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The price and volume response to earnings announcements in the corporate bond market

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Abstract

We examine abnormal returns and trading activity in bond markets around earnings announcements. Previous work provides mixed evidence on the relative impact of positive and negative surprises and the degree of response in investment-grade and speculative-grade bonds. We find that these announcements convey value-relevant information for both positive and negative earnings surprises in both investment and speculative-grade bonds. We also document significant heterogeneity in the response across industries, with muted responses in both abnormal returns and trading activity for bonds of firms in the financial and utilities industries.

KEYWORDS
bond market efficiency, earnings surprise, event studies

JEL CLASSIFICATION
G120, G140

1 | INTRODUCTION

Both debt and equity represent claims on the future cash flows of the firm. Therefore, to the extent that earnings announcements affect investors' expectations of the distribution of future cash flows, earnings announcements should be value relevant to bondholders as well as equity holders. Numerous studies examine the relevance of earnings announcements to equity holders; however, few consider the effect of these announcements on debt securities. Due to historical data limitations, the handful of existing studies of bond market reactions to these announcements focus either on subsets of the corporate bond market or on dealer quotes rather than actual trade-based prices. These studies reach mixed conclusions, making the extent of the corporate bond market response to earnings news an open question.[1] We revisit and extend previous work on the information content of earnings announcements to the corporate bond market using more powerful bond market event study methodology, more comprehensive data provided in the Trade Reporting and Compliance Engine (TRACE) system, and an analysis of trading activity as an information proxy.

Datta and Dhillon (1993) provide evidence that investment-grade and speculative-grade bond returns react in the direction of an earnings surprise and that the relationship is stronger for speculative-grade issues. Easton, Monahan, and Vasvari (2009) find bonds are more likely to trade in the days following an earnings announcement, with the likelihood of a transaction peaking on the second trading day following the announcement. They also provide weak evidence of a return reaction; however, the announcement-period return reaction is limited to negative surprises in speculative-grade bonds and their result loses statistical significance when both effects are included the same specification. Defond and Zhang (2014) show that trader quotations react to both positive and negative earnings surprises, but the impact is limited to speculative grade issues.

These studies leave several questions unresolved. Does the bond market react to both positive and negative surprises, or only to negative news? Do earnings announcements impact value for both investment-grade and speculative-grade bonds, or is the reaction limited to only the latter? What is the timing of the market's reaction? Does the market react to the information content of earnings announcements with a delay?

This mixed evidence is partially attributable to historical limitations of bond data. Datta and Dhillon (1993) use a small sample of exchange-traded bonds, which comprise only a small portion of the overwhelmingly over-the-counter corporate bond market. Easton et al.'s (2009) sample is limited to transactions reported by insurance companies. Because insurance companies face risk-based capital requirements that are correlated with credit risk, their trading decisions are unlikely to reflect the market. In fact, studies using these data often eliminate the noninvestment grade bonds on which the primary results of Easton et al. rely because they are unlikely to be representative of the broader speculative-grade market (e.g., Campbell & Taksler, 2003).

We alleviate generalizability concerns associated with the subsets of the market analyzed in earlier work by using a comprehensive set of over-the-counter transaction records from TRACE along with the bond event study methodological improvements (Bessembinder, Kahle, Maxwell, & Xu, 2009; Ederington, Guan, & Yang, 2015) to present evidence that the information content of earnings surprises in corporate bond markets is much broader than found by previous studies. In univariate tests, we find significant abnormal returns in the direction of the surprise for speculative grade bonds around both positive and negative surprises and for investment-grade bonds following negative surprises. In multivariate settings, we find that abnormal returns are positively related to the level of the earnings surprise and find no statistically significant difference between the magnitude of the response between the two credit classes. However, the specifics of the abnormal return reaction differ between positive and negative surprises. Positive surprises are associated with increasing abnormal return in the direction of the surprise, while negative surprises are associated with a return penalty that is not an increasing function of the magnitude of the negative surprise. This return penalty following negative news is significantly larger for speculative-grade bonds, consistent with an increased investor sensitivity to negative news in lower quality bonds.

We complement and extend our returns-based evidence with an examination of abnormal trading activity around earnings announcements. Numerous studies use equity trading volume as a measure of the information content conveyed by announcements (e.g., earnings announcements in Hirshleifer, Lim, & Teoh, 2009; Federal Reserve stress test announcements in Bamber, Barron, & Stevens, 2011; Flannery, Hirtle, & Kovner, 2017 survey this literature), yet relatively few have applied this approach to bond markets. Brogaard, Koski, and Siegel (2019) take this approach in their examination of bond market reactions to credit ratings news, arguing that the lack of a reaction documented

[1] Although we focus on the announcement period impact of earnings news on abnormal corporate bond returns, many studies examine dimensions of the relations between bond pricing and earnings management or earnings forecasts in other settings. As examples, see Chen, Tseng, and Hsieh (2015) and Ge and Kim (2014) on earnings management and the cost of debt, Jiang (2008) on benchmark-beating earnings and the cost of debt, and Konstantinidi and Pope (2016), Güntay and Hackbarth (2010), and Crabtree and Maher (2005) on various dimensions of risk in earnings and bond yields or spreads. In addition, Kerr and Ozel (2015) find that decreases in information asymmetry associated with earnings announcements affect the likelihood of debt versus equity offerings.

in previous work may be an artifact of illiquidity in the bond market and the resulting relatively low power of return-based event studies. They posit that while infrequent trading makes return-based analyses difficult, infrequent trading poses no problem when analyzing bond trading activity because zero-trading days provide economically relevant information.

Abnormal trading activity around earnings announcements provides confirmatory evidence for our returns-based analysis. Abnormal trading activity is positively related to the magnitude of the earnings surprise for both positive and negative surprises, and in both investment-grade and speculative-grade bonds. We find no evidence of the delayed response of Easton et al. (2009); these increases in trading activity are observed as early as 5 days prior to the earnings announcement, and after peaking on the announcement date, persist for up to 4 days following the announcement.

The remainder of the study proceeds as follows: Section 2 places our study in the context of related work. Section 3 describes our data and methodology. Section 4 presents the results of our analyses. Section 5 demonstrates the robustness of our findings, and Section 6 concludes.

2 | RELATED LITERATURE

Although a large number of studies examine the bond market reaction to firm-specific events (Maul & Schiereck, 2017 survey this literature), relatively few have conducted similar examinations around earnings releases. In short, these studies generally agree that earnings affect bond prices, yet disagree on the relative impact of positive versus negative surprises, and whether they affect only speculative grade bonds, or also affect investment grade debt.

Datta and Dhillon (1993) began this research stream by analyzing abnormal returns for a sample of 250 large earnings surprises for 135 firms with exchange-traded bonds. They find evidence that earnings surprises have a greater valuation effect on speculative than on investment-grade debt. They do not, however, examine whether reactions differ between positive and negative surprises, and their focus on exchange-traded bonds (a relatively small portion of the corporate debt market) limits the generalizability of their findings.

Easton et al. (2009) analyze excess bond returns (bond return minus maturity and coupon-matched Treasury return) for a much larger sample of earnings announcements (10,197 bond-quarter observations). They consider quarterly and annual earnings announcements, measuring surprise using seasonal earnings differences and analyst forecast errors (AFEs). Seasonal earnings differences are not an acceptable information measure because there is no control for market expectations. Likewise, inferring a linkage between annual return and annual forecast error is problematic due to the certainty of confounding events in a year-long event window. Therefore, we focus solely on their analysis of quarterly announcements and surprises based on AFEs (panel B of their table 5). When considered independently, they find that corporate bonds' reaction to negative earnings surprises is stronger than to positive surprises and that speculative-grade bonds are more sensitive to earnings news than investment-grade ones. However, when both effects are included in the same regression specification, the statistical significance of both effects disappears, as does the significance of the overall reaction to earnings news.

Although Easton et al. (2009) seek to address the same basic research question, their results are weak and likely unreliable due to methodological flaws. First, they use Treasury-adjusted returns rather than abnormal returns. Their lack of additional controls for credit quality implicitly assumes that all bonds have expected Treasury-adjusted returns that are equal and constant across time. This assumption is incorrect in a sample containing investment-grade and speculative-grade bonds and is particularly problematic when examining whether there are differences in returns based on credit quality. Second, they treat each bond issue as a separate observation and include multiple issues from the same issuer. This approach violates the assumption of independence across observations and results in biased *t*-statistics. It also effectively overweights firms with a larger number of bond issues (Bessembinder et al., 2009). In our initial sample, the average number of issues per issuer is 9.37 for financial firms, 4.99 for utilities, and 1.34 for industrials, implying that tests based on issue-level metrics are likely skewed toward issuers in the financial and utility industries. Finally, they base their analysis on bond prices derived from insurance companies' trades as reported to the National Association of Insurance Commissioners (NAIC). These data are attractive because the coverage period is relatively long; however, representativeness is a concern because insurance companies have incentive to avoid lower rated bonds due to risk-based reserve requirements. Indeed, insurance companies own 34% of the investment-grade issues outstanding, but only 8% of speculative-grade issues (Ellul, Jotikasthira, & Lundblad, 2011). Other researchers using NAIC data eliminate speculative-grade issues entirely because transactions of insurance companies in speculative-grade bonds are unlikely to be representative of the entire market (Campbell & Taksler, 2003). Given that a key finding of Easton et al. is that the reaction to earnings news is stronger in speculative-grade bonds, their reliance on NAIC data is potentially problematic.

Finally, DeFond and Zhang (2014) examine information content of earnings announcements using risk-adjusted returns derived from quotes in Datastream.[2] They find that speculative-grade bonds react with equal intensity to the information in both positive and negative surprises in the window surrounding the announcement but find no significant reaction for investment-grade bonds. Further, they find that in the days prior to the announcement, both investment and speculative-grade bonds anticipate the information in negative surprises, but not positive ones. They also provide evidence that the reaction to negative surprises reverses in the days following the announcement, an effect they attribute to overreaction in the announcement period.

