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Trade and information in the corporate bond market[☆]

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Abstract

This paper examines the impact of shifting liquidity and institutional trading in the corporate bond market on inferences regarding informational efficiency. We find that when institutional trade dominance and other bond trading features are accounted for, stock leads evidenced in earlier studies surprisingly disappear. Short windows after firm-specific news releases are examined, and bond trading advantages are shown to be pronounced particularly when equity market liquidity is low (during after-market hours). Cross-sectionally, the effect of credit risk and other firm/bond level characteristics are determined. Finally, 'top bonds' are identified, and their common ex ante identifiable characteristics are determined.
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1. Introduction

The market efficiency of corporate bonds has not been established in the literature without controversy. Indeed, there are seemingly conflicting results (and hence conclusions) regarding the market efficiency of corporate bonds. In this paper, we demonstrate that the lack of consensus regarding bond market efficiency can be reconciled when bond market liquidity patterns and other institutional features specific to the bond market are explicitly considered. Specifically, we examine the importance of incorporating these features when examining efficiency and the extent of price discovery of corporate bonds, as well as for the comparison of informational efficiency across markets in general. First, since for any given firm there typically is a multiplicity of bond issues, examining the efficiency of a firm's bonds in pair-wise comparisons with the issuer's stock can lead to misleading inferences, as liquidity and informed trading in different issues may differ cross-sectionally and over time. Second, the corporate bond market in the United States has been shown to have a dominant institutional presence, with potential trade disadvantages for retail traders. Since retail trades account for about 65% of transactions (but represent only 1.8% of volume), tests that do not differentiate between the two trading sectors may artificially magnify the effect of potentially noisier retail trades. Third, the around-the-clock corporate bond market may provide an important informational role when the equity market displays low liquidity and poor price discovery. The impact of these observations can be significant not only when examining the efficiency of the market in isolation (or relative to that of equity market), but can also contribute to recent advances in corporate bond liquidity research.

On a methodological note, this paper aims to address some of the difficulties inherent in the comparison of informational efficiency across markets. Analysis in early studies that has focused on the relative informational efficiency of the bond and equity markets using a Vector Autoregression (VAR) approach based on pair-wise comparisons of each bond with the issuer's stock can be misleading. Resulting inferences are limited, in that they cannot reveal more than whether the firm's bonds are on average slower in reflecting information than the firm's stock. Further, inferences regarding this 'average' are predicated on the implicit assumption that liquidity and trading activity of the issuer's bonds are immediately comparable both across bonds and uniformly with the equity. As the variation in both of these is known to be considerable, relying on an average may create a bias towards finding a stock lead. In fact, accounting for dynamic liquidity, trade size and timing effects can generate surprising reversals of previously documented results: Granger-causality tests indicate that stock leads disappear, and that bond efficiency can be deemed comparable to that of the equity.

More importantly, these tests cannot uncover the information most desired by traders (i.e., whether there are some bonds on an informational par with equity). Further, if these bonds switch off over time, such liquidity patterns cannot be captured by pair-wise comparisons within a time series framework. Indeed, we find that institutional trade in a firm's bonds following earnings announcements is highly concentrated in certain issues. We define the bond with the highest institutional trade volume immediately following an earnings announcement (and before NYSE market open) as the 'top bond' for the firm. We show that the identity of these top bonds changes over time, and that they share common characteristics, such as age, maturity, credit quality, and bond complexity. Moreover, their identity can be predicted ex ante based on these common characteristics, and a logistic model yields a fairly high degree of out-of-sample predictive accuracy.

Notably, the majority of price discovery for these bonds occurs before the equity market opens. These results point to the importance of conducting efficiency analysis that incorporates both the intraday trading patterns and the dynamic liquidity of different bonds issued by the same firm. Ignoring such factors underestimates the ability of a trader to move on firm-specific information using a fixed income instrument.

We examine trading and price discovery at short time windows around earnings announcements and find that information incorporation patterns differ systematically across different traders and bonds. Tests conducted on samples that are pooled across trade sizes are shown to yield results driven by the predominant (in terms of frequency) noisy small trades, thereby masking informational efficiency. This result holds even after we account for the potentially confounding effect of a few large issuers dominating the bond market, the timing of earnings announcements, and issuer and issue characteristics. Further, we find that the nature of information impacts the way in which it is impounded into prices, with patterns differing on good and bad news days. Finally, BBB-rated bonds with imminent downgrades (within one year) display rapid reactions to news, on a par with high-yield issues.

Opportunities to preempt equity traders may exist immediately after earnings announcements, which most often occur overnight. While equity traders are relatively liquidity-disadvantaged in the market for NYSE-listed stocks during these hours, the around-the-clock over-the-counter bond market provides a useful vehicle for trading on information. This is particularly true for institutional bond traders who are shown to be dominant players in this market. In fact, our collective results are indicative of strategic information-based trading. Since increasing benefits or stakes should encourage greater information gathering/absorption for large traders, situations that offer bond traders comparative advantages should be marked by a greater propensity to trade. The ability of bond investors to trade in large amounts, particularly when liquidity is low in the equity market, renders the corporate bond market a legitimate vehicle for information revelation.

We also examine the timing of the earnings announcements and its relationship to the intraday distribution of trades. We find some evidence that bad news gets released later in the early morning hours, closer to market open, than good news. Even after controlling for announcement times, we find evidence of bond trades occurring significantly before regular trading hours for some bonds and news events.

On a policy note, the comparative advantages of institutional traders can be potentially mitigated by decreasing the permissible trade reporting lag for dealers. We find evidence of increased price discovery accompanying TRACE reporting lag window decreases implemented in a phased-in fashion over our sample period. Specifically, retail trade disadvantages are alleviated in that price dispersions decrease with the regulatory changes, suggesting that additional reductions in mandatory reporting windows could further improve terms of trade for retail investors.

This paper is organized as follows. Section 1 discusses and reviews some salient characteristics of corporate bond market trade and illustrates the importance of incorporating liquidity and trading patterns in empirical tests of bond market efficiency. Section 2 describes the TRACE data used in this study and provides evidence regarding the distribution of institutional trades in our sample. Section 3 uses a VAR approach to revisit the lead-lag relations between stocks and bonds, and illustrates the importance of explicitly accounting for shifting liquidity and other bond trading patterns in statistical analysis. Section 4 examines overnight liquidity and weighted price contributions. We identify common salient characteristics of top bonds and discuss their link to liquidity and ex ante determination. We present our predictive model and out-of-sample tests for a priori identification of top bonds. Section 5 analyzes the effect of trade size, as well as the firm-level and bond-specific features on the sensitivity to information. Additionally, we examine the impact of the timing of earnings announcements on the reaction to information. Section 6 concludes.

2. Liquidity and trade size effects in the corporate bond market

While it is a largely accepted fact that the U.S. corporate bond market operates differently from equity markets, the literature documenting these differences, particularly with regard to the patterns and behavior of prices and trades, is decidedly thin. Still, some pivotal differences have been established. For example, corporate bonds tend to trade in substantially larger amounts, and less frequently, than do the stocks issued by the same firms. Institutional corporate bond trades have been shown to often be at least 50 times as large as a typical stock exchange transaction.

Considerable evidence exists documenting liquidity patterns for corporate bond trades that differ substantially from those for stocks, in that bond investors typically engage in ‘buy and hold’ strategies. Schultz (2001), for example, shows that after bonds are absorbed into portfolios, their liquidity rapidly declines. This is particularly true for investment-grade bonds, which are believed to be purchased primarily as non-speculative investments, are expected to be priced within a narrow range of the correct value, and are generally considered easy substitutes for portfolio management needs (Warga, 2004). Once bonds are absorbed into portfolios, liquidity tends to rapidly decline. See Alexander, Edwards, and Ferri (2000), Schultz (2001), Warga (2004), Goldstein and Hotchkiss (2007), Mahanti, Nashikkar, Subrahmanyam, Chacko, and Mallik (2008), and Bao, Pan, and Wang (2011), among others, who provide evidence that bond liquidity is negatively related to age. Although overall trading activity is considered to be relatively low in corporate bonds, Dick-Nielsen, Feldhutter, and Lando (2011) show that there is usually at least some bond for each issuer trading at a given time.

Corporate bond dealers often specialize in offering highly ‘bundled’ portfolio services, such as solving portfolio, research, and strategy problems.[2] Edwards and Nimalendran (2007) find evidence of market segmentation, with dealers often trading only large- or small-sized trades, but not both. In addition, institutional bond investors include investment companies, pension funds, and hedge funds who potentially dominate smaller investors both in their ability to acquire/process information and in their institutional relationships with bond dealers. Such advantages could result in differential informational impacts for large and small corporate bond trades, which in turn may differ from equity trade reactions. In the absence of explicit information regarding the wealth maximization functions of institutional versus retail investors, certain conjectures can be made. In particular, the sheer quantities institutions buy for their fixed income portfolios may have larger consequences to their portfolio returns than the more modest transactions made by individual diversified traders. Hence, the benefit to

[2]See Saunders, Srinivasan, and Walter (2002) for a thorough description of the institutional bond dealer market. They find the market to be very competitive, with inter-dealer brokers who maintain both sides of the market while providing trader anonymity. Bond traders generally initiate contact with other institutional traders or brokers with potential interest in a particular bond, who in turn submit quotes, which are not legally binding but reputation constrained. Bid response time is usually as quick as less than 1–2 minutes, particularly when both parties are familiar with the bond and when it has no special provisions.

institutional traders, not only from gathering information, but from also quickly interpreting and acting on it, is potentially larger than that for retail investors.

