$Hedge Fund Ownership_{it} \times Ret_{i,t-1}^E$	-0.025* [0.056]
<i>Convertible</i>	-0.3959*** [0.000]	$Media Coverage_{it} \times Ret_{i,t-1}^E$	-0.471 [0.296]
<i>Book to Market</i>	0.2073*** [0.000]	$EF_{it} \times Ret_{i,t-1}^E$	0.514 [0.655]
<i>Volatility</i>	1.4505*** [0.000]	$EF_{it} \times Ret_{i,t+1}^E$	-0.005 [0.742]
<i>Institutional Ownership</i>	0.0814*** [0.000]	$PostInit_{it} \times InitFirms_{it}$	1.535 [0.146]
<i>Hedge Fund Ownership</i>	0.1405*** [0.000]	$PostInit_{it} \times Ret_{i,t-1}^E$	0.009 [0.572]
<i>Media Coverage (×100)</i>	6.5159*** [0.000]	$InitFirms_{it} \times Ret_{i,t-1}^E$	0.069* [0.094]
<i>Firm Disclosure (×100)</i>	9.4298*** [0.000]	$PostInit_{it} \times InitFirms_{it} \times Ret_{i,t-1}^E$	-0.030** [0.016]
Constant	-2.9128*** [0.000]		
Number of observations	74,388	Observations	21,951
Pseudo R ²	0.23	Adjusted R ²	0.059

Notes. This table examines the effect of debt analyst coverage initiation on the lag with which debt prices incorporate information. Panel A describes the determinants of debt analyst following. Panel B reports the results from a probit model of debt analyst following. Panel C reports difference in difference results. The sample analyzed in panel C 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 probit 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, $PostInit_{it} \times InitFirms_{it}$, $InitFirms_{it} \times Ret_{i,t-1}^E$, $PostInit_{it} \times Ret_{i,t-1}^E$, and $PostInit_{it} \times InitFirms_{it} \times Ret_{i,t-1}^E$, to capture the effect of debt coverage initiation. $InitFirms_{it}$ is a binary variable equal to one for observations on treated firms. $PostInit_{it}$ 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 1994).

***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix B. Sell-Side Debt Analyst Report Content

Because 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% of the debt reports appear to be triggered by various corporate events (merger and acquisitions, IPO of a subsidiary, or court decision) or announcements (share repurchase, debt reduction, or credit rating agency downgrade) that may affect debt holders differently from equity holders (De Franco et al. 2014). Close to 10% of the reports are written in the wake of a meeting with management (analyst meeting, lunch with management, or investor day), which suggests management are an important source of information not only for equity analysts but also for debt analysts.

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