Maul and Schiereck (2017) list over 100 studies using bond prices or returns as a measure of the information content of corporate announcements. In contrast, relatively few studies employ bond trading volume as a measure of the information content of these announcements. Beaver (1968) first argued that changes in prices and volume capture different aspects of the information content of an announcement.[3] Bamber et al. (2011) review and synthesize well over 100 studies using equity trading volume as measure of the information content of accounting disclosures; recent examples of this approach include Hirshleifer et al. (2009) and Flannery et al. (2017), who use equity trading volume as a measure of the information content of earnings and Federal Reserve Bank stress test announcements, respectively.

Volume-based tests of information content are particularly suited to analyze bond markets. Cready and Hurtt (2002) show that volume-based tests are significantly more powerful than price-based ones. This greater power becomes important when examining the relatively small effects of announcements on bond values. In addition, while thin trading in many corporate bonds makes abnormal return-based analyses problematic, low (or zero) trading days still provide economically relevant information (i.e., that investors were not motivated to trade). Brogaard et al. (2019) demonstrate the value of using trading volume in their analysis of credit rating changes. They find that abnormal trading volume indicates that credit rating upgrades convey new information to bond markets, even though previous return-based work failed to find such evidence.

Instead of volume, Easton et al. (2009) examine the incidence of trade (i.e., whether there is at least one trade in a bond on a given day). They find that the incidence of trade increases following an earnings announcement, but with a delay: the largest increase in trade incidence occurs on the second day following the announcement. This increase in incidence of trade is larger following negative surprises, an effect driven entirely by speculative-grade bonds (there is no difference by surprise direction in investment-grade bonds). Because Easton et al. focus on incidence of trade rather than trading volume, they examine not the *total* information in an announcement, but instead whether the announcement contains sufficient information to induce *at least one* investor to trade.

Two other studies examine bond trading volume around earnings announcements, but address research questions that are fundamentally different from ours. Ronen and Zhou (2013) use earnings announcements to investigate the

[2] Daily prices in Datastream are primarily dealer quotes, augmented with trading prices when available. Datastream does not provide an indication of whether a reported price is an actual transaction or a quote, or given that the reported price is a quote, if the quote is based on a matrix price (Jostova, Nikolova, Philipov, & Stahel, 2013). Biases due to matrix pricing are a concern when using these data (Dick-Nielsen, 2009).

[3] Beaver (1968) argues that price changes capture the *average* change in investor expectations, while volume changes reflect the *total* change in the expectations of individual investors. An event or announcement can result in no change in the price of the firm's securities but can still cause significant changes in trading volume. To see this, consider a setting with two investors: if investor A interprets the announcement as indicating that a security is overvalued at the current price, while investor B interprets the same announcement as indicating that the same security is undervalued, trade will occur at the current price, with zero return. In this example, an event study focusing on returns would incorrectly conclude that the event contained no value-relevant information, while an analysis of trading volume would correctly identify the announcement as having value-relevant information.

informational efficiency of the bond market relative to the equity market. Hence, they examine not the overall wealth effects of earnings announcements on bondholders, but instead whether *some* bonds are on an informational par with equity. Accordingly, they examine only issuers with the most heavily traded bonds, yielding a final sample analyzing only 66 firms. Wei and Zhou (2016) also examine bond trading volume and earnings announcements but focus only on whether there is informed trading activity *prior* to earnings announcements.[4] They find that, in comparison to trading activity over the previous 3 years, insurance companies display more selling activity than buying activity for speculative grade bonds in the (−10, −1) window leading up to large negative surprises. However, because their goal is to determine whether trade is informed rather than why a bond is traded, they exclude all bonds that do not trade in the (−10, −1) window. Although this sample selection procedure is appropriate for their research question, it is inappropriate for a broader examination of the impact of earnings news on bondholder wealth.

3 | DATA AND METHODOLOGY

We collect corporate bond transactions between July 2002 and December 2014 from enhanced TRACE.[5] We remove transactions identified as primary market, when-issued or occurring on weekends or holidays, and clean corrected, canceled, and reversed transactions following Dick-Nielsen (2009, 2014). We merge the remaining transactions with descriptive data from Mergent's Fixed Income Securities Database (FISD), and retain transactions in U.S. dollar-denominated, fixed-coupon bonds with a remaining maturity between 1 and 50 years as of the transaction date. We eliminate government agency issues, as well as issues that are pass-through, pay-in-kind, asset-backed, preferred, credit-enhanced, convertible, exchangeable, putable, or callable (unless the call is make whole), and require a minimum level of liquidity by requiring each bond to be outstanding for at least 250 trading days during the sample window and trade on at least 10% of the days it is outstanding.

Following Ederington et al. (2015), we verify the match between FISD and TRACE by using the yield (price) reported in TRACE to compute the price (yield) using the maturity, day count convention, coupon rate, and payment frequency in FISD, and eliminate transactions where our computed price (yield) differs from the reported price (yield) in TRACE by more than $0.10 (10 basis points). We also remove trade reports that are both preceded and followed by a 20% or greater return reversal (Edwards, Harris, & Piwowar, 2007) and trade reports that represent a departure of more than 100% from the median of price reports for the same issue in a 21-day window centered on the trade date. Further requiring a nonmissing credit rating from either Moody's or S&P yields an initial sample of 13,798 issues by 2,368 issuers. These bonds are then used both for our sample firms and as the components of the return benchmark portfolios described below.

We measure earnings surprise by computing the median analyst earnings expectation for each firm-quarter announcement. We use the most recently released or reviewed estimate for each analyst in the Institutional Brokers' Estimate System (IBES) detail file prior to the earnings announcement date, conditional on those estimates being less than 60 calendar days old to eliminate stale forecasts. For each firm with at least three analyst earnings forecasts, AFE for firm i on announcement date t ($\text{AFE}_{i,t}$) is the difference between the actual reported earnings and the median analyst forecast, scaled by the share price at the end of the reporting period as reported in CRSP. We merge TRACE with IBES and CRSP and eliminate observations with a credit rating change by either Moody's or S&P within 50 trading days of the earnings announcement date (i.e., within the estimation period for abnormal returns/trading activity described below), resulting in an initial earnings sample of 5,079 bonds from 710 issuers.

[4] Batta, Qiu, and Yu (2016) adopt this intuition in using CDS to proxy for the pre-announcement information environment.

[5] The enhanced version of TRACE includes the full set of transactions reported to FINRA from the beginning of TRACE reporting in July 2002, including data censored in the original version of TRACE.

3.1 Abnormal return computation

Daily bond price is the trade size–weighted average transaction price for bond n on date t, $P_{n,t}$. These daily prices are the basis for the holding period return between days $t-i$ and $t+j$:

$$BR_n\left(t-i,t+j\right)=\frac{P_{n,t+j}-P_{n,t-i}+\Delta AI_n\left(t-i,t+j\right)+CPN_n\left(t-i,t+j\right)}{P_{n,t-i}+AI_{n,t-i}}, \tag{1}$$

where CPN_n is the value of any coupon paid in the window ($t-i$, $t+j$), and AI is accrued interest.[6] Abnormal bond return is then defined as:

$$ABR_n\left(t-i,t+j\right)=BR_n\left(t-i,t+j\right)-BM\left(t-i,t+j\right), \tag{2}$$

where the benchmark return, BM($t-i$, $t+j$), is the issue size–weighted average return on an industry, credit and maturity-matched portfolio over the corresponding interval. Benchmark portfolios are constructed using three industry classifications (industrial, financial, and utilities) based on issuer SIC codes, six credit classes (Aaa and Aa, A, Baa, Ba, B, and Caa through C) based on Moody's ratings (S&P if Moody's is unavailable), and four maturity classes (1 to 3 years, 3+ to 5 years, 5+ to 10 years, and greater than 10 years), yielding 24 benchmark portfolios for each industry. Bonds are eliminated from the benchmark portfolio for the 5 trading days following a rating change by either Moody's or S&P. For a valid bond-level abnormal return observation, ABR($t-i,t+j$), we require nonmissing return observations for at least five bonds in the benchmark portfolio.

Bond returns exhibit considerable heterogeneity in volatility across maturities and credit ratings; failing to control for this heterogeneity results in misspecified test statistics and a reduction in the power of tests to identify abnormal performance (Ederington et al., 2015). As such, we standardize abnormal returns using the standard deviation of abnormal return during the estimation window (−51, −11) and (11, 51) relative to each earnings announcement date. This split window utilizes data from both before and after the event date to mitigate the effect of bond aging on price volatility estimates and is limited to 40 days on each side of the event date to avoid adjacent-quarter announcement dates. For each issue with at least six nonmissing observations of ABR($t-i,t+j$) in the estimation period, we compute standardized abnormal bond return, SABR ($t-i,t+j$), as ABR($t-i,t+j$) divided by the standard deviation of ABR($t-i,t+j$) during the estimation period.

We handle missing price observations using the approach introduced by Ederington et al. (2015) and compute a composite event window abnormal return using the average of multiple holding period returns spanning the event date. For each bond on each announcement date, we compute composite abnormal bond return, ABR{−2, 2}, and composite standardized abnormal bond return, SABR{−2, 2}, as the average of all of nonmissing possible holding periods between event days $t-2$ and $t+2$ that span the event day: (−2, 2), (−2, 1), (−1, 1), and (−1, 2).[7] For example, the composite standardized abnormal return for issue n, $\text{SABR}_n\{-2, 2\}$, is

$$SABR_n\left\{-2,2\right\}=\frac{SABR_n\left(-2,2\right)+SABR_n\left(-2,1\right)+SABR_n\left(-1,1\right)+SABR_n\left(-1,2\right)}{N_{SABR}}, \tag{3}$$

where the abnormal returns in the numerator are computed following Equation (2) and N_{SABR} is the number of nonmissing window standardized abnormal returns; composite abnormal (nonstandardized) bond returns are computed

6 Bessembinder, Kahle, Maxwell, and Xu (2009) demonstrate that constructing daily prices from intraday average price (as opposed to using the last price of the day) mitigates bid–ask bounce and results in less volatile return series. Ederington, Guan, and Yang (2015) find that trade-size weighting results in a more powerful test than the alternate method of considering only institutional-sized trades (≥$100,000 par value). Small trades are likely to contain more noise, but eliminating small trades substantially decreases the number of days with a reported price and thereby sample size. In an untabulated robustness check, we confirm that our conclusions hold if only institutional-sized trades are considered.