When bonds do trade, they appear to do so in larger chunks and less frequently than stocks. However, the relatively lower trading frequencies observed in the bond market (as compared to equity markets) are not necessarily indicative of inefficiency. Infrequent but large trades may reflect investors waiting for relevant and material information, and then rapidly acting on it in large blocks. Thus, the lack of trade on a particular day does not necessarily imply a lack of efficiency, and the resulting trading frequency differences between equity and bond markets may yield different results regarding market quality measures. For example, unlike in the equity markets, trading costs and liquidity for corporate bonds do not seem to decline with trading activity. That is, the fact that corporate bond trades tend to be more clustered and less frequent than equity trades does not imply lower market quality. See Edwards, Harris, and Piwowar (2007), who find a significant relationship between transaction costs and trading activity only for the most active bonds, which exhibit the highest trading costs, especially when the trades are retail sized.[3]

Several papers examining corporate bond prices document different levels of spreads for retail and large trades, with a negative relationship between trade size and trading costs. Edwards, Harris, and Piwowar (2007) find one-way transaction costs of 7 basis points for \$2 million trade sizes and 4 basis points for \$5 million, similar to Bessembinder, Maxwell, and Venkataraman (2006), who find one-way transaction costs of about 6–7 basis points for their mean trade size of \$3 million. Saunders, Srinivasan, and Walter (2002) find that large-block (over \$10 million) trades are not associated with negative price impacts, implying that they most likely are not associated with adverse market information and do not impose liquidity constraints on dealers. Goldstein, Hotchkiss, and Sirri (2007) find for their sample of BBB-rated bonds that "spreads fell markedly as trade size increases, with median costs of 0.34 per \$100 of face value for institutional trades over 1000 bonds (\$1 million face value), as compared with median costs of \$2.13 per \$100 of face value for trade sizes of 10 or fewer bonds." The authors attribute this disparity to either a high fixed cost level for small trades, or to retail investors being relatively uninformed, thereby susceptible to larger dealer rents. Finally, Schultz (2001) finds that all else equal, corporate bond spreads decrease with trade size, dealer size, and how active the institution is. See also Hong and Warga (2000), Chakravarty and Sarkar (2003), and Warga (2004).

This combined evidence suggests that dealers are more likely to lose money on the lower spread large trades and less likely to offer good pricing on small bond orders. Green, Hollifield, and Schürhoff (2007a) estimate a structural bargaining model to show that dealers exercise substantial market power. In Green, Hollifield, and Schürhoff (2007b), the same authors show that small newly issued municipal bond trades occur at a wide range of prices almost simultaneously, with some small investors trading at prices as much as 5% away from those of informed traders, and others who appear informed trading on attractive terms. Relatedly, Goldstein and Hotchkiss (2007) find different price dispersions for large and small trade sizes in the corporate bond new issues aftermarket. Finally, Biais and Green (2007) show that the migration of liquidity in corporate bond trading volume

[3]Trading activity for a bond in Edwards, Harris, and Piwowar (2007) is defined as follows: Low trade activity bonds are those with one or fewer trades per week, medium trade activity bonds are those with between one transaction per week and one transaction per day, and high trade activity bonds are defined as those with more than one transaction per day.

increased dramatically in periods when institutional investors and dealers gained importance relative to retail investors. The authors suggest that this migration may have increased transaction costs for retail investors.[4]

3. Data description

On July 1, 2002, NASD (FINRA as of July 2007) initiated TRACE, an automated trade reporting system for corporate bonds. This over-the-counter corporate bond market real-time dissemination service is the first to provide comprehensive, real-time access to public corporate bond transactions. Trade information can be accessed by individual investors (both retail and institutional) and market professionals, and covers all OTC activity, which represents over 99% of domestic corporate bond market activity.[5]

For TRACE transactions disseminated from January 1, 2003 to December 31, 2006, we obtain descriptive firm characteristics (Compustat) and bond characteristics/credit rating changes (Mergent FISD). We partition the sample into four S&P credit rating categories (AAA/AA, A, BBB, and BB and lower), and sort bonds within each credit rating category by descending trading volume over the entire sample period. We then select the 30 distinct issuers for the highest volume ranked bonds for each category. Finally, for these 30 firms in each credit category, we then include all bonds issued throughout the class period, regardless of volume. Since the bonds issued by some firms span more than one credit rating category, some issuers may be identified as having the most active bonds across multiple rating categories, resulting in a total of 103 unique issuing firms. The data are then restricted to include only those 66 firms with publicly traded equity for which we can identify time stamped earnings announcements, such as to allow comparisons on corporate news days across bonds and stocks issued by the same firm. We obtain analysts' earnings forecast data from IBES and earnings announcement time stamps from Factiva. For the 16 quarters and 66 firms in our sample, we are able to identify exact time stamps for 951 of the 1,056 announcements. For 833 of these cases, we observe bond trades during the day following the news release.

We exclude all trades that occur in the first three months of issuance for each bond (see Goldstein and Hotchkiss (2007) for a discussion on newly issued corporate bonds). The final sample of 8,400,190 transactions in 8,470 bonds represents nearly 50% of all TRACE trades over the 4-year sample period.[6] Stock transaction data are obtained from the TAQ database. Summary characteristics for the sample bonds and their issuing firms are presented in Table 1. The mean offering amount is over $193 million dollars, and increases with credit quality. Forty-three percent of bonds are issued with long term maturities, 44% with medium-term maturities, and the remaining bonds are issued as short-term instruments.

[4]Guo, Sarkar, and Schuermann (2007) show that the market compensates retail traders in the corporate bond market for the greater illiquidity of their trades. They illustrate the importance of accounting for investor heterogeneity in understanding the determinants of credit risk.

[5]Fully so since February 7, 2005. This includes all U.S. dollar-denominated debt securities that are eligible under rule 11310(d). Specifically excluded are exchange trades in listed bonds, mortgage- and asset-backed securities, debt issued by government sponsored entities, collateralized mortgage obligations, and money market instruments.

[6]Following Edwards, Harris, and Piwowar (2007), we implement certain data filters. Trades occurring in 2002 are excluded to avoid the potentially confounding effects of system initiation related behavior; canceled, reversed, and delay-reversed prior day transactions are deleted. Also all trades with price deviations from surrounding trades greater than 10% are removed.

Table 1
Characteristics of sample corporate bonds and issuing firms.

This table contains descriptive information about the 8,470 bonds issued by the 66 firms in our sample. The financial characteristics of the issuing companies are compiled from Compustat. Bond characteristics are obtained from Mergent FISD. A straight bond is defined as one that has a fixed coupon rate and no embedded options (callable, convertible, putable, pay-in-kind, sinking fund provisions, or other complexities). Bonds issued with maturities of over 10 (under 3) years are classified as long (short) term bonds, with the remainder defined as medium term. Credit rating partitions are created by identifying the number of bonds in a particular rating at any given point of time within the sample period.

	Bond composition		Offering amount ($ Million)		Coupon rate (%)		Original maturity (%)			Straight bonds	Issuer total assets ($ Million)		Issuer total liabilities/total assets		Age (year)		Time to Maturity (year)	
	#	%	Mean	Median	Mean	Median	Long	Medium	Short	%	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Whole sample	8,470		193.65	15.00	5.12	5.35	43.29	44.49	12.22	37.84	148,981.98	40,587.50	0.79	0.80	3.85	2.92	5.90	2.57
AAA & AA	2,218	26.19	261.76	18.26	4.65	4.85	42.38	49.73	7.89	34.17	312,893.76	149,725.00	0.79	0.85	3.71	2.77	6.78	3.08
A	3,060	36.13	198.41	14.35	4.89	5.30	52.25	38.01	9.74	46.34	233,745.29	96,175.00	0.79	0.84	3.74	2.93	7.50	4.01
BBB	990	11.69	203.76	9.26	5.25	5.30	29.60	49.70	20.71	19.39	190,070.73	46,342.80	0.76	0.75	3.98	2.98	3.79	0.62
BB & lower	2,115	24.97	101.71	15.27	5.84	6.00	36.97	46.34	16.69	38.35	141,501.72	13,170.00	0.88	0.85	3.99	2.95	3.65	1.76

Sixty-two percent of bonds in the sample have at least one embedded option attached. The distribution of bonds across credit ratings is as follows: approximately 26% have a rating of AAA or AA, 36% are rated A, 12% are rated BBB, and 25% of bonds are in the BB or lower rating categories. The average age of a bond (calculated as the average over the 5-year period) is nearly 4 years, with an average maturity of 6 years. On average, the maturity of low-rated bonds is shorter than that of the higher-rated bonds in our sample.

Table 2 provides detailed information by issuer for each of the 66 firms in our sample. Bond concentration, defined as the number of bonds per firm as a percentage of all bonds in the sample, is shown to vary across issuers, with General Motors, General Electric, Ford Motor Company, Bank of America, and American Insurance Group representing the highest concentrations (17.69%, 11.31%, 8.51%, 8.50%, and 7.11%, respectively). Industry concentration of bonds also varies across firms, with 12 of the 66 firms' bonds fully represented by the three-digit finance industry SIC code. Average daily bond trading volume per bond is $24.94 million, ranging from $3.37 to $86.27 across firms.

The distribution of bond transactions across institutional and retail-sized trades is presented in Table 3. Trades are classified as institutional (retail) if their par value is greater than (less than) $500,000.[7] Retail trades are nearly seven times more prevalent than institutional trades, accounting for almost 87% of the total number of trades in our sample, but account for at most 11% of total trading volume. Institutional trading volume is expected to be even higher than this figure suggests, and perhaps substantially so. We cannot identify this number since reported TRACE volume is capped at $5 ($1) million for investment-grade (high-yield) issues.

4. Do stocks really lead bonds?

The extant literature provides mixed results on the lead-lag relationship between individual stocks and bonds, with recent evidence pointing to significant stock leads. Specifically, while Hotchkiss and Ronen (2002) find no causal relation between stock and bond returns, Downing, Underwood, and Xing (2009) find that stocks lead bonds using a comprehensive sample of TRACE bonds and infer therefore that the corporate bond market is less informationally efficient than the stock market.[8]

In this section we reconcile previously mixed results by showing that when bond market-specific features are properly accounted for, inference reversals are obtained, and the finding of relative bond market inefficiency disappears. Specifically, we illustrate the importance of accounting for several methodological issues. First, studies that exclude all overnight bond trades are shown to be inherently biased towards ignoring the relative efficiency of bonds. Second, pooling retail and institutional trades in this predominantly institutional market can confound inferences, and third we conduct VAR tests focused specifically around corporate earnings announcements, when information effects should be heightened.