7 Because our price observations are the weighted average of intraday prices, this is analogous to a 3-day event window return.

analogously. For each announcement date we combine these issue-level abnormal returns to form a company-level observation by computing the issue size–weighted average.

We also consider the possibility of a return reaction in the pre-announcement window that preempts the announcement period return, as well as a delayed reaction in the post-announcement window. Pre-announcement ABR{−11, −2} and SABR{−11, −2} are computed using the same methodology as announcement period returns, except the composites are created using nonmissing abnormal returns over the (−11, 2), (−10, −2), (−9, −2), (−11, −3), (−10, −3), and (−9, −3) windows. Likewise, post-announcement ABR{2, 11} and SABR{2, 11} are computed by averaging nonmissing abnormal and standardized abnormal returns over the (2, 11), (2, 10), (2, 9), (3, 11), (3, 10), and (3, 9) windows. Requiring a nonmissing composite SABR in each of the windows {−11, −2}, {−2, 2}, and {2, 11} yields a final return sample of 4,147 bonds by 635 issuers with 9,309 firm-announcement observations.

3.2 | Abnormal trading activity

We measure abnormal trading activity using the natural logarithm of (1 + turnover), where turnover is trading volume divided by total amount outstanding for the issue,[8] as the measure of trading activity because this measure has the advantage of a built-in control for issue size (Chae, 2005).[9] For each bond issue outstanding during the (−10, 10) event window relative to the earnings announcement date, abnormal trading activity for bond n on event day t ($\text{AbnormalActivity}_{n,t}$) is the level of each trading activity measure ($\text{Activity}_{n,t}$) less the average daily level of the measure over the composite estimation window (−51, −11) and (11, 51):

$$AbnormalActivity_{n,t} = Activity_{n,t} - \frac{1}{80}\left(\sum_{k=t-51}^{t-11} Activity_{n,k} + \sum_{k=t+11}^{t+51} Activity_{n,k}\right). \tag{4}$$

Like corporate bond returns, trading activity varies widely across issues. We control for this heterogeneity by standardizing issue-level trading activity using the estimation window standard deviation of trading activity in the same way we standardize abnormal returns.

Because the sample selection procedure for our investigation of abnormal return requires nonmissing returns (and therefore transactions) on multiple dates around earnings announcements, it is biased toward bonds that trade in the announcement window, and therefore inappropriate for studying abnormal trading activity. Hence, for our trading activity analysis we require each sample bond to trade on at least half of the days during the estimation windows (−51, −11) and (11, 51), but we do not impose any trade restrictions during the (−10, 10) event window. Applying this restriction to the initial earnings announcement sample yields a final trading activity sample of 3,983 bonds by 619 issuers with 10,026 firm-announcement observations.

3.3 | Descriptive statistics

Table 1 summarizes the sample distribution by year and industry for both the return and volume samples. For both samples 2002 has the fewest announcements, as it represents only the last 6 months of the year after the implementation of TRACE on July 1. The distribution of firms across industries is based on the Fama–French 12-industry

[8] Amount outstanding is adjusted for changes due to corporate actions, such as reopenings, partial calls, and so on, using historical corporate action data from FISD.

[9] For robustness, we repeat the analysis using standardized abnormal volume, standardized abnormal number of trades, and standardized abnormal turnover after eliminating interdealer trades. Our results are insensitive to the choice of trading activity measure. The full results using these measures are available from the authors on request.

TABLE 1 Sample composition

Panel A: Sample composition by year				
	Return sample		Trading activity sample	
Year	Firm-quarters	Percentage of sample	Firm-quarters	Percentage of sample
2002	286	3.1%	235	2.3%
2003	656	7.0%	703	7.0%
2004	666	7.2%	715	7.1%
2005	623	6.7%	657	6.6%
2006	605	6.5%	624	6.2%
2007	545	5.9%	598	6.0%
2008	530	5.7%	597	6.0%
2009	752	8.1%	842	8.4%
2010	902	9.7%	987	9.8%
2011	938	10.1%	1,019	10.2%
2012	902	9.7%	995	9.9%
2013	1,015	10.9%	1,110	11.1%
2014	889	9.5%	944	9.4%
Panel B: Sample composition by industry				
	Return sample		Trading activity sample	
Industry	Firm-quarters	Percentage of sample	Firm-quarters	Percentage of sample
Consumer nondurables	815	8.8%	889	8.9%
Consumer durables	131	1.4%	126	1.3%
Manufacturing	1,172	12.6%	1,270	12.7%
Energy	668	7.2%	735	7.3%
Chemicals	378	4.1%	437	4.4%
Business Equipment	778	8.4%	821	8.2%
Telecommunications	398	4.3%	367	3.7%
Utilities	612	6.6%	721	7.2%
Shops	1,076	11.6%	1,145	11.4%
Healthcare	625	6.7%	677	6.8%
Finance	1,635	17.6%	1,742	17.4%
Other	1,021	11.0%	1,096	10.9%
Panel C: Announcement descriptive statistics				
	Return sample		Trading activity sample	
	Mean	Median	Mean	Median
Earnings per share	0.74	0.60	0.73	0.60
AFE (%)	0.08%	0.05%	0.08%	0.05%
Bonds per issuer	3.60	2	3.95	2
Amount outstanding ($ thousand)	616,211	500,000	589,252	500,000

(Continues)

TABLE 1 (Continued)

Panel C: Announcement descriptive statistics				
	Return sample		Trading activity sample	
	Mean	Median	Mean	Median
Credit rating	8.45	8.06	8.56	8.67
Age	3.80	3.26	3.90	3.40
Remaining maturity	8.48	7.11	8.40	7.18

Note. In this table, quarterly earnings announcements are assigned to year based on the calendar year of the announcement date. Total sample size is 9,309 firm-quarterly earnings announcements for the return sample and 10,026 firm-quarter announcements for the trading activity sample. Sample industries are based on 12 Fama–French industry classifications. Announcement descriptive statistics are computed at the firm-quarter level. Analyst forecast error (AFE) is the difference between the actual earnings per share and the median analyst forecast scaled by the price per share as of reporting period end. Bonds per issuer are the number of individual bond issues in the firm-level composite. Issue-level characteristics in panel C are first averaged at the firm-quarter level, reported values are based on the distribution of these averages.

classification system. Financial firms represent approximately 17% of both the return and trading activity samples, followed by manufacturing firms at just under 13% of each sample.

Excluding financials and utilities is common practice because bonds in these heavily regulated industries differ from industrial bonds in their sensitivity to both idiosyncratic and systematic shocks (Elton, Gruber, Agrawal, & Mann, 2001; Kalimipalli, Nayak, & Perez, 2013). Easton et al. (2009) eliminate financial institutions but DeFond and Zhang (2014) do not, while neither eliminates utilities, which are the second-largest industry group in Easton et al. We retain these bonds in our sample to test for a differential response to earnings news by industry.

Table 1 also reports summary statistics for the earnings announcements and characteristics of the sample bonds in our return and trading activity samples. Mean and median AFEs are identical across samples. The average issuer has 3.60 (3.95) issues that meet the requirements of the return (trading activity) sample. For purposes of reporting credit quality, we convert credit ratings to a numerical scale with AAA equal to 1 and D equal to 26. The mean rating for both samples is approximately 8.5, which translates to between A– and BBB+ using the S&P scale. Amount outstanding, time since issuance, and remaining maturity are also very similar across samples.

Table 2 compares composite holding period returns and trading activity for our sample bonds to the larger group of benchmark bonds. Because of the trading restrictions we impose, our return-sample bonds are slightly more liquid than the full group of benchmark bonds: the 3-day composite return $BR\{t-2, t+2\}$ is missing on 38.63% (44.32%) of issue/trading days for our sample investment-grade (speculative-grade) bonds versus 54.73% (57.16%) of issue/trading days for investment-grade (speculative-grade) bonds in the benchmark group. A similar pattern holds in our trading activity sample: on the average trading day 55.21% (58.41%) of outstanding investment-grade (speculative-grade) bonds in the benchmark group do not trade compared to zero activity in 39.98% (47.34%) of the investment-grade (speculative-grade) bonds in the final trading volume sample. These differences are unlikely to bias our results because, as previously discussed, we adjust issue-level return and trading activity for issue-level return variability and trading activity during the estimation window.

4 | RESULTS

We begin with a univariate analysis of information content based on the direction of the earnings surprise. Panel A of Table 3 presents this analysis for abnormal return. For ease of assessing economic significance, we report both the composite abnormal return and composite standardized abnormal return (henceforth abnormal return and standardized abnormal return); however, all tests and statistical inferences are based on standardized abnormal returns.