[7]Other cutoff points such as $100,000, $250,000 or $1,000,000 are also considered but do not yield qualitatively different results. Warga (2004) defines retail trades as those that are less than or equal to $100,000 par value, and institutional as above $500,000. We set the cutoff arbitrarily high in order to avoid erroneously misclassifying retail trades as institutional ones.

[8]Gurun, Johnston, and Markov (2008) find evidence of stock leads for equally-weighted indices of daily bond returns. However, information events (sell side debt research reports) reduce the stock leads significantly. Also, Kwan (1996), who finds evidence of stock leads for bonds (using weekly quote level data), infers only that "stocks lead in reflecting firm specific information."

Table 2
Summary statistics of bond characteristics by issuer.

This table presents summary information on the bonds issued by each of the 66 sample firms. Bond DIST is the number of bonds issued by the firm as a percentage of all bonds in our sample. Finance Industry is defined as the percentage of the issuer's bonds that are classified as finance industry. Special Features refer to the share of the issuer's bonds that carry at least one embedded option. We also provide the median credit rating (Rating) average age (Age), time to maturity (Term), issue size, coupon rate, daily trading volume (VOL), daily number of trades and number of days traded per quarter.

Firm	No. of bonds	Bond DIST	Rating	Age year	Term year	Issue size $ M	Coupon %	VOL $ M	Daily # trades	Days Traded	Finance Industry	Special Features
Alcoa	17	0.20%	A	7.06	3.90	418.63	6.84	17.33	4.36	26	0.00%	47.06%
AEP	41	0.48%	BBB	6.76	7.59	175.89	6.31	12.25	2.14	10	0.00%	34.15%
AIG	602	7.11%	AA	2.75	2.50	82.35	4.13	8.08	2.34	9	48.34%	35.88%
AK Steel	2	0.02%	B	5.73	3.80	500.00	7.81	37.61	9.88	54	0.00%	0.00%
Allstate CP	31	0.37%	AA	3.65	8.12	387.42	5.42	23.44	2.92	24	100.00%	29.03%
Amgen	6	0.07%	A	4.74	25.42	1397.58	3.91	86.27	6.27	29	0.00%	33.33%
Amazon	2	0.02%	B	7.64	2.10	1250.00	4.75	30.43	7.80	56	0.00%	0.00%
American Express	75	0.89%	A	1.89	2.36	456.88	4.35	46.65	2.45	14	100.00%	6.67%
Boeing	179	2.11%	A	4.84	3.73	68.30	5.12	6.13	2.34	11	91.62%	60.89%
Bank of America	720	8.50%	A	3.51	11.75	105.51	5.24	5.81	2.49	14	100.00%	60.42%
Best Buy	2	0.02%	BBB	4.36	15.29	447.45	1.13	43.52	4.88	29	0.00%	0.00%
Bear Sterns	347	4.10%	A	2.80	8.81	103.47	4.61	13.25	2.21	10	100.00%	48.70%
Citi Group	236	2.79%	AA	6.49	3.97	493.75	5.80	24.66	3.30	21	100.00%	45.34%
C.I.T. Group	359	4.24%	A	2.38	3.49	137.06	4.50	8.40	2.73	13	100.00%	81.89%
Conocophillips	5	0.06%	A	2.29	8.55	800.00	5.05	30.39	5.94	45	40.00%	0.00%
Chevron Texaco	21	0.25%	AA	10.92	9.58	368.81	7.15	12.57	3.25	21	0.00%	52.38%
Dobson Communications	8	0.09%	CCC	2.17	7.08	373.13	8.66	23.52	4.06	29	0.00%	12.50%
Daimler Chrysler	536	6.33%	BBB	2.77	3.01	74.57	4.70	3.37	2.16	8	99.44%	1.49%
E. I. Dupont	22	0.26%	A	6.96	14.56	302.21	5.74	12.33	4.27	25	0.00%	50.00%
Walt Disney	21	0.25%	A	6.08	14.21	491.67	6.03	28.42	5.16	34	0.00%	42.86%
EchoStar Communications	7	0.08%	BB	2.74	3.54	882.40	7.54	24.58	4.88	42	0.00%	0.00%
Duke Energy	38	0.45%	BBB	5.92	9.96	326.88	5.98	15.51	3.04	27	0.00%	47.37%
Electronic Data	8	0.09%	BBB	4.33	8.65	625.09	6.02	39.69	5.95	32	0.00%	37.50%
Ford	721	8.51%	B	3.75	2.94	129.01	5.59	6.88	4.10	17	95.42%	34.67%
Sprint	24	0.28%	BBB	9.06	6.34	808.00	7.12	49.50	6.54	33	54.17%	41.67%
GE	958	11.31%	AAA	3.03	9.78	182.48	4.73	9.90	2.82	14	99.69%	40.08%
Genzyme	2	0.02%	BBB	3.13	16.49	632.50	2.13	49.66	7.34	39	0.00%	0.00%
GM	1498	17.69%	BB	3.92	3.31	69.43	5.68	3.73	3.39	20	98.87%	41.86%
Goodyear Tire	9	0.11%	B	4.89	7.98	316.67	8.20	13.39	6.80	39	0.00%	44.44%
Halliburton	9	0.11%	BBB	7.34	17.43	362.40	6.22	31.87	3.32	26	0.00%	55.56%
Home Depot	6	0.07%	A	2.42	3.29	1164.83	5.14	57.32	17.03	52	0.00%	50.00%

Table 2 (*continued*)

Firm	No. of bonds	Bond DIST	Rating	Age year	Term year	Issue size $ M	Coupon %	VOL $ M	Daily # trades	Days Traded	Finance Industry	Special Features
IBM	65	0.77%	A	4.99	5.69	242.69	4.35	10.21	3.29	18	0.00%	63.08%
International Paper	31	0.37%	BBB	9.40	8.30	357.25	6.67	24.65	2.66	19	0.00%	38.71%
Johnson & Johnson	8	0.09%	AAA	7.95	14.53	511.09	4.72	13.17	3.88	34	0.00%	50.00%
JP Morgan	202	2.38%	A	4.06	7.60	343.32	4.25	18.41	3.15	19	100.00%	18.81%
James River Coal	2	0.02%	CCC	1.60	5.43	150.00	9.38	23.16	6.85	37	0.00%	0.00%
Kraft Foods	10	0.12%	BBB	6.08	5.14	970.00	5.06	48.46	9.59	54	0.00%	10.00%
Kinder Morgan	12	0.14%	BBB	6.21	18.12	410.40	6.48	26.63	3.55	25	25.00%	41.67%
Lear	4	0.05%	B	4.75	6.30	610.00	5.46	53.95	6.69	32	0.00%	0.00%
Lehman Brothers	340	4.01%	A	2.76	9.44	146.10	4.64	13.16	2.65	12	100.00%	12.06%
LSI Logic	2	0.02%	B	3.82	1.69	420.00	4.00	15.23	5.39	41	0.00%	0.00%
Level 3 Communications	15	0.18%	CCC	3.94	3.64	648.19	8.98	23.38	6.31	34	0.00%	13.33%
Lyondell	14	0.17%	BB	5.28	4.67	539.86	9.34	18.09	4.84	34	0.00%	35.71%
Merrill Lynch	361	4.26%	AA	3.06	3.38	245.03	4.14	23.25	2.53	12	100.00%	15.51%
Altria Group	16	0.19%	BBB	8.91	4.35	506.25	7.07	25.11	8.73	44	0.00%	62.50%
Merck	20	0.24%	AA	5.15	24.95	250.54	4.97	16.64	3.56	20	0.00%	20.00%
Morgan Stanley	172	2.03%	A	3.48	3.94	517.46	4.09	27.18	3.39	18	100.00%	14.53%
Northwestern Airlines	38	0.45%	CCC	7.16	7.27	160.82	8.31	21.85	3.63	16	0.00%	2.63%
Nextel Communications	10	0.12%	BBB	3.54	6.28	1195.78	7.52	60.42	12.07	41	0.00%	30.00%
P G & E	23	0.27%	AAA	8.45	12.25	364.35	6.87	13.76	2.81	18	0.00%	8.70%
Procter and Gamble	24	0.28%	AA	7.16	18.10	429.64	5.96	16.25	4.23	28	0.00%	29.17%
Primus Telecommunications	5	0.06%	CC	4.02	3.33	189.70	7.45	20.88	4.72	23	0.00%	0.00%
Qwest Communications	40	0.47%	BB	9.50	11.70	600.78	7.24	12.34	2.87	28	0.00%	30.00%
Revlon	2	0.02%	CCC	1.62	4.26	310.00	9.50	17.28	5.01	46	0.00%	0.00%
A T & T	45	0.53%	BBB	8.78	7.82	849.94	7.70	26.34	5.12	27	0.00%	53.33%
Target	31	0.37%	A	9.24	9.07	356.47	7.22	12.04	4.50	29	0.00%	67.74%
Tenet Healthcare	9	0.11%	CCC	3.64	7.26	688.69	7.32	26.88	5.08	39	0.00%	11.11%
Triton PCS	3	0.04%	CCC	4.66	5.16	491.67	8.88	54.49	7.02	36	0.00%	33.33%
Triquint Semi -conductors	2	0.02%	NR	6.63	0.17	345.00	4.00	3.77	4.53	51	0.00%	0.00%
US Bankcorp	97	1.15%	AA	4.21	2.99	515.81	4.26	38.87	2.11	14	100.00%	38.14%
Visteon	3	0.04%	CCC	4.72	3.62	550.00	7.73	61.61	9.38	40	0.00%	0.00%
Verizon	133	1.57%	A	9.61	10.01	392.96	6.74	14.08	5.50	31	0.00%	59.40%
Wells Fargo	161	1.90%	AA	4.23	3.60	530.30	4.57	18.24	2.91	20	100.00%	21.74%
Walmat	35	0.41%	AA	7.19	4.95	832.38	5.96	31.12	7.42	36	0.00%	45.71%
Weyerhaeuser	18	0.21%	BBB	8.70	9.98	530.00	6.94	23.81	3.41	27	0.00%	38.89%
Exxon Mobil	5	0.06%	AAA	14.06	6.68	720.79	5.88	14.60	4.85	19	60.00%	60.00%
Mean	128	1.52%		5.38	7.75	467.54	5.99	24.936	4.85	28	28.98%	29.72%
Standard Deviation	130	1.54%		5.35	7.81	468.29	5.98	25.053	4.86	28	29.42%	29.45%

Table 3
Percentage of large and small trades in corporate bonds.

This table presents the relative incidence of large and small trades, both in terms of number of trades and trading volume. A trade is classified as 'large' if it is $500,000.00 in par value or greater. Percentages are calculated for our sample as well as for the entire TRACE universe during the sample period (2003–2006). Bonds that are unrated (by S&P), or are in default are absent from credit rating partitions. TRACE volume is capped at $5($1) million for investment-grade (high-yield) issues.

	Number of Trades					*Trading Volume*				
	All Trades	*Small Trades*		*Large Trades*		*All Trades*	*Small Trades*		*Large Trades*	
	(*in 1000s*)	(*in 1000s*)	*as % of all*	(*in 1000s*)	*as % of all*	(*$ Billion*)	(*$ Billion*)	*as % of all*	(*$ Billion*)	*as % of all*
TRACE Universe	17,042.80	13,564.60	79.59	3,478.20	20.41	7,729.45	659.62	8.53	7,069.83	91.47
Whole Sample	8,400.19	7,303.23	86.94	1,096.97	13.06	2,832.21	312.97195	11.05	2,519.23	88.95
AAA & AA	1,681.45	1,477.21	87.85	204.25	12.15	569.34	69.894324	12.28	499.45	87.72
A	2,566.25	2,226.15	86.75	340.11	13.25	960.28	102.07156	10.63	858.21	89.37
BBB	2,221.06	1,905.84	85.81	315.23	14.19	977.09	76.936667	7.87	900.16	92.13
BB & lower	1,899.97	1,671.72	87.99	228.24	12.01	309.48	63.012943	20.36	246.47	79.64

Moreover, we show that the bivariate VAR approach may not always be optimal in addressing the informational efficiency of the corporate bond market. Pair-wise comparisons of each bond (or alternatively, a portfolio of bonds) with the issuer's stock can be misleading, since they cannot indicate more than whether the firm's bonds on average lag stocks. Specifically, the ability of a trader to act quickly upon information in the bond market with one or a few of an issuer's bonds is masked, yielding potentially confounded inferences. Thus, the VAR approach may not reveal the information most desired by traders in this context (i.e., whether or not there is at least one bond constituting an information-based trading venue).

We first analyze the effect of excluding overnight bond trades (those occurring before equity market open) in the VAR tests, such as in those of Downing, Underwood, and Xing (2009). The potential bias this may introduce against finding relative bond market efficiency can be exacerbated on days when information is released overnight, particularly if overnight bond trading is higher when overnight announcements are released. Panel A of Table 4 does in fact document significantly larger overnight bond trading volume and frequency on days with earnings announcements (vs. those without). The number of institutional trades before the market opens is more than double on these days. An illustrative graph of trading activity immediately surrounding news releases is presented in Fig. 1, which plots trading activity around all earnings announcements for two bond/stock pairs (issued by Ford and GM).[9] Institutional bond trading volume and frequency are both elevated immediately after announcements, with subsequent monotonic decreases. Most notably, large trade volumes appear to pre-empt both their equity and retail bond trade counterparts.

In order to examine the impact of these methodological issues on the inferences obtained from such VAR tests, we begin by conducting a benchmark test corresponding to Downing, Underwood, and Xing (2009). We estimate a bivariate VAR on the returns of each issuer's stock and most liquid bond.[10]

$$R_{s,t} = \alpha_s + \sum_{i=1}^{I} \beta_{s,s}^{i} R_{s,t-i} + \sum_{i=1}^{L} \gamma_{s,b}^{i} R_{b,t-i} + \varepsilon_{s,t}, \tag{1}$$

$$R_{b,t} = \alpha_b + \sum_{i=1}^{I} \beta_{b,s}^{i} R_{s,t-i} + \sum_{i=1}^{L} \gamma_{b,b}^{i} R_{b,t-i} + \varepsilon_{b,t} \tag{2}$$

where $R_{s,t}$ ($R_{b,t}$) represents the return on the stock (bond) at time t.[11] Tests are conducted at both the hourly and 15-minute return horizon frequencies.[12]

[9]Both plotted issues (Ford 345370CA6 and GM 370442BT1) correspond to the illustrative examples chosen for the VAR analysis presented. They constitute the most active issues for these firms, capturing 7.47% (5.99%) of trade over the sample period for Ford (GM). The firms' 734 (1,515) bonds display striking differences in liquidity and trading frequency patterns, with the 10 most active Ford (GM) bonds accounting for 51.98% (32.31%) of the issuer's bond trades.

[10]Hotchkiss and Ronen (2002) and Zhou (2009) first test these relationships, but due to data constraints in those studies, stock returns are matched with the returns of an issuer's very liquid high-yield bond and therefore are not directly subject to the trading frequency concerns raised here.

[11]The Akaike Information Criterion (AIC) determines lag length choice. Different lag lengths are considered, with qualitatively similar results. We present the results using $I=10$ for the hourly regressions (and the comparable $I=40$ for the shorter horizons) for direct comparison with previous studies. Missing prices are backfilled to maintain full specification. Finally, the above analysis is constrained to data from Ford and GM and as such is illustrative in nature.

[12]Since intraday interest rates are not available, we do not incorporate them here. However, earlier studies using longer horizons have found qualitatively similar results for returns that account for interest rate movements.

Table 4
Overnight Bond Trade on Information/Non-information Days. This table summarizes corporate bond trading activity during both earnings announcement days and non-earnings announcement days. For each firm or bond, we calculate the overnight total trading volume, total number of trades and number of large trades (greater than $0.5 million) per each of the 833 announcement dates, and report the mean and median values across earnings announcement and non-announcement days. The results are presented at both the firm and bond levels in Panel A. Panel B presents the percentage of overnight trade for each hour. Panel B: Percentage of overnight trade by hour.

Panel A: Corporate bond trading activity during earnings announcement days and non-earnings announcement days

	Earnings Announcement Days		*Non-Earnings Announcement Days*		*Tests on Difference*	
	Mean	*Median*	*Mean*	*Median*	*t-test*	*Wilcoxon test*
Firm Level:						
Average Overnight Volume Per Firm ($ Million)	22.446	6.229	9.926	1.156	6.55***	15.22***
Average Overnight Number of Trades Per Firm	36.734	12.000	22.348	5.000	4.19***	13.68***
Average Overnight Number of Large Trades Per Firm	9.524	3.000	3.790	1.000	7.01***	13.80***
Bond Level:						
Average Overnight Volume Per Bond ($ Million)	1.027	0.085	0.214	0.028	5.28***	15.70***
Average Overnight Number of Trades Per Bond	1.218	0.296	0.400	0.153	4.88***	14.52***
Average Overnight Number of Large Trades Per Bond	0.780	0.038	0.116	0.007	4.46***	13.66***
Number of Observations	838		66,508			

Panel B: Percentage of overnight trade by hour.

	Earnings announcement Days				*Non-earnings announcement days*			
	Volume (%)	Volume of Large Trades (%)	Number of Trades (%)	Number of Large Trades (%)	Volume (%)	Volume of Large Trades (%)	Number of Trades (%)	Number of Large Trades (%)
0	0.09	0.11	0.24	0.09	0.22	0.21	0.42	0.18
1	0.02	0.03	0.07	0.03	0.15	0.15	0.12	0.14
2	0.09	0.12	0.12	0.08	0.22	0.21	0.17	0.22
3	0.29	0.27	0.31	0.31	0.42	0.39	0.36	0.41
4	0.31	0.35	0.53	0.27	0.58	0.55	0.49	0.56
5	0.39	0.40	0.39	0.34	0.61	0.58	0.47	0.58
6	1.15	1.28	0.66	1.00	1.49	1.52	0.63	1.33
7	8.68	7.77	4.28	8.13	5.99	6.30	3.20	5.74
8	29.88	25.85	17.66	31.26	22.69	23.52	13.59	22.55
9	22.03	20.17	15.48	22.94	18.74	19.20	13.49	19.21
16	27.29	32.44	47.95	25.68	38.58	37.04	54.27	39.10
17	9.21	10.38	10.86	9.22	9.09	9.12	11.11	8.81
18	0.45	0.57	1.03	0.54	0.76	0.74	1.30	0.78
19	0.04	0.10	0.28	0.05	0.20	0.20	0.23	0.19
20	0.00	0.00	0.06	0.00	0.04	0.04	0.07	0.03
21	0.03	0.05	0.03	0.01	0.08	0.09	0.04	0.06
22	0.00	0.07	0.03	0.00	0.06	0.07	0.02	0.05
23	0.04	0.03	0.02	0.05	0.07	0.07	0.03	0.07

We do conclude, as did Downing, Underwood, and Xing (2009) for their sample, that stocks lead bonds when we implement their sample truncations and aggregations. We begin with our Ford and GM bond/stock pairs as an initial illustrative example and then expand the analysis for the full sample of bonds.[13] Panel A of Table 5 shows that using all sized trades for both our Ford and GM pairs, hourly lagged stock returns Granger cause current bond returns but not vice versa. For example, Panel A of Table 5 shows that for Ford, the *p*-value for the *F*-test of $\beta^i_{b,s} = 0\ \forall\ i \in [1,...,I]$ is less than 0.0001 while the bond return is not found to Granger-cause the stock return at any reasonable level of significance (with a *p*-value of 0.2913). Similar results are obtained for the 15 minutes interval returns.