TABLE 2 Return and trading activity measures

Panel A: Benchmark and sample return distribution										
	Benchmarks (N = 14,581,919 issue/days)					Return sample (N = 4,746,896 issue/days)				
Investment grade	Missing	Mean	P25	Median	P75	Missing	Mean	P25	Median	P75
BR $\{t-2, t+2\}$	0.5473	0.0011	−0.0032	0.0007	0.0053	0.3863	0.0010	−0.0031	0.0007	0.0050
BR $\{t-11, t-2\}$	0.5184	0.0022	−0.0035	0.0016	0.0080	0.3557	0.0021	−0.0034	0.0016	0.0078
BR $\{t+2, t+11\}$	0.5190	0.0021	−0.0036	0.0015	0.0079	0.3563	0.0020	−0.0034	0.0016	0.0077
	Benchmarks (N = 3,452,333 issue/days)					Return sample (N = 1,191,073 issue/days)				
Speculative grade	Missing	Mean	P25	Median	P75	Missing	Mean	P25	Median	P75
BR $\{t-2, t+2\}$	0.5716	0.0021	−0.0054	0.0014	0.0086	0.4432	0.0017	−0.0051	0.0012	0.0079
BR $\{t-11, t-2\}$	0.5434	0.0043	−0.0062	0.0031	0.0132	0.4120	0.0035	−0.0058	0.0029	0.0122
BR $\{t+2, t+11\}$	0.5452	0.0043	−0.0062	0.0030	0.0131	0.4135	0.0036	−0.0057	0.0029	0.0122

Panel B: Benchmark and trading activity sample distribution										
	Benchmarks (N = 14,581,919 issue/days)					Trading activity sample (N = 4,476,388 issue/days)				
Investment grade	Zero days	Mean	P25	Median	P75	Zero Days	Mean	P25	Median	P75
Volume	0.5521	2,027,335	0	128	315,715	0.3998	2,971,636	0	59,818	1,064,150
Turnover	0.5521	0.0029	0.0000	0.0000	0.0008	0.3998	0.0038	0.0000	0.0001	0.0016
# Trades	0.5521	4.44	0.00	0.01	3.81	0.3998	7.17	0.00	1.63	7.45
	Benchmarks (N = 3,452,333 issue/days)					Trading activity sample (N = 1,180,852 issue/days)				
Speculative grade	Zero days	Mean	P25	Median	P75	Zero days	Mean	P25	Median	P75
Volume	0.5841	2,054,842	0	5	375,994	0.4734	2,623,582	0	14,168	1,105,086
Turnover	0.5841	0.0042	0.0000	0.0000	0.0013	0.4734	0.0054	0.0000	0.0000	0.0025
# Trades	0.5841	3.95	0.00	0.00	3.40	0.4734	5.32	0.00	1.04	5.34

Note. This table presents distribution of return and activity measures derived from daily observations between July 2002 and December 2014. Benchmark issue statistics are based on the 13,798 bonds that meet the issue characteristic requirements. Return sample is the 4,147 issues (trading activity sample is the 3,983 issues) that meet the additional return (trading activity) sample requirements. BR$\{t-2, t+2\}$, BR$\{t-11, t-2\}$, and BR$\{t+2, t+11\}$ are composite returns created by averaging non-missing holding period returns. The return and trading activity distributions are estimated using pooled data for all issues and dates. Missing is the fraction of total return observations missing due to lack of transaction data. Zero days is the percentage of bond/trading day observations with zero trading activity.

For the entire sample, earnings announcements are accompanied by statistically significant abnormal returns in the direction of the surprise. Average abnormal return around negative (positive) news is negative 12 basis points (positive 4 basis points), while announcements that meet analyst expectations are not associated with significant abnormal returns. Partitioning by credit quality, speculative-grade bonds exhibit significant abnormal returns in the direction of both positive and negative surprises. Negative surprises are accompanied by an average abnormal return of −27 basis points and positive surprises by an abnormal return of 19 basis points. For a sense of the economic significance of these reactions, the average composite *raw* return BR$\{-2, 2\}$ for a speculative-grade bond in our sample is 17 basis points (Table 2, Panel A). Consistent with investment-grade bondholders being more sensitive to downside risk than upside potential (Goodman & Melentyev, 2017), the mean reaction to positive surprises is insignificant for investment-grade bonds, while negative surprise announcements are accompanied by a mean abnormal return of −7 basis points. This reaction to negative surprises is statistically significant and arguably economically significant in comparison to the average raw return of 10 basis points for our sample investment-grade bonds over a comparable holding period. Further, the reaction to both positive and negative surprises is larger for speculative-grade bonds (the t-statistic for the difference in mean abnormal return for investment-grade versus speculative-grade bonds is 2.24 for negative

TABLE 3 Impact of earnings announcements by surprise direction

Panel A: Return response												
	Negative surprise				No surprise				Positive surprise			
	N	ABR{−2, 2}	SABR{−2, 2}	*t*	*N*	ABR{−2, 2}	SABR{−2, 2}	*t*	*N*	ABR{−2, 2}	SABR{−2, 2}	*t*
Entire sample	2,165	−0.0012	−0.1377**	−8.06	820	−0.0003	−0.0327	−1.27	6,165	0.0004	0.0263**	2.81
Investment grade	1,597	−0.0007	−0.1123**	−6.08	688	−0.0005	−0.0550*	−1.98	5,108	0.0000	−0.0039	−0.40
Speculative grade	568	−0.0027	−0.2091^{**,b}	−5.35	148	0.0005	0.0714	1.07	1,200	0.0019	0.1548^{**,a}	5.69
Industrial	1,558	−0.0015	−0.1610**	−7.95	698	−0.0002	−0.0248	−0.93	4,806	0.0005	0.0358**	3.33
Financial	399	−0.0009	−0.0981**	−2.75	101	−0.0013	−0.0624	−0.87	1,135	0.0001	−0.0025	−0.12
Utility	208	−0.0002	−0.0391	−0.63	37	0.0011	−0.0996	−0.46	367	−0.0001	−0.0085	−0.18
Panel B: Trading activity response												
	Negative surprise				No surprise				Positive surprise			
	N	ABT(0, 1)	SABLT(0, 1)	*t*	*N*	ABT(0, 1)	SABLT(0, 1)	*t*	*N*	ABT(0, 1)	SABLT(0, 1)	*t*
Entire sample	2,357	0.0048	0.4244**	12.03	869	0.0032	0.3096**	6.36	6,800	0.0033	0.3551**	19.35
Investment grade	1,720	0.0031	0.3116**	8.45	727	0.0024	0.2555**	5.09	5,550	0.0023	0.2956**	15.58
Speculative grade	637	0.0094	0.7288^{**,a}	8.74	142	0.0070	0.5869^{**,b}	3.94	1,250	0.0074	0.6192^{**,a}	11.70
Industrial	1,678	0.0055	0.4640**	10.83	720	0.0032	0.3353**	6.23	5,165	0.0036	0.3699**	17.27
Financial	435	0.0029	0.3173**	4.17	115	0.0029	0.1740	1.28	1,192	0.0025	0.3162**	7.66
Utility	244	0.0037	0.3425**	3.29	34	0.0029	0.2258	1.21	443	0.0020	0.2863**	4.22

Note. ABR{−2, 2} is the composite abnormal bond return and SABR{−2, 2} is the composite standardized abnormal bond return; both are computed using Equation (3). ABT(0, 1) is the cumulative abnormal bond turnover and SABLT(0, 1) is the standardized abnormal log turnover computed using Equation (4) and aggregated over the announcement day and the following day. All measures are computed at the issue level, then aggregated at the firm-announcement level using an issue size–weighted average. *t*-Statistics and significance are for SABR{−2, 2} and SABLT(0,1).

** and * indicate the mean differs from zero at the 1% or 5% levels, respectively. Within credit quality (industry) groupings, [a] and [b] indicate that the mean differs from the investment grade (industrial) mean at the 1% or 5% levels, respectively.

surprises and 5.50 for positive surprises), consistent with lower credit quality bonds exhibiting greater sensitivity to firm-specific information.

We next partition our sample by industry and find a significant difference in abnormal returns: abnormal returns for industrial bonds are statistically significant for both negative and positive surprises, while abnormal returns are significant only around negative surprises for financials and are not significant for either positive or negative surprises in utilities. This muted reaction to firm-specific information for nonindustrial bonds provides further justification for the common practice of eliminating bonds from these categories in empirical fixed-income research. However, it does raise questions about recent examinations of earnings surprises in the corporate bond market: Easton et al. (2009) eliminate issues by financial institutions, but utilities constitute approximately 10% of their sample, while DeFond and Zhang (2014) retain both financials and utilities, and neither study controls for differential effects by industry.

In Panel B of Table 3, we report abnormal trading activity over the 2-day announcement window by earnings surprise direction. Except for no surprise announcements in financials and utilities, trading activity significantly increases during the announcement window for all categories of surprises. Abnormal turnover for investment-grade bonds ranges between 0.23% and 0.31%, an increase of 60–80% over the average daily raw turnover of 0.38% for comparable investment-grade issues reported in Table 2. Likewise, abnormal turnover for speculative-grade bonds ranges from 0.70% to 0.94%, implying that trading activity around earnings announcements more than doubles in comparison to the average daily raw turnover of 0.54% for these issues.[10] Further, abnormal turnover for speculative-grade bonds is roughly three times larger than that of investment-grade bonds. This difference is statistically significant at the 1% level.

We next examine whether the response differs for earnings surprises of different magnitude by partitioning positive and negative surprises into AFE quintiles, where quintile 1 (5) is the smallest (largest) surprise. Panel A of Table 4 presents the results of this analysis for abnormal returns. For the entire sample, abnormal returns around negative surprises are negative in all five surprise quintiles and increasing in magnitude almost monotonically with the magnitude of the surprise. In contrast, the abnormal return varies little in magnitude across smaller positive surprises (quintiles 1–4), becoming statistically significant only in the most extreme positive announcement quintile. Partitioning into investment-grade and speculative-grade, we find patterns that are largely consistent with those in Table 3. Investment-grade bond abnormal returns are negative and significant for at least some quintiles of negative earnings surprises but are insignificant for all positive earnings surprise quintiles. Speculative-grade bonds exhibit abnormal returns in the direction of the earnings surprise, but these returns are significant primarily in the two most extreme quintiles for both positive and negative surprises. Note, however, that AFE quintiles are based on the distribution of forecast for the entire sample, and speculative-grade issuer announcements are proportionately overrepresented in the extreme surprise quintiles. We address this issue in our multivariate analysis.

Panel B of Table 4 presents a similar analysis, but with partitions based on industry classification. The results of this analysis provide further evidence that bond market responses to earnings announcements differ significantly across industry classification. In general, significant abnormal returns are observed primarily in industrial bonds. For industrials, positive earnings surprises are associated with significant abnormal returns only in the extreme quintiles. Negative surprises are associated with negative abnormal returns that are almost monotonically increasing in the magnitude of the surprise. The relation between the magnitude of the earnings surprise and the resulting abnormal returns is much less apparent in bonds of financial firms and utilities. Financials exhibit significant abnormal returns in two of the five negative surprise quintiles (and are significant in the wrong direction in one of the positive surprise quintiles), but there is no discernable pattern between the magnitude of the surprise and the associated abnormal return. Utilities exhibit significant abnormal returns only for the most extreme negative earnings surprises.

Table 5 replicates the analysis of abnormal returns in Table 4 with an analysis of abnormal trading activity. For the entire sample, trading activity is elevated for surprises if all magnitude. This heightened trading activity is

[10] This pattern of across-the-board abnormal trading activity is consistent with the prediction of an increase in speculative trading activity in response to the resolution of informational asymmetry found in Harris and Raviv (1993) and Kandel and Pearson (1995).

TABLE 4 Return response by surprise magnitude

Panel A: By credit	Entire sample				Investment grade				Speculative grade			
AFE quintile	N	ABR {−2, 2}	SABR {−2, +2}	t	N	ABR {−2, 2}	SABR {−2, +2}	t	N	ABR {−2, 2}	SABR {−2, +2}	t
Negative surprise												
5	433	−0.0027	−0.1955**	−4.33	201	−0.0007	−0.0613	−1.10	232	−0.0045	−0.3119**,a	−4.57
4	433	−0.0017	−0.1741**	−4.80	299	−0.0013	−0.1639**	−4.10	134	−0.0026	−0.1969*	−2.58
3	433	−0.0004	−0.0835*	−2.27	338	0.0001	−0.0436	−1.08	95	−0.0022	−0.2253**,b	−2.64
2	433	−0.0006	−0.1134**	−3.20	363	−0.0010	−0.1486**	−3.81	70	0.0014	0.0691	0.84
1	433	−0.0007	−0.1220**	−3.37	396	−0.0006	−0.1247**	−3.37	37	−0.0014	−0.0940	−0.61
0	836	−0.0003	−0.0327	−1.27	688	−0.0005	−0.0550*	−1.98	148	0.0005	0.0714	1.07
Positive surprise												
1	1,261	0.0003	0.0101	0.52	1,139	0.0003	0.0087	0.44	122	0.0004	0.0235	0.30
2	1,262	−0.0002	−0.0404*	−2.03	1,101	−0.0003	−0.0369	−1.78	161	0.0001	−0.0641	−0.98
3	1,262	−0.0002	−0.0174	−0.86	1,052	−0.0003	−0.0255	−1.20	210	0.0002	0.0228	0.38
4	1,262	0.0003	0.0359	1.81	995	0.0000	0.0123	0.57	267	0.0014	0.1239*,b	2.52
5	1,261	0.0016	0.1435**	5.86	821	0.0003	0.0312	1.26	440	0.0041	0.3530**,a	6.88

(Continues)

TABLE 4 (Continued)

Panel B: By industry												
	Industrial				Financial				Utility			
AFE quintile	*N*	ABR{−2, 2}	SABR{−2, +2}	*t*	*N*	ABR{−2, 2}	SABR{−2, +2}	*t*	*N*	ABR{−2, 2}	SABR{−2, +2}	*t*
Negative surprise												
5	293	−0.0032	−0.2245**	−3.80	98	−0.0009	−0.0717	−0.89	42	−0.0034	−0.2827*	−2.08
4	285	−0.0020	−0.2111**	−4.43	94	−0.0018	−0.1586*	−2.59	54	0.0000	−0.0057	−0.03
3	298	−0.0009	−0.1379**	−3.43	87	−0.0005	−0.0778	−0.87	48	0.0030	0.2442[b]	1.69
2	339	−0.0006	−0.1087**	−2.89	57	−0.0019	−0.2024*	−2.43	37	0.0008	−0.0189	0.37
1	343	−0.0008	−0.1369**	−3.28	63	0.0010	0.0173	0.22	27	−0.0025	−0.2580	−1.55
0	698	−0.0002	−0.0248	−0.93	101	−0.0013	−0.0624	−0.87	37	0.0011	−0.0996	0.44
Positive surprise												
1	1,045	0.0002	0.0007	0.03	167	0.0004	0.0182	0.37	49	0.0021	0.1845	1.65
2	1,015	−0.0001	−0.0234	−1.11	191	−0.0007	−0.1226*	−2.14	56	−0.0009	−0.0679	−0.96
3	1,003	−0.0001	−0.0180	−0.81	175	−0.0004	0.0193	0.37	84	−0.0012	−0.0877	−0.93
4	933	0.0004	0.0505*	2.23	241	0.0003	0.0157	0.38	88	−0.0011	−0.0643	−1.03
5	810	0.0023	0.2047**	6.12	361	0.0004	0.0289[a]	0.85	90	0.0010	0.0520	0.67

Note. Analyst forecast error (AFE) is actual earnings minus the median IBES analyst forecast error, scaled by the stock price as of the end of the reporting period. AFE quintiles are defined separately for positive and negative surprises, with 5 (1) being the most (least) extreme quintile with the positive/negative surprise group. ABR{−2, 2} and SABR{−2, 2} are as described in Table 4.

** and * indicate the mean differs from zero at the 1% or 5% levels, respectively. Within credit quality (industry) groupings, [a] and [b] indicate that the mean differs from the investment grade (industrial) mean at the 1% or 5% levels, respectively.

TABLE 5 Abnormal trading activity by surprise magnitude

Panel A: By credit												
	Entire sample				Investment grade				Speculative grade			
AFE quintile	*N*	ABT (0, 1)	SABLT(0, 1)	*t*	*N*	ABT (0, 1)	SABLT (0, 1)	*t*	*N*	ABT(0, 1)	SABLT(0, 1)	*t*
Negative surprise												
5	471	0.0099	0.7675**	8.07	209	0.0053	0.5029**	4.36	262	0.0135	0.9785^{**,a}	6.84
4	472	0.0044	0.3456**	4.44	338	0.0029	0.2302**	2.97	134	0.0083	0.6366^{**,b}	3.34
3	471	0.0050	0.4081**	5.39	365	0.0037	0.3181**	3.96	106	0.0093	0.7181**	3.79
2	472	0.0023	0.2838**	4.03	386	0.0024	0.3143**	3.92	86	0.0016	0.1468	1.04
1	471	0.0026	0.3173**	4.47	422	0.0024	0.2740**	3.78	49	0.0047	0.6907*	2.52
0	869	0.0032	0.3096**	6.36	727	0.0024	0.2555**	5.09	142	0.0070	0.5869^{**,b}	3.94
Positive surprise												
1	1,360	0.0016	0.2515**	6.48	1,240	0.0016	0.2514**	6.15	120	0.0019	0.2521*	2.05
2	1,360	0.0023	0.2586**	6.77	1,188	0.0016	0.2210**	5.62	172	0.0067	0.5181^{**,b}	3.95
3	1,360	0.0028	0.3271**	8.22	1,159	0.0021	0.2659**	6.69	201	0.0067	0.6797^{**,a}	4.88
4	1,360	0.0030	0.3161**	8.19	1,084	0.0026	0.3113**	7.45	276	0.0044	0.3351**	3.48
5	1,360	0.0068	0.6221**	12.94	879	0.0044	0.4784**	9.12	481	0.0111	0.8846^{**,a}	9.28

(Continues)

TABLE 5 (Continued)

Panel B: By industry	Industrial				Financial				Utility			
AFE quintile	*N*	ABT(0, 1)	SABLT(0, 1)	*t*	*N*	ABT(0, 1)	SABLT(0 ,1)	*t*	*N*	ABT(0, 1)	SABLT(0, 1)	*t*
Negative surprise												
5	316	0.0124	0.9306**	7.33	103	0.0042	0.4642**,b	2.82	52	0.0057	0.3768*,b	2.04
4	302	0.0056	0.4492**	4.12	108	0.0025	0.1583	1.30	62	0.0021	0.1668	1.11
3	324	0.0065	0.5115**	5.31	96	0.0033	0.3302*	2.20	51	−0.0015	−0.1017[a]	−0.58
2	361	0.0016	0.1948**	2.88	63	0.0021	0.3295	1.43	48	0.0074	0.8928*	2.53
1	375	0.0025	0.3009**	3.95	65	0.0017	0.3181	1.38	31	0.0062	0.5147	1.77
0	720	0.0032	0.3353**	6.23	115	0.0029	0.1740	1.28	34	0.0029	0.2258	1.21
Positive surprise												
1	1,119	0.0015	0.2376**	5.49	183	0.0030	0.3810**	3.69	58	0.0004	0.1104	0.72
2	1,088	0.0028	0.3025**	6.83	198	0.0000	0.0483[a]	0.65	74	0.0011	0.1756	1.04
3	1,077	0.0027	0.2965**	6.85	189	0.0024	0.3628**	3.28	94	0.0043	0.6064**	3.22
4	1,002	0.0033	0.3385**	7.27	250	0.0026	0.2494**	3.17	108	0.0009	0.2626*	2.02
5	879	0.0087	0.7478**	11.85	372	0.0035	0.4480**,a	5.26	109	0.0024	0.2023[a]	1.78

Note. Analyst forecast error (AFE) is actual earnings minus the median IBES analyst forecast error, scaled by the stock price as of the end of the reporting period. AFE quintiles are defined separately for positive and negative surprises, with 5 (1) being the most (least) extreme quintile with the positive/negative surprise group. ABT(0, 1) and SABLT(0, 1) are as described in Table 4.