However, inference reversals are obtained when we recognize the distinction between the institutional and retail bond market sectors. Specifically, the conclusion that stocks lead bonds *disappears* for the large-sized bond trade sample, and we now find a two-way lead-lag relationship, with the null hypothesis that lagged returns of institutional bond trades have no explanatory power for current stock returns rejected at the 1% level. These inference reversals persist even after the exclusion of after hour trades, highlighting the importance of accounting for institutional trades in the testing procedure.[14] While past bond returns based on trades of all sizes do not explain current stock returns, past bond returns from large-sized trades do, indicating that at least some bond trades of a particular issuing firm react as quickly as the firm's equity. Hence, the conclusion that the entire bond market is less efficient is premature at best.

The illustrative example above sets the stage for the bivariate VAR analysis conducted on the full sample. We first conduct a test similar to Downing, Underwood, and Xing (2009), by matching each bond with the issuer's stock for each of the 66 firms.[15] Bond returns are calculated using all-sized trades (excluding overnight trades). The results are summarized in Panel B of Table 5. Consistent with the findings in Downing, Underwood, and Xing (2009), the coefficient of the lagged stock returns and bond returns exhibit significant variations across bonds. Granger causality tests indicate that over 63% of the time, there is no lead-lag relationship between stocks and bonds, and a two-way lead-lag relationship is observed 5.77% of the time. More importantly, stocks lead the bonds 23.69% of the time, compared to a mere 7.82% of times in which the bonds lead.

We now re-estimate the model, accounting for the methodological issues raised above. We examine the lead-lag relationships using hourly stock and bond returns over the five days following each of the 833 earnings announcements over the four-year period.[16] In addition to incorporating overnight trades and trade size effects, we also account for the shifting liquidity patterns in bonds issued by the same firm. Since some bonds issued by a

[13] Ford and GM represent the two most bond market active issuers throughout the sample period, jointly constituting 19.5% of all trades reported on TRACE. The two bonds chosen, CUSIP 345370CA6 for Ford and CUSIP 370442BT1 for GM, represent actively traded bonds that have no embedded options, a 30-year original maturity, maturities of 20–25 years, and mixed ratings during our sample period.

[14] Relatedly, Boehmer and Kelley (2009) show that stock prices become more efficient with increased institutional trading.

[15] We impose a liquidity inclusion filter requiring bonds to trade at least once a week. This yields a sample of 663 bond firm pairs. The bivariate VAR model is estimated on the stock and bond daily returns, for each pair over the four-year sample period, with lag length set to five days (as in Downing, Underwood, and Xing (2009)).

[16] In this test, as well as in the illustrative example, we differentiate across institutional and retail trade sizes for the bonds but do not do so for the equity transactions. Since equity price impacts are high for large trades, order splitting would render this difficult at best. Finally, the focus here is restricted to showing that inference reversals occur when certain bond market features are accounted for.

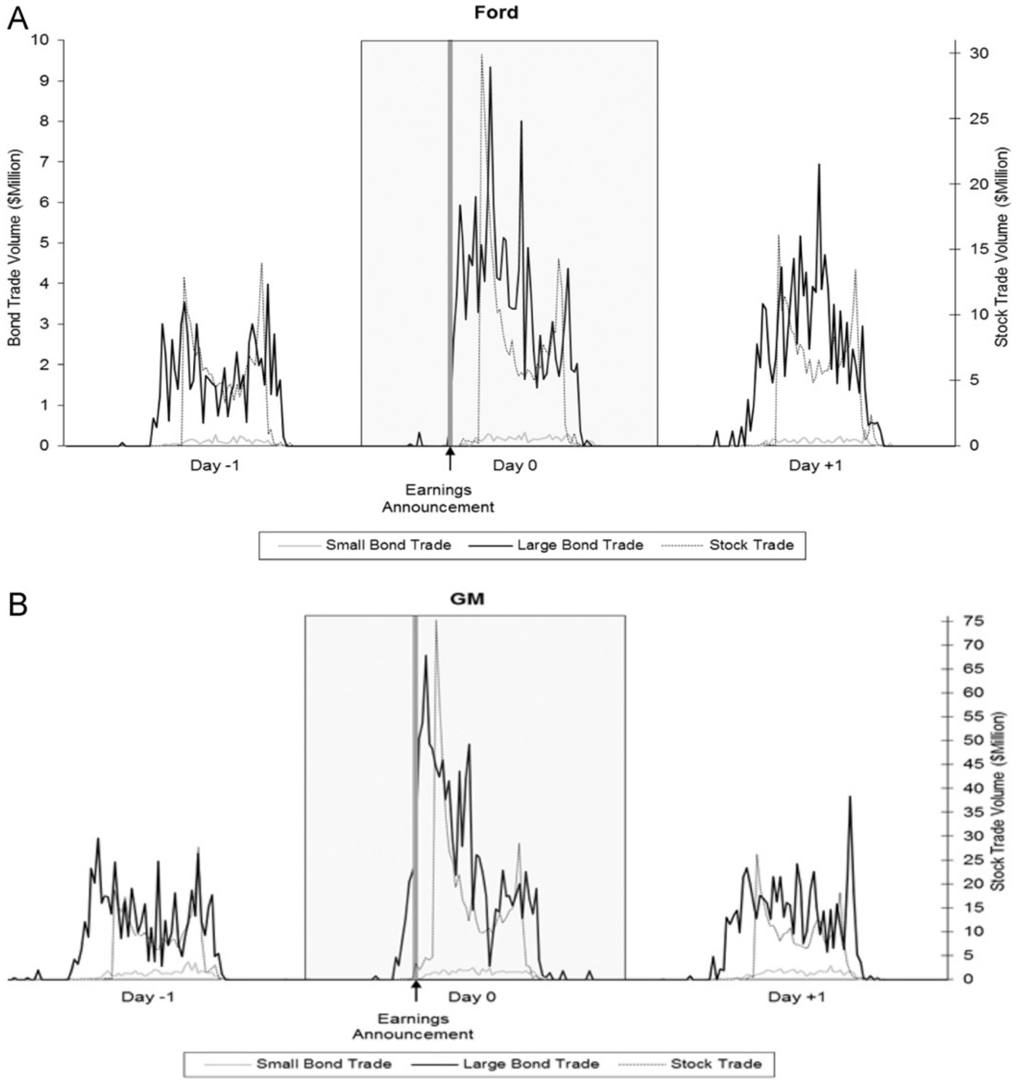

Fig. 1. Trading volume of corporate bonds and stocks. This figure describes trading patterns for the stock and one corporate bond each of two issuing firms (Ford and GM) in three-day windows around the firms' earnings announcements over the sample period. Total dollar trading stock volumes are plotted against the right vertical axes. Total dollar volumes of large and small bond trades for Ford 345370CA6 and GM 370442BT1are plotted against the left vertical lines. The highlighted box areas correspond to earnings announcement days. Panel A: Trading patten for the stock and one bond of Ford in the three-day window around its earnings announcements. Panel B: Trading patten for the stock and one bond of GM in the three-day window around its earnings announcements.

firm will trade more actively than others, the inclusion of all bonds in the tests can confound the relative informational efficiency of one or a few more active bonds versus the equity of the same firm. Each issuing firm's stock is matched with the issuer's single bond that attracts the highest concentration of large trades immediately following each earnings announcement (top bond). We find that institutional-sized trades exhibit informational efficiency comparable to that of the equity (see Panel C in Table 5). Specifically, Granger causality tests reveal that these bond trades lead stocks in 16.43% of all firm/earnings announcements, while stocks lead bonds in 17.39% of cases, significant at the 5% level. In 62.80% of cases, there is no lead-lag relationship indicated; 3.38% of the time, two-way causality prevails.

5. Overnight information and liquidity

5.1. Top bonds

The results above illustrate that the corporate bond market can serve as an important venue for information-based trading pre-open, immediately after most earnings announcements are released. We also find that some bonds attract more order flow than others after announcements, with notably distinct patterns of large institutional trades clustering in one or few bonds issued by the same firm. Panel A of Table 6 presents basic statistics on all top bonds in our sample. On average, a firm's top bond attracts roughly 71% of institutional trades immediately after earnings announcements are made, both in terms of the number of trades and dollar volume. The top three bonds account for a combined 95% of institutional trade. Interestingly, the 'top' role for an issuer's bonds shifts across issues over time. We find that 63% of our top bonds are 'one-hit wonders' (shift off their role after one announcement). An additional 18% act as top bonds twice, with 89% maintaining their position for less than (or at most) three quarters.

Certain common characteristics are determined to be associated with top bonds. Seventy-six percent of the time, the top bond has the longest original maturity of those TRACE bonds issued by the same firm. In a vast majority of the cases (91.37% overall, and 94.37% for firms that only have investment-grade bonds trading on announcement days), the leading bond is also the most recently issued, (with an average age of 2.9 years ranging from 3 months to 17 years). This last finding extends upon evidence that corporate bonds trade actively only for the first few months after issuance and then display decreased liquidity.[17] Since our sample is constrained not to include the first three months of a bond's issuance, our results reveal that corporate bonds may continue trading actively beyond this limit, after certain information events.[18] In over 80% of the cases, the top bond is both a long-term bond and that is most recently issued. Further, the top bond has at least one attached embedded option in about 85% of the cases. Finally, the average top bond offering amount is $1,261.52 million, compared to an average offering amount of $193.65 million for the whole sample. This is not inconsistent with documented positive links between issue size and liquidity, such as in Alexander, Edwardsw, and Ferri (2000), Hong and Warga (2000),

[17]See Fabozzi (1996). Empirical evidence supporting the on-the-run versus off-the-run effect is also given in Sarig and Warga (1989), Chakravarty and Sarkar (2003), Hong and Warga (2000), Schultz (2001), and Hotchkiss, and Jostova (2007) Also, Bao, Pan, and Wang (2011) show that liquidity is lower for older bonds, and Mahanti, Nashikkar, Subrahmanyam, Chacko, and Mallik (2008) provide evidence of peak latent liquidity levels at issuance with steady decreases thereafter. Alexander, Edwards, and Ferri (2000) are able to show for their sample of high-yield FIPS bonds that the highest volume issues are seasoned up to as much as 2 years. Warga (1992) estimates similar patterns. The on-the-run phenomenon for Treasury markets is similarly well documented, dating back to at least Amihud and Mendelson (1991).