** and * indicate the mean differs from zero at the 1% or 5% levels, respectively. Within credit quality (industry) groupings, [a] and [b] indicate that the mean differs from the investment grade (industrial) mean at the 1% or 5% levels, respectively.

near-monotonically increasing in surprise magnitude for both positive and negative surprises, reaching its highest level in the extreme quintile (quintile 5) in both cases. For negative surprises, the trading activity response is largely consistent with the return response; however, in striking contrast to a significant return response only in the most extreme positive surprise quintile, abnormal trading activity is significant for "all" positive surprise quintiles. Partitioning on credit quality, trading activity remains elevated for all surprise quintiles in investment-grade bonds, but loses significance for small surprises in speculative-grade debt.[11] In six of the 11 partitions, abnormal trading activity is significantly larger for speculative-grade bonds than for the corresponding quintile for investment-grade.

Panel B presents analysis of subsamples based on industry classification, and further illustrates the differences between industrial and nonindustrial bonds. For industrial bonds, trading activity is elevated in all surprise quintiles, peaking at the extremes for both positive and negative surprises. Consistent with the patterns in the return analysis, the trading response is relatively muted for financials and utilities when compared with industrials. However, these subgroups also exhibit higher levels of abnormal trading activity in the more extreme positive and negative quintiles, though the response in these quintiles is significantly smaller for financials and utilities than it is for industrials.

4.1 | Regression results

We test the information content of earnings announcements while controlling for other factors in a regression framework. To test for a differential impact between negative and positive surprises, we construct a dummy variable *NEG* that is equal to 1 if *AFE* is less than 0, and 0 otherwise. We also test for a differential impact across credit quality by constructing a dummy variable *SPEC* that is equal to 1 if the average credit rating of the bonds in the firm-level composite is less than investment-grade and for industry effects using dummy variables *FINANCIAL (UTILITY)* that take the value 1 if the announcing firm is classified as a financial (utility) firm, respectively.

We control for earnings persistence and volatility following Hirshleifer et al. (2009), and include the first-order autocorrelation and standard deviation of the firm's 16 most recent quarterly earnings realization, respectively. We include analyst forecast dispersion and the natural logarithm of the number of analyst estimates as controls for the information environment prior to the announcement and annual fixed effects to account for differences across time. Standardized abnormal returns control for market performance by construction, but our abnormal trading activity measures do not. For regression specifications with an abnormal trading activity measure as the dependent variable, we include the equivalent market-level abnormal trading activity measure as an additional control variable.[12] Because earnings announcements tend to occur within a relatively short span following the end of a fiscal quarter, many announcements occur on the same calendar day. The sample also contains announcements by the same firm in different calendar quarters; accordingly, we adjust standard errors for clustering at the firm and announcement date levels using Thompson (2011) two-way clustered robust standard errors.

Table 6 presents regression results with event period standardized abnormal returns as the dependent variable in Models 1–4. The results provide strong evidence that the announcement period abnormal returns are increasing in the level of the earnings surprise: the coefficient on *AFE* is positive and significant in both a univariate specification (Model 1) and when we control for additional factors (Models 2–4). Models 2–4 provide evidence that bond price reactions are greater in magnitude for negative surprises than for positive ones. Even after correcting for the magnitude of the earnings surprise, the significant coefficient on the *NEG* dummy variable indicates that the mean standardized abnormal return over the (−2, 2) event window is lower for negative earnings surprises than for positive ones. However, in

[11] This generally lower level of statistical significance appears to be an artifact of larger standard errors for the standardized abnormal turnover in speculative-grade debt, as the magnitude of the mean abnormal turnover in each quintile is generally two or more times as high for speculative-grade debt than for the corresponding quintile for investment grade debt.

[12] Market-level abnormal trading activity is computed following the procedure for individual issues (Equation 4).

TABLE 6 Price and trading response regressions

Model:	1	2	3	4	5	6	7	8
Dependent variable:	**SABR{−2, 2}**	**SABR{−2, 2}**	**SABR{−2, 2}**	**SABR{−2, 2}**	**SABLT(0, 1)**	**SABLT(0, 1)**	**SABLT(0, 1)**	**SABLT(0, 1)**
AFE	0.1110**	0.1854**	0.1026**	0.1335**	0.2639**	0.3351**	0.2548**	0.2933**
	4.38	5.13	2.99	3.35	5.44	5.84	3.21	3.28
NEG		−0.1093**	−0.0881**	−0.1089**		0.0664	0.0637	0.0639
		−5.28	−4.31	−4.41		1.57	1.52	1.27
AFE*NEG		−0.1706**	−0.1227**	−0.1437*		0.1203	0.2199	0.1587
		−3.32	−2.77	−2.31		1.48	2.22	1.33
SPEC			0.0775**	0.0746**			0.2565**	0.2480**
			2.73	2.62			4.34	4.16
AFE*SPEC			0.1085	0.0931			0.0580	0.0331
			1.77	1.62			0.55	0.32
SPEC*NEG			−0.1575**	−0.1420*			−0.0253	−0.0381
			−2.73	−2.44			−0.23	−0.35
AFE*SPEC*NEG			−0.0712	−0.0578			−0.2952*	−0.2284
			−0.85	−0.68			−2.09	−1.54
FINANCIAL				−0.0220				−0.0673
				−0.77				−1.27
AFE*FINANCIAL				−0.0247				−0.0120
				−0.40				−0.08
NEG*FINANCIAL				0.0585				0.0169
				1.17				0.16
AFE* NEG*FINANCIAL				0.0107				0.1844
				0.12				1.00

(Continues)

TABLE 6 (Continued)

Model:	1	2	3	4	5	6	7	8
Dependent variable:	SABR{−2, 2}	SABR{−2, 2}	SABR{−2, 2}	SABR{−2, 2}	SABLT(0, 1)	SABLT(0, 1)	SABLT(0, 1)	SABLT(0, 1)
UTILITY				0.0154				−0.0121
				0.32				−0.15
AFE* UTILITY				−0.2302*				−0.2300
				−2.53				−1.68
NEG* UTILITY				0.0860				−0.0130
				1.09				−0.09
AFE* NEG* UTILITY				0.2110				0.4207*
				1.57				2.17
N	9,309	9,309	9,309	9,309	10,026	10,026	10,026	10,026
Firm clusters	635	635	635	635	619	619	619	619
Date clusters	1,890	1,890	1,890	1,890	1,927	1,927	1,927	1,927
Adjusted R^2	0.0096	0.0163	0.0195	0.0201	0.0249	0.0253	0.0312	0.0317

Note. SABR{−2, 2} and SABLT(0, 1) are described in Table 3. Analyst forecast error (AFE) is actual earnings minus the median IBES analyst forecast error, scaled by the stock price as of the last day of the reporting period. NEG is a dummy variable equal to 1 if AFE is negative, 0 otherwise. SPEC is a dummy variable equal to 1 if the weighted-average credit rating of the bonds in the firm-level composite is less than investment grade, 0 otherwise. FINANCIAL and UTILITY are dummy variables taking the value 1 if the issuer's primary SIC falls between 6000 and 6999 and 4900 and 4999, respectively, and 0 otherwise. Control variables include earnings persistence, earnings volatility, forecast dispersion, and the natural logarithm of the number of analysts following the firm. Specifications analyzing SABLT(0, 1) also control for market-level SABLT(0, 1). All specifications include year fixed effects. We calculate *t*-statistics using robust standard errors based on two-way clustering by firm and by announcement date.

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

the case of earnings disappointments, changes in the level of the earnings surprise have a much less marked effect on abnormal returns. The coefficient on *AFE* conditional on *AFE* being negative can be obtained by summing the coefficients on *AFE* and *AFE*NEG*. In Models 2–4, this reconstructed coefficient ranges from +0.0148 to −0.0201. The sum of these two coefficients (i.e., the reconstructed coefficient on AFE for negative surprises) is less than one-tenth the magnitude of the coefficient on *AFE* by itself, and is statistically insignificant (*t*-statistics for these joint tests are not included in Table 6, but range from 0.42 to −0.73). Taken as a whole, these results indicate that while mean abnormal returns are more negative for negative surprises (i.e., there is a return penalty for negative surprises), they are not affected as much by variations in the magnitude of the surprise.

Models 3 and 4 of Table 6 test for a differential reaction to earnings news across credit classes. The results of these analyses provide evidence of greater sensitivity of speculative-grade bond returns to the information in negative surprises, but little evidence of a difference in the magnitude of the overall earnings/returns relationship across credit quality. Although announcement period returns are, on average, more negative for speculative-grade bonds than for investment-grade ones, the coefficient on the interaction term, *AFE*SPEC*, is not significant in either model. Hence, contrary to the finding in Datta and Dhillon (1993) and Easton et al. (2009), we find little evidence that earnings surprises, on average, provide more value-relevant information for speculative-grade bonds. However, the coefficient on the interaction term *SPEC*NEG* indicates that the negative average return around negative earnings surprise (i.e., the return penalty for announcing negative news) is stronger for speculative-grade bonds than for investment-grade ones.

Model 4 provides evidence that the bond market reaction to earnings announcements differs across industries. The coefficient on the interaction between *AFE* and the utility indicator variable is negative and significant, indicating that positive relationship between abnormal returns and the level of earnings surprise implied by the positive and significant coefficient for AFE is muted for utility firms. Further, combining the coefficients for *AFE* and *AFE*UTILITY* yields an implied coefficient on utility firms alone of −0.0967 ($t = -1.10$). This implies that utility firms do not exhibit a statistically significant return response to earnings news.

Our regression specifications are similar to those used by Easton et al. (2009), which allows us to compare our results with theirs. In contrast to their short window findings (panel B of table 5 on p. 748 of their paper), we find that *AFE* has explanatory power for announcement period abnormal returns in every specification, even after controlling for credit quality, consistent with the hypothesis that earnings announcements convey information to the corporate bond market. After controlling for credit quality and surprise direction (their Model 4), Easton et al. find that *AFE* is no longer significant, and the interaction term *AFE*NEG* is only marginally significant ($t = 1.65$). They interpret this as evidence that “bondholders react to earnings information, particularly bad news.” More correctly, this implies that the reaction to bad news is stronger than the reaction to good news, but not necessarily that the reaction to either is statistically significant. They do not conduct a test of the joint significance of the two coefficients, but given that the two coefficients are of different signs and only one is marginally significant in isolation, it is unlikely that their sum would be significant.

As discussed earlier, focusing solely on abnormal returns around an event averages out individual trader responses and might therefore underestimate the total information content of an announcement. Therefore, we extend our analysis by examining trading responses to earnings surprises in Models 5–8. These specifications mirror regression Models 1–4, but with the announcement period cumulative standardized abnormal bond log turnover, SABLT (0,1) as the dependent variable and market-level SABLT(0,1) as an additional control variable. In these specifications, we use the absolute value of *AFE* (rather than its signed value) as an independent variable, which allows us to capture the relationship between the magnitude of an earnings surprise, regardless of its sign, and the magnitude of the trading response.

Whether alone (Model 5) or with other controls (Models 6–8), we find strong and consistent evidence that bond trading activity increases in response to earnings news. The coefficient on *AFE* is positive and statistically significant in all four specifications (*t*-statistics are in excess of 3 in all cases), indicating that there is information content in earnings surprises that is associated with a significant increase in trading activity by bond market participants. Models

6-8 examine the differential impact of positive versus negative earnings surprises. Results from these specifications provide little support for a difference in the trading activity reaction by the direction of the earnings surprise. In particular, the coefficient on *NEG* is insignificant, as is the interaction term *AFE*NEG* in two of the three specifications (it is significant at the 5% level in Model 7). These results are consistent with the positive earnings–return relation found in our returns analysis, but not with there being a differential sensitivity of trading volume to earnings surprises around negative surprises.

Models 7 and 8 test for differences in the trading activity reaction to earnings surprise announcements across credit quality. The results in these specifications provide evidence that announcement period trading activity is greater for speculative grade bonds, but the increase is in the form of an increase in the conditional mean trading activity, rather than a higher sensitivity of trading volume to earnings surprises. Finally, Model 8 tests for a difference in trading response by industry. The industry interaction terms (*AFE*FINANCIAL* and *AFE*UTILITY*) are statistically insignificant, indicating that the magnitude of the trading response does not differ in the magnitude of *AFE* across industries. However, the reconstructed *AFE* coefficient of 0.0633 for utility firms (*AFE* + *AFE*UTILITY*) is insignificantly different from zero ($t = 0.48$), indicating that utilities do not exhibit announcement period trading activity that is increasing in the magnitude of the surprise.

In summary, contrary to the results of DeFond and Zhang (2014), we find that earnings announcements contain value-relevant information for *both* investment-grade and speculative-grade bonds. Although average trading volume is significantly higher in speculative-grade bonds, abnormal returns and trading activity are positively associated with the magnitude of the earnings surprise for both. Consistent with the nonlinear payoffs faced by bondholders, negative earnings surprise announcements are associated with more negative abnormal returns than positive surprises; however, these announcements do not result in a greater degree of trading activity. Further, we find that speculative–grade bonds react more strongly to earnings surprises than do investment-grade ones. And finally, we find evidence that bonds of utility firms react to earnings surprises differently than industrial bonds.

4.2 | Extended event window

DeFond and Zhang (2014) present evidence that negative earnings surprises are partially anticipated in the speculative-grade bond market, a result supported by evidence that speculative-grade corporate bond prices impound negative information substantially before equity prices (Bittlingmayer & Moser, 2014). In this case, considering only the abnormal return and trading activity in the short window immediately around the announcement understates the magnitude of the information conveyed. On the other hand, DeFond and Zhang (2014) also find evidence that speculative-grade bonds overreact to earnings announcements during the pre-announcement and announcement periods and that abnormal returns during these periods partially reverse during the post-announcement period. If the same pattern holds in our data, we would see a reversal in the post-announcement window. A third possibility, consistent with Easton et al. (2009)) finding that the propensity to trade peaks on the second trading day after earnings announcements, is that search frictions caused by the over-the-counter structure of the corporate bond market cause a delay in the bond market's reaction to earnings. In this case, we would observe a continuation of the announcement period results in the post-announcement period. We repeat our analysis for the 10-day pre-announcement period leading up to our announcement period windows, as well as the corresponding 10-day post-announcement windows. For brevity's sake, we only report specifications that control for differences in credit quality and industry.

Table 7 presents results of our pre- and post-announcement period analyses.[13] We test Models 1 and 2 for an anticipation effect in the pre-announcement period. The results of these analyses differ somewhat from those found in DeFond and Zhang (2014). The positive coefficient on *AFE* in both the abnormal return and trading activity models is

[13] Because of the construction of the SABR measures, SABR{−11, −2} in Model 1 covers the same 10-day period ending 1 day before the announcement as SABLT(−10, −1) does. Likewise, SABR{2, 11} and SABLT(2, 10) both cover the same 10-day period beginning 2 days after the announcement.

TABLE 7 Extended window regressions

	Pre-announcement period		Post-announcement period	
Model:	**1**	**2**	**3**	**4**
Dependent variable:	**SABR{−11, −2}**	**SABLT(−10, −1)**	**SABR{2, 11}**	**SABLT (2, 10)**
AFE	0.1135*	0.3004*	0.0552	0.2670*
	2.29	1.83	1.50	1.67
Neg	0.0323	0.1806	−0.0177	0.2189**
	1.24	1.63	−0.68	1.98
AFE*Neg	−0.0797	0.3146	−0.0578	0.2321
	−1.19	1.57	−1.22	1.07
Spec	−0.0388	0.3249**	−0.0680*	0.2821**
	−1.40	2.42	−2.37	2.05
AFE*Spec	−0.0944	−0.3239	0.0194	−0.2223
	−1.79	−1.63	0.39	−1.22
Spec*Neg	−0.0097	−0.5711**	0.0608	−0.3368
	−0.16	−2.57	1.06	−1.48
AFE*Spec*Neg	0.1161	0.1875	0.0088	0.0486
	1.60	0.78	0.14	0.19
Financial	−0.0160	−0.0425	−0.0308	0.0101
	−0.67	−0.35	−1.22	0.10
AFE*Financial	−0.0217	−0.0754	0.0726	−0.2179
	−0.38	−0.36	1.25	−1.00
Neg*Financial	−0.0834	−0.1667	0.0823	0.0690
	−1.48	−0.67	1.75	0.29
AFE*Neg*Financial	−0.0646	−0.1071	−0.0771	0.2550
	−0.77	−0.41	−1.18	0.86
Utility	0.0411	0.1577	−0.0212	0.0175
	0.95	0.95	−0.33	0.09
AFE*Utility	−0.2370**	0.2727	−0.0354	0.3296
	−2.72	0.89	−0.52	0.89
Neg*Utility	−0.0609	0.2284	0.0565	0.3806
	−0.82	0.75	0.61	1.12
AFE*Neg*Utility	0.2058	−0.1462	0.0721	−0.0533
	2.27	−0.46	0.75	−0.14
N	9,309	10,026	9,309	10,026
Firm clusters	635	619	635	619

(Continues)

TABLE 7 (Continued)

	Pre-announcement period		Post-announcement period	
Model:	**1**	**2**	**3**	**4**
Dependent variable:	**SABR{−11, −2}**	**SABLT(−10, −1)**	**SABR{2, 11}**	**SABLT (2, 10)**
Date clusters	1,890	1,927	1,890	1,927
Adjusted R^2	0.0025	0.0171	0.0066	0.0221

Note. SABR{−11, −2} is the pre-announcement and SABR{2, 11} is the post-announcement firm-level composite standardized abnormal return computed as described in Section 3.1. SABLT(−10, −1) is the pre-announcement and SABLT(2, 10) is the post-announcement cumulate abnormal log turnover computed as described in Section 3.3. Analyst forecast error (AFE) is actual earnings minus the median IBES analyst forecast error, scaled by the stock price as of the end of the reporting period. Neg is a dummy variable equal to 1 if AFE is negative, 0 otherwise. SPEC is a dummy variable equal to 1 if the weighted-average credit rating of the bonds in the firm-level composite is less than investment grade, 0 otherwise. Financial and Utility are industry dummy variables based on the issuer's primary SIC. Control variables include earnings persistence, earnings volatility, forecast dispersion, log number of estimates, and year fixed effects. Specifications analyzing SABLT also control for market-level SABLT over the same period. Robust standard errors are corrected for two-way clustering by firm and by announcement date.
** and * indicate significance at the 1% and 5% levels, respectively.

consistent with DeFond and Zhang's finding that bond markets anticipate the information in earnings releases. However, in contrast to DeFond and Zhang, the interaction terms *AFE*SPEC* and *AFE*SPEC*NEG* are insignificantly different from zero, providing no evidence that the effect is concentrated in speculative-grade issues or speculative-grade issues with impending negative surprises. Models 3 and 4 conduct similar examinations for post-announcement reactions. In Model 3, the coefficients for *AFE* and all interactions with *AFE* are insignificant, providing no evidence of an overreaction and subsequent reversal of returns to the news in earnings. In contrast, Model 4 provides support that trading activity continues to respond to earnings after the initial announcement. Specifically, post-announcement trading remains positively related to the magnitude of the earnings surprise and is higher for speculative-grade bonds as well as for firms reporting negative news.

5 | ROBUSTNESS CHECKS

5.1 | Impact of crisis periods

Our sample spans two unusual periods for the bond market: the automotive and financial crises. To determine whether these periods drive our results, we separately analyze noncrisis announcements and those occurring during the automotive crisis (January 2005–July 2005) or the financial crisis (July 2007–September 2009). Table 8 presents evidence that rather than driving our results, crisis periods weaken them. Specifically, statistical significance for all variables disappears in the abnormal return regression (Model 3 vs. Model 1) and is generally lower in the cases it remains in the trading activity regressions (Model 4 vs. Model 2).