[18]Corroborative evidence exists in Edwards, Harris, and Piwowar (2007), who show that 44% of transactions occur in bonds aged between one year and one-half of the original time to maturity. Goldstein and Hotchkiss (2007) examine trading in newly issued corporate bonds and find a swift falloff in trading after the initial period. They also provide evidence of different trading activity for institutional and retail investors in these issues.

Table 5
Lead-lag relationships between intraday stock and corporate bond returns.

This table reports the results from estimation of the following bivariate VAR model on the stock and one of the most liquid bonds issued by Ford and GM:

$$R_{s,t} = \alpha_s + \sum_{i=1}^{I} \beta_{s,s}^{i} R_{s,t-i} + \sum_{i=1}^{L} \gamma_{s,b}^{i} R_{b,t-i} + \varepsilon_{s,t}, \quad R_{b,t} = \alpha_b + \sum_{i=1}^{I} \beta_{b,s}^{i} R_{s,t-i} + \sum_{i=1}^{L} \gamma_{b,b}^{i} R_{b,t-i} + \varepsilon_{b,t},$$

where $R_{s,t}$ ($R_{b,t}$) represents the return on the stock (bond) at time t. $I=10$ for regressions on hours returns and $I=40$ for regressions on 15-minute returns. We test the null hypotheses that lagged bond (stock) returns do not Granger-cause current stock (bond) returns and the p-values for the tests are reported in the table. This test is conducted on various sub-samples to identify the possible effects of bond trade size on the lead-lag relationship between stock and bond returns. Results for returns calculated on both the hourly and 15 minutes frequencies for a pair of stocks and bonds for Ford and GM are presented in Panel A. In Panel B, we pair each bond with the issuer's stock, and estimate the VAR model using bond returns calculated from all-sized trades (excluding overnight trades). In Panel C, we replicate the test in Panel B except that we pair each issuer's stock with the top bond only and estimate the VAR model during the 5-day period following the earnings announcement using bond returns from top bond large trades only (including overnight trades). Large trades are defined as those that are no less than $500,000 in par value.*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Ford and GM

	Ford					*GM*				
	Current stock return		*Current bond return*		*N*	*Current stock return*		*Current bond return*		*N*
	Granger test on lagged bond returns (p-val)	*Adj. R^2 (%)*	*Granger test on lagged stock returns (p-val)*	*Adj. R^2 (%)*		*Granger test on lagged bond returns (p-val)*	*Adj. R^2 (%)*	*Granger test on lagged stock returns (p-val)*	*Adj. R^2 (%)*	
Hourly returns										
All bond Trades (including after-hour trades)	0.2913	0.87	<0.0001***	24.83	16,690	0.1797	1.09	<0.0001***	22.97	16,617
Large bond trades only (including after-hour trades)	<0.0001***	1.43	<0.0001***	10.10	15,668	0.0008***	1.57	<0.0001***	6.29	13,857
All bond trades (excluding after-hour trades)	0.4080	0.33	0.0002***	16.07	12,313	0.6359	0.35	0.0037***	16.36	12,967
Large bond trades only (excluding after-hour trades)	0.0009***	0.62	<0.0001***	7.85	12,201	0.5073	0.43	<0.0001***	3.97	11,188
15-minute Returns										

Table 5 (*continued*)

Panel A: Ford and GM

	Ford					*GM*				
	Current stock return		*Current bond return*		*N*	*Current stock return*		*Current bond return*		*N*
	Granger test on lagged bond returns (*p-val*)	*Adj.* R^2 (%)	*Granger test on lagged stock returns* (*p-val*)	*Adj.* R^2 (%)		*Granger test on lagged bond returns* (*p-val*)	*Adj.* R^2 (%)	*Granger test on lagged stock returns* (*p-val*)	*Adj.* R^2 (%)	
All bond trades (including after-hour trades)	0.2058	1.97	<0.0001***	25.88	48,727	0.0411**	2.83	0.0180**	20.69	46,802
Large bond trades only (including after-hour trades)	<0.0001***	2.67	<0.0001***	7.53	41,690	0.0377**	3.55	<0.0001***	3.65	38,202
All Bond Trades (excluding after-hour trades)	0.2286	0.76	<0.0091***	22.09	41,103	0.4164	1.44	0.2111	18.44	40,724
Large Bond Trades Only (excluding after-hour trades)	0.0001***	1.16	<0.0001***	6.68	35,536	0.2007	1.76	<0.0001***	2.39	33,583

Panel B: Using all-sized trades for all bonds over the full sample period (excluding overnight trades).

		Stock return		Bond return	
		Est. average	Est. std	Est. average	Est. std.
Lagged Stock Return:	S1	−0.0112	0.0920	0.0471	1.5033
	S2	−0.0362	0.0836	−0.0577	2.3687
	S3	0.0045	0.0773	0.0657	2.0319
	S4	0.0216	0.0712	−0.0479	1.7744
	S5	0.0086	0.0739	−0.0061	2.1847

Lagged Bond Return:	B1	0.0089	0.0735	−0.3925	0.2198
	B2	−0.0011	0.0820	−0.2883	0.1810
	B3	0.0073	0.0752	−0.2045	0.1342
	B4	−0.0004	0.0715	−0.1535	0.1148
	B5	0.0069	0.0597	−0.0920	0.0803
Granger-causality Tests:	No Lead-lag:		63.27%		
	One-way Lead-lag:				
	Stock lead		23.69%		
	Bond lead		7.28%		
	Two-way Lead-lag:		5.77%		

Panel C: Using large trades in top bonds during the 5-day period following earnings announcement (including overnight trades).

		Stock return		Bond return	
		Est. average	Est. std	Est. average	Est. std
Lagged Stock Return:	S1	−0.0106	0.1394	0.0125	0.1890
	S2	−0.1130	0.2831	0.0004	0.1908
	S3	−0.0987	0.2642	0.0143	0.1725
	S4	−0.0460	0.2334	0.0065	0.1809
	S5	−0.0771	0.2228	0.0088	0.1692
Lagged Bond Return:	B1	0.0694	1.4706	−0.1517	0.2863
	B2	−0.0068	1.5778	−0.1461	0.2846
	B3	−0.0211	1.7092	−0.0923	0.3851
	B4	0.0102	2.0537	−0.1124	0.3099
	B5	−0.0701	2.5063	−0.0659	0.4231
Granger-causality Tests:	No Lead-lag:		62.80%		
	One-way Lead-lag:				
	Stock lead		17.39%		
	Bond lead		16.43%		
	Two-way Lead-lag:		3.38%		

Hotchkiss and Jostova (2007), Mahanti, Nashikkar, Subrahmanyam, Chacko, Mllik (2008), and Bao, Pan, and Wang (2011) [unlike Crabbe and Turner (1995), who find no such links].

While recent corporate bond research has focused on either efficiency or liquidity in isolation, the link between the two remains relatively unexplored. Since ultimately we would like to be able to identify ex ante which bonds will attract most institutional trade after announcements, we first examine the potential overlap between top bonds and shifting liquidity in general. While several studies have focused on the liquidity of corporate bonds using different approaches, Jankowitsch, Nashikkar, and Subrahmanyam (2008), hereafter JNS, propose a concrete new measure based upon price dispersion effects (interpreted as the volatility of price dispersion). Specifically, the authors calculate the root mean squared difference between the traded prices of a particular bond and its respective market valuation, provided by Markit.[19] We compare the identity of each of our top bonds to that of the issuer's most liquid bond, which we identify as the bond with the lowest JNS price dispersion estimate (for the issuer over the quarter).[20] In 43% of the matched cases, our price leader is also the issuer's most liquid bond for that quarter. Thus, while a certain correspondence does exist between the identity of an issuer's quarterly most liquid bonds and our top bonds, a direct link cannot be established, indicating that information sensitivity may be attributable to factors above and beyond bond liquidity. That is, while the liquidity measures may be useful in identifying a candidate basket of top bonds, the characteristics summarized in Table 6 (such as original maturity or attached options) prove to be of additional value in constructing ex-ante rules with which to identify the top bonds surrounding information events.

Since market participants appear to flock the top bond immediately after announcements, we examine how well investors can predict (ex ante) which bond will prevail as 'top' for each firm after each announcement. Such as not to condition the tests on only those trades that have already occurred, the entire universe of bonds issued by the firm is included in estimation, regardless of the existence of observed trade. We run the following logistic model, with right hand variables determined by the common top bond characteristics as identified in Panel A of Table 6:

$$\log\left(P/1-P\right) = \alpha + \beta_1 {*} OntherunLTDummy + \beta_2 {*} SpecialDummy + \beta_3 {*} LiquidityDummy + \beta_4 {*} HighestRatingDummy \qquad (3)$$

where P is the probability of a particular bond being the top bond following an earnings announcement. The four dummy variables, *OntherunLTDummy*, *SpecialDummy*, *Liquidity-Dummy*, and *HighestRatingDummy*, are equal to 1 if the bond is the most recently issued long-term bond, has at least one special feature, is one of the issuer's three most liquid bonds, or is the issuer's highest rated bond before the earnings announcement respectively, and 0 otherwise.[21] Panel B of Table 6 indicates that all four variables are statistically significant and positive, consistent with the summary statistics in Panel A for the top bond characteristics.

[19]The authors compare TRACE bond transaction prices from 2004 to the end of day market quotes compiled by the Markit Group Limited. Measures are computed on a quarterly basis, for those bonds included in the Markit data. We thank the authors for providing their quarterly price dispersion estimates for the October 2004–September 2006 period.

[20]Of the 498 price leaders in our sample, 276 announcement-leader combinations correspond to the two years of data for which the JNS price dispersion estimates are available. Of these, 63% (174 leader points) have a JNS price dispersion measure.

[21]Our sample is broken down as follows, 35% are straight bonds, 15% have variable coupon rates, 9% are fungible, 8.5% have credit enhancements, 2% are putable, less than 2% are zero coupon bonds, and less than

Overall, tests on the association of predicted probabilities and observed responses show that the percentage concordance in our sample is 90.08% and the percentage discordant is only 2.7%. Further, the effectiveness of prediction in our model estimated by the Receiver Operating Characteristic (ROC) measure is a high 0.941. To assess how well the prediction model works out of sample, we use two year rolling periods for estimation of the logistic model (starting with 2003–2004), and calculate the log odds ratio for each bond in the following quarter using the estimated coefficients. For the eight out-of-sample quarters (during 2005–2006), the bond with the highest predicted probability corresponds to the top bond in 70.41% of cases.

Finally, since the top bond attracts the majority of overnight institutional order flow in the firm's bonds, we examine the contribution of its overnight trades to the bond's price discovery. We calculate the average Weighted Price Contribution (WPC) measure in the spirit of Barclay and Warner (1993):

$$WPC = \sum_{i=1}^{I} \left(\frac{|\Delta P^{t}_{pre\text{-}EZ,pre\text{-}close}|}{\sum_{t=1}^{T} |\Delta P^{t}_{pre\text{-}EZ,pre\text{-}close}|} \right) \left(\frac{\Delta P^{t}_{pre\text{-}EZ,pre\text{-}close}}{\Delta P^{t}_{pre\text{-}EZ,pre\text{-}close}} \right) \tag{4}$$

where the price contribution is measured from the last trade pre-announcement until the last trade before the equity market opens, and where $\Delta P_{pre\text{-}EA,\ pre\text{-}open}$ and $\Delta P_{pre\text{-}EA,\ pre\text{-}close}$ are the price changes until the last trade before market open or until the subsequent market close, respectively. We find that the top bonds contribute 54.79% of price discovery by equity market open.[22] Thus, shifting bond liquidity is shown to play an important role in determining informational efficiency of the corporate bond market. Thus, tests/analyses that implicitly require the entire universe of an issuer's bonds to be traded with frequencies compatible both to each other and to the firm's traded equity potentially yield confounded inferences, masking bond traders' clear ability to act quickly upon information with a few (or one) distinct bonds.

5.2. *What happens when equity market liquidity is low?*

Although top bonds are shown to attract high concentration of institutional trades following earnings announcements, the period immediately following news releases (which typically occur overnight) can provide corporate bond trading advantages in general. While it is theoretically possible for both equity and bond traders to transact during overnight hours (after NYSE close or before NYSE open), these periods are generally marked by thin stock trading and low equity market price discovery. Bonds issued by NYSE-listed firms should therefore experience potential comparative price discovery advantages during off exchange hours, when stocks suffer worse than usual terms to trade. This advantage may not be as pronounced for bonds issued by NASDAQ firms, which are characterized by non-trivial trading volume during the pre-open and post-trade sessions.[23]

(*footnote continued*)
0.5% are convertible, asset-backed or exchangeable. The remaining bonds constitute other 'special features.' Five of the 1,469 bonds could not be classified as either 'special' or straight.

[22]For the NYSE sample. For the NASDAQ sample, this number is only 7.98%, consistent with the bond market serving an informational role particularly when equity market liquidity is low, such as in the NYSE sample overnight over this time period.

[23]McInish, Van Ness, and Van Ness (2002) provide evidence that the majority of price discovery and demand for NYSE-listed stocks after hours occurs on the exchange (not the regionals). Barclay and Hendershott (2008) show that there is substantial volume in the NASDAQ pre and post trade sessions, as early as 1999. Also, Barclay

Table 6
Top bond characteristics.

Panel A presents characteristic information on the bond that attracts most of the institutional trades (top bond) following earnings announcement by each firm. The sample consists of the 498 earnings announcements for which a top bond emerges before market open. We document the average share of large trades in the top bond occurring between the earnings release time until the following market open (both in terms on number of trades and dollar volume). We also calculate the percentage number of times that the top bond: represents the longest maturity bond among all issues trading from that firm, is a long term bond, is the most recently issued, or has at least one embedded option. We also indicate the average initial offering amount. Long Term (Medium term) bonds are defined as those with original maturities of >10 (3–10) years. Panel B provides the results from estimating the following logistic model on the entire universe of bonds issued by the 66 sample firms:

$$\log(P/1-P) = \alpha + \beta_1 * OntherunLTDummy + \beta_2 * SpecialDummy + \beta_3 * LiquidityDummy + \beta_4 * HighestRatingDummy,$$

where P is the probability of a particular bond being the top bond following an earnings announcement, *OntherunLTDummy, SpecialDummy, LiquidityDummy*, and *HighestRatingDummy*, equal to 1 if the bond is the most recently issued long term bond, has at least one special feature, is one of the issuer's three most liquid bonds, or is the issuer's highest rated bond before the earnings announcement respectively, and 0 otherwise.

Panel A: Top Bond Characteristics

Number of Earnings Announcements	*Top Bond's Share of Institutional Trades Following Earnings Announcements (%)*		*Top Bond Has the Longest Maturity (%)*	*Top Bond is a Long Term Bond (%)*	*Top Bond is Most Recently Issued (%)*	*Top Bond is Most Recently Issued Long Term Bond (%)*	*Top Bond Has Embedded Options (%)*	*Top Bond Offering Amount ($ Million)*
	Number of Trades	*Dollar Volume*						
Whole Sample								
498	71.65	71.72	77.91	87.95	91.37	80.52	84.54	1,261.52
Firms with only Investment-grade Bonds								
373	72.16	72.26	78.82	89.01	94.37	84.18	82.04	1,338.18
Firms with only High-yield Bonds								
117	71.63	71.73	79.49	88.03	81.2	71.79	91.46	979.66

Number of Consecutive quarters a bond is a top bond	Once	No more than twice	No more than three times
Percentage of all top bonds	63%	81%	89%

Panel B: Predicting Top Bonds

	Model estimation		Association of predicted probabilities and observed responses	
	Estimate	P-value		
			Percent Concordant	90.08
OntheRunLT Dummy	0.7165	<0.0001	Percent Discordant	2.7
SpecialDummy	0.7036	<0.0001	Percent Tied	6.5
LiquidDummy	1.5507	<0.0001	Pairs	19,853,580
HighestratingDummy	5.0213	<0.0001	Sommer's D	0.881
			Gamma	0.942
			c	0.941

Indeed, we find that on announcement days, the ratio of stock trading volume overnight to stock volume during the trading day (following announcements) is 1.85% for NYSE-listed firms, compared with a ratio of 5.67% for NASDAQ firms. As expected, the corresponding bond trading volume ratios are 52.16% and only 33.47% for NYSE and NASDAQ firms, respectively.[24] This is consistent with the lower price impact of larger bond trades enabling trade in corporate bonds, and the higher equity price impacts (combined with low equity price discovery during off exchange hours) dampening significant order flow for exchange listed stocks.

6. Corporate bond market efficiency issues and determinants

Since reduced stock liquidity and potentially higher adverse selection costs during off exchange hours can render the bond market a more natural arena for trade after overnight announcements, we now explore bond trade behavior in further depth during the short windows following earnings releases.

6.1. Trade size and informational efficiency tests

The predominant institutional trading sector in the corporate bond market has been shown in Section 3 to play an important role in determining relative information efficiency of the market when using the VAR methodology. To further explore the importance of distinguishing between retail and institutional trades in efficiency tests, we conduct tests on the reaction of bond prices to information events (earnings surprises) as in Hotchkiss and Ronen (2002). These authors study the relative informational efficiency of a sample of 50 high-yield bonds and the issuer's equity using hourly transaction summaries from the Fixed Income Pricing System (FIPS). We extend their work by using the finer grid transaction-level data set provided by TRACE to focus on the impact of using different sized trades' prices on resulting inferences.

Specifically, we regress bond price changes calculated from different sized trades on the surprise component of earnings announcements:

$$(\Delta P/P)_t = \alpha + \beta S + \varepsilon \tag{5}$$

where $(\Delta P/P)_t = (P_t - P_{-close})/P_{-close}$, and t denotes the number of minutes after the announcement. The independent variable is the surprise component in the earnings announcement, $S = \ln(A/F)$, where A is the announced earnings per share, and F is the median forecast earnings per share just before the announcement. Since each of the 762 announcements occur either after market close or before market open, percentage price changes for our pooled sample regressions are calculated as changes from the previous

(*footnote continued*)
and Hendershott (2003) show that even relatively little trading after hours (NASDAQ sample) can generate significant price discovery, albeit with noisier prices.

[24]It is also possible that some ECN transactions would indicate different responses. However, Barclay, Hendershott, and McCormick (2003) document ECNs as accounting for approximately 40% of dollar volume traded in NASDAQ securities, but only about 3% for listed securities. Finally, Goldstein, Hotchkiss, and Sirri (2007) find consistent evidence in terms of ECN market share of NASDAQ stocks in 2003.

Table 7
Effect of trade size on response inferences.