5.2 | Alternative return and trading activity measures

We include all trades when computing the daily trade size–weighted average price to maximize sample size; however, this also means including smaller transactions that are noisier and characterized by higher transaction costs (Edwards et al., 2007). We test the sensitivity of our results to the inclusion of small transactions by repeating our

TABLE 8 Impact of crisis periods

	Not crisis period		Crisis period	
Model:	1	2	3	4
Dependent variable:	SABR{−2, +2}	SABLT(0, 1)	SABR{−2, +2}	SABLT(0, 1)
AFE	0.1502*	0.3838**	0.0963	0.1498
	2.28	3.82	1.34	1.31
NEG	−0.1284**	0.0454	−0.0174	0.1541
	−4.63	0.74	−0.32	1.55
AFE*NEG	−0.1862*	0.1033	−0.0335	0.3003*
	−2.27	0.62	−0.32	2.39
SPEC	0.0620	0.2372**	0.0996	0.2988*
	1.95	3.63	1.30	1.99
AFE*SPEC	0.1183	−0.0232	0.0573	0.1153
	1.35	−0.20	0.69	0.70
SPEC*NEG	−0.1275*	−0.0229	−0.2216	−0.1020
	−2.10	−0.19	−1.51	−0.37
AFE*SPEC*NEG	−0.1301	0.0054	0.1073	−0.7729**
	−1.18	0.03	0.82	−2.60
FINANCIAL	−0.0218	−0.0818	0.0222	−0.0149
	−0.71	−1.33	0.27	−0.12
AFE*FINANCIAL	−0.0783	0.0052	0.0948	−0.0725
	−0.96	0.03	0.90	−0.41
NEG*FINANCIAL	0.0755	0.0672	−0.0105	−0.2450
	1.35	0.55	−0.09	−1.00
AFE*NEG*FINANCIAL	0.1421	0.2096	−0.1966	−0.0647
	1.23	0.96	−1.54	−0.32
UTILITY	0.0175	0.0273	0.0107	−0.1817
	0.27	0.29	0.08	−0.94
AFE*UTILITY	−0.3565**	−0.3363*	0.1502	0.1629
	−2.64	−2.50	0.42	0.38
NEG*UTILITY	0.0688	−0.0396	0.2179	0.1087
	0.88	−0.26	0.82	0.28
AFE*NEG*UTILITY	0.3870*	0.5103*	−0.2794	0.1258
	2.16	2.50	−0.73	0.25
N	7,571	8,110	1,738	1,738
Firm clusters	612	605	374	368

(Continues)

TABLE 8 (Continued)

	Not crisis period		Crisis period	
Model:	**1**	**2**	**3**	**4**
Dependent variable:	**SABR{−2, +2}**	**SABLT(0, 1)**	**SABR{−2, +2}**	**SABLT(0, 1)**
Date clusters	1,490	1,512	400	415
Adjusted R^2	0.0210	0.0291	0.0320	0.0485

Note. Crisis period announcements are earnings reported on dates during the automotive crisis (January 2005–July 2005) or the financial crisis (July 2007–September 2009). SABR{−2, 2} and SABLT(0, 1) are described in Table 4. Analyst forecast error (AFE) is actual earnings minus the median IBES analyst forecast error, scaled by the stock price as of the last day of the reporting period. NEG is a dummy variable equal to 1 if AFE is negative and 0 otherwise. SPEC is a dummy variable equal to 1 if the weighted-average credit rating of the bonds in the firm-level composite is less than investment grade and 0 otherwise. FINANCIAL and UTILITY are dummy variables taking the value 1 if the issuer's primary SIC falls between 6000 and 6999 and 4900–4999, respectively, and 0 otherwise. Control variables include earnings persistence, earnings volatility, forecast dispersion, log number of estimates, and year fixed effects. We calculate *t*-statistics using robust standard errors based on two-way clustering by firm and by announcement date.
** and * indicate significance at the 1% and 5% levels, respectively.

primary analysis using only institutional-sized trades (par value ≥ $100,000). In untabulated results, we find that our primary results are robust to this modification. Positive surprises remain associated with abnormal returns that are increasing in the level of the surprise, while negative surprises remain associated with a return penalty that is not a function of the surprise magnitude and earnings news continues to be less informative for utility and financial bonds.

We focus our trading activity analysis on cumulative standardized abnormal log turnover in the 2-day announcement window. In untabulated results, we consider alternative measures and find that all our conclusions are robust to other measures of trading activity including announcement day turnover, turnover computed using only transactions where the reported counterparty is a customer (as opposed to another dealer), abnormal volume, and abnormal number of trades.

5.3 | Evidence from credit default swaps

Although our primary interest is the impact of earnings news on the corporate bond market, the credit default swap (CDS) market represents an alternative venue where credit-related information may be revealed. In our final robustness check, we collect daily CDS premia for January 2002–December 2014 from Bloomberg and estimate the abnormal change in CDS premia during the ($t-1$, $t+1$) earnings announcement window. Because CDS premia are available only for companies with existing CDS contracts, a relatively small subset of the universe of firms with bond issues (Friewald, Jankowitsch, & Subrahmanyam, 2012), this results in a smaller sample of 2,522 quarterly earnings announcements by 289 firms.

The results of this analysis, presented in Table 9, show that the response in the CDS market closely tracks our result from the bond market. CDS premia increase (credit risk rises) around negative earnings surprises and decrease around positive surprises. This reaction is not limited to speculative-grade issuers; both the investment-grade and speculative-grade subsamples display significant abnormal CDS premia changes in the direction opposite the surprise. We also find additional support for an industry effect; the change in CDS premia is statistically significant only for industrial firms, with no evidence of a CDS market reaction for financials and utilities.

TABLE 9 Announcement period CDS premia changes

	Negative surprise			No surprise			Positive surprise		
	N	ΔCDS(−1, 1)	*t*	*N*	ΔCDS(−1, 1)	*t*	*N*	ΔCDS(−1, 1)	*t*
Entire sample	214	1.32%**	2.45	51	0.75%	1.02	2,257	−0.72%***	−5.23
Investment grade	153	1.11%*	1.73	34	0.15%	0.23	1,787	−0.48%***	−2.99
Speculative grade	61	1.84%*	1.84	17	1.95%	1.10	470	−1.63%***	−6.46
Industrial	173	1.77%***	3.08	45	0.85%	1.16	1,834	−0.89%***	−6.53
Financial	22	−0.10%	−0.05	4	0.30%	0.06	230	−0.37%	−0.92
Utility	19	−1.18%	−0.72	2	−0.76%	−0.60	193	0.52%	0.65

Note. ΔCDS is the abnormal change in 5-year CDS premium in the announcement window, computed as the percentage change in the 5-year CDS premium during the 3-day announcement window (−1, 1) less the average 3-day percentage change in the 5-year CDS premium over the estimation period (−50, −11) relative to the earnings announcement date.
***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

6 | CONCLUSIONS

Numerous studies examine either abnormal returns or trading activity in equity markets around earnings announcements. Due to a combination of data restrictions and methodological limitations, similar studies in bond markets are much less common. Only a handful of studies examine abnormal bond returns around earnings announcements, and there are currently no comprehensive, market-wide analyses of trading volume around these events. We take advantage of the near-exhaustive data available in TRACE, improvements in event-study methods, and uncensored bond trading volume data in enhanced TRACE to conduct the first comprehensive examination of bond market reactions to earnings announcements encompassing analyses of both abnormal returns and trading activity.

Our results provide evidence that earnings announcements convey significantly more information to bond markets than previously believed. In contrast to Easton et al. (2009) and DeFond and Zhang (2014), we find that earnings announcements convey value-relevant information for *both* investment-grade and speculative-grade debt. In a univariate setting, we show that abnormal returns are statistically significant in the direction of the surprise for both positive and negative surprises for speculative-grade bonds, but only for negative surprises in investment-grade bonds. Extending the analysis to a multivariate setting, we find that the form of the return response differs by the direction of the surprise. Positive surprises are associated with abnormal returns that are increasing in the magnitude of the surprise, with no difference in the magnitude of the response by credit quality. In contrast, negative surprises are associated with a negative mean return that does not vary with the magnitude of the negative surprise. Further, this return penalty associated with negative news, while larger for speculative-grade debt, is present in both investment-grade and speculative-grade bonds. We also provide evidence that the information content for bonds issued by firms in the financial and utility industries is significantly muted in comparison to bonds issued by industrial firms.

There are several potential explanations for our differing results. First, controlling for heteroskedasticity in bond-level abnormal returns results in higher test power that allows us to identify effects that earlier studies could not. Second, our sample contains actual trade data for the universe of over-the-counter transactions rather than dealer quotes (Defond & Zhang, 2014) or insurance company trades (Easton et al., 2009). Third, we control for a differential reaction by companies in heavily regulated industries. In contrast, Easton et al. (2009) exclude financial institutions but include utilities, while Defond and Zhang (2014) include both industries. Our analyses suggest that including these firms could induce sample-selection issues and noise due to these issuers typically having large numbers of issues and relatively muted reactions to earnings announcements. Taken together, these factors bias previous studies against finding results for positive earnings surprises and/or investment grade debt.

We confirm the abnormal return results with, what to our knowledge, is the first comprehensive analysis of bond trading activity around earnings announcements in the corporate bond market. This analysis of abnormal trading activity provides further evidence that earnings news is value-relevant for both investment-grade and speculative-grade bonds. Specifically, earnings announcements are associated with abnormal trading activity that is increasing in the magnitude of the surprise across both credit quality classes, although the overall level of abnormal trading activity is higher for speculative-grade debt. The muted abnormal return response to earnings news for bonds from financial and utilities issuers is also confirmed by a smaller increase in trading activity in bonds issued by these firms.

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