We analyze the effect of trade size on inferences regarding bond price reactions to earnings surprises for the sample of 5,959 bond/quarters in which trades are identified within 3 hours of earnings announcements. We present the results from estimating the following model on the pooled sample, as well as small and large trade sub-samples respectively:

$$(\Delta P/P)_t = \alpha + \beta S + \varepsilon,$$

where the dependent variable is the price change from the previous day's close until t minutes after the announcement, and S is the surprise component in the earnings announcement. We also examine this model at different time windows following the announcement, i.e., 5 minutes, 15 minutes, 30 minutes, 1 hour, 2 hours, and 3 hours. The results are presented in Panels A–F respectively. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

	Est.	*t*-stat	Adj R^2 (%)	*N.*	% of Full Sample
Panel A: 5-Minute Window					
Using Large Trades Only:					
	0.41	1.70*	9.07	426	30.78
Using Small Trades Only:					
	−0.07	−0.79	−0.05	1,232	89.02
Using All Trades:					
	0.09	0.74	−0.01	1,384	100
Panel B: 15-Minute Window					
Using Large Trades Only:					
	0.41	1.86*	8.24	462	31.60
Using Small Trades Only:					
	0	0.04	−0.08	1,291	88.30
Using All Trades:					
	0.14	0.95	0.08	1,462	100
Panel C: 30-Minute Window					
Using Large Trades Only:					
	0.46	2.48**	8.64	519	31.94
Using Small Trades Only:					
	0.12	1.53	0.06	1,419	87.32
Using All Trades:					
	0.23	2.12**	0.39	1,625	100.00
Panel D: 1-Hour Window					
Using Large Trades Only:					
	0.46	5.24***	6.76	678	33.30
Using Small Trades Only:					
	0.2	5.28***	0.32	1,727	84.82
Using All Trades:					
	0.29	3.83***	0.73	2,036	100.00
Panel E: 2-Hour Window					
Using Large Trades Only:					
	0.38	4.55***	3.12	1,119	31.05
Using Small Trades Only:					
	0.26	3.93***	0.52	3,051	84.66
Using All Trades:					
	0.3	3.29***	0.75	3,604	100.00
Panel F: 3-Hour Window					
Using Large Trades Only:					
	0.35	5.26***	1.95	1,725	28.95
Using Small Trades Only:					
	0.34	6.38***	0.82	5,179	86.91
Using All Trades:					
	0.34	6.98***	0.88	5,959	100.00

day's closing price, P_{-close}.[25] Thompson (2011) standard error corrections are used to account for both serial correlation and contemporaneous correlation across bonds.

We construct five-minute windows following each earnings announcement. As shown in Panel A of Table 7, when price movements are calculated using prices of large trades only, price changes display statistically significant reactions to earnings surprises. However, when price changes are computed from retail trade prices, no significant reactions are observed, a result that carries over into the mixed sample of large and small trades, seemingly due to the preponderance of retail trade observations. Panel B indicates a similar pattern for 15-minute windows. The combined results highlight our methodological point: The dominant (in terms of number of trades) noisier retail trades produce prices that confound inferences in efficiency tests. Retail trade prices display increasingly significant reaction to information as the window intervals increase (Panels C–F), consistent with retail investors learning from the trades of institutional traders.

Notably, the sample size for our tests differs when we use the price changes calculated from different trade size groups. For example, Panel A of Table 7 reveals that approximately 89% of the bonds trading within five minutes of earnings releases have at least one small trade, compared to a mere 30.78% with at least one large trade. Longer window lengths display similar differences in the prevalence of large and small trades. To account for the fact that these tests are conditional upon the observation of a trade (of either large or small size), we replicate our analysis by assuming that the total number of bonds that could potentially trade at any window and for any size category is equal to the total number of bonds traded (5,959) over the longest window examined (three hours), and replacing 'missing' returns with a value of zero.[26] Table 8 confirms the patterns found in Table 7: Noisy small trade prices confound inferences in efficiency tests using samples pooled across all trade sizes.[27]

Lastly, since the number of bonds trading per issuer varies across the sample, a relevant concern is that our results are driven by big issuers (those with many bond issuers). We re-estimate the model using top bonds only (both with and without backfilling). The results are presented in Table 9. This ensures that firms with a larger presence in the corporate bond market are not over represented. Similar patterns emerge: sample pooling masks the efficiency of the less noisy prices.

6.2. *Timing of announcements and corporate bond trade*

The above analysis begs the question of whether the timing of announcements impacts the bond trade responses. Of the 762 announcements examined in our sample, the distribution of releases seems to cluster at certain hours, with 16.01% released between 6:00 am and 7:00 am, 33.33% between 7:00 am and 8:00 am, 32.81% between 8:00 am and

[25] While all of the announcements occur after (NYSE) market close or before market open, nearly 83% occur between 6:00 am and 9:00 am. The number of earnings announcements used in the reaction to information tests declines from 833 to 762, because some bonds do not trade within the first three hours after the announcement is made, and we do not include those dates in the sample. The bond closing price used in these tests is the last transaction price by 4:00 pm.

[26] A total of 5,959 bond/quarters were used, representing 2,271 unique bonds. This suggests that 73% of our sample bonds did not trade within three hours of earnings announcement.

[27] Public information releases can cause belief revisions reflected in market quotes regardless of trade existence (e.g., Madhavan, Richardson, and Roomans (1997)). As we cannot observe quotes, we consider different specifications, in which we either zero 'missing' returns or do not.

Table 8
Effect of trade size on response inferences with backfilling.

This table replicates the analysis in Table 4 by replacing missing returns with a value of zero. Since there are a total of 5,959 bonds traded (small or large) within the three hour window, the sample size is 5959 bonds for each test, irrespective of trade size and time window. As in Table 4, we estimate the following model using bond price changes calculated from different sized trades:

$$(\Delta P/P)_t = \alpha + \beta S + \varepsilon,$$

where the dependent variable is the price change from the previous day's close until t minutes after the announcement, and S is the surprise component in the earnings announcement. Such analysis is conducted at different time windows, and the results are presented in Panels A–F respectively. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

	Est.	t-stat	Adj R^2 (%)
Panel A: 5-Minute Window			
Using Large Trades Only:			
	0.014	4.249***	0.29
Using Small Trades Only:			
	−0.007	−0.497	−0.01
Using All Trades:			
	0.009	0.564	−0.01
Panel B: 15-Minute Window			
Using Large Trades Only:			
	0.015	4.185***	0.28
Using Small Trades Only:			
	−0.002	−0.149	−0.02
Using All Trades:			
	0.015	0.922	−0
Panel C: 30-Minute Window			
Using Large Trades Only:			
	0.020	4.572***	0.33
Using Small Trades Only:			
	0.011	0.656	−0.01
Using All Trades:			
	0.032	1.836*	0.04
Panel D: 1-Hour Window			
Using Large Trades Only:			
	0.033	5.417***	0.47
Using Small Trades Only:			
	0.032	1.675	0.03
Using All Trades:			
	0.060	2.966***	0.13
Panel E: 2-Hour Window			
Using Large Trades Only:			
	0.048	4.844***	0.38
Using Small Trades Only:			
	0.124	3.958***	0.25
Using All Trades:			
	0.157	4.855***	0.38
Panel F: 3-Hour Window			
Using Large Trades Only:			
	0.062	4.590***	0.34
Using Small Trades Only:			
	0.325	7.092***	0.82
Using All Trades:			
	0.343	7.343***	0.88

Table 9
Effect of trade size on response inferences using top bonds.

This table provides results from estimating the following model using bond price changes calculated from different sized trades using the top bond subsample S:

$$(\Delta P/P)_t = \alpha + \beta S + \varepsilon,$$

where the dependent variable is the price change from the previous day's close until t minutes after the announcement, and S is the surprise component in the earnings announcement. We estimate this model both with and without backfilling dependent variable missing values with zeroes. Analysis on the differences (between results based on large- and small-sized trade prices) is conducted at different time windows, and the results are presented in Panels A–F respectively. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

	Without Backfilling				With Backfilling			
	Est.	t-stat	Adj R^2 (%)	N	Est.	t-stat	Adj R^2 (%)	N
Panel A: 5-Minute Window								
Using Large Trades Only:								
	0.260	2.237**	5.27	73	0.075	2.669***	1.57	385
Using Small Trades Only:								
	0.345	1.161	0.42	84	0.143	1.601	0.41	385
Using All Trades:								
	0.077	0.263	−0.91	104	0.036	0.330	−0.23	385
Panel B: 15-Minute Window								
Using Large Trades Only:								
	0.252	1.948*	3.22	85	0.073	2.114**	0.90	385
Using Small Trades Only:								
	0.311	1.131	0.32	89	0.155	1.689*	0.48	385
Using All Trades:								
	−0.041	−0.143	−0.87	114	−0.035	−0.316	−0.23	385
Panel C: 30-Minute Window								
Using Large Trades Only:								
	0.346	2.083***	2.95	111	0.096	2.212**	1.00	385
Using Small Trades Only:								
	0.287	1.038	0.08	96	0.155	1.672*	0.47	385
Using All Trades:								
	0.015	0.054	−0.75	135	0.005	0.047	−0.26	385
Panel D: 1-Hour Window								
Using Large Trades Only:								
	0.618	3.624***	6.09	188	0.421	4.253***	4.26	385
Using Small Trades Only:								
	0.504	2.220**	3.57	107	0.266	3.128***	2.24	385
Using All Trades:								
	0.210	0.907	−0.09	206	0.128	0.904	−0.05	385
Panel E: 2-Hour Window								
Using Large Trades Only:								
	0.735	4.444***	5.79	306	0.667	4.783***	5.39	385
Using Small Trades Only:								
	0.584	1.751*	1.38	149	0.300	1.948*	0.72	385
Using All Trades:								
	0.221	0.988	−0.01	322	0.207	1.063	0.03	385
Panel F: 3-Hour Window								
Using Large Trades Only:								
	0.498	3.405***	2.76	374	0.492	3.432***	2.73	385
Using Small Trades Only:								
	0.162	0.607	−0.32	202	0.107	0.674	−0.14	385
Using All Trades:								
	0.030	0.148	−0.26	385	0.030	0.148	−0.26	385

9:00 am, and 13.25% between 4:00 am and 4:30 am (Fig. 2). Thus, while none of the announcements occurs during the course of the core NYSE trading sessions (9:30 am–4:00 pm), 14.04% occur during the first and last half hour of trading hours combined, and 82.15% occur between 6:00 am and 9:00 am.

Panel A of Table 10 presents the bond trade distribution for all bonds over all sample days by half hour, both in terms of number and volume of trades. While the majority of bond trading in our sample occurs between 9:30 am and 4:00 pm (75.34% of volume and 81.38% of trades), 12.18% (5.82%) of volume (trades) occurs between 6:00 am and 9:30 am (with 5.54% (3.70%) between 9:00 am and 9:30 am), and 9.41% (10.05%) of volume (trades) occurring between 4:00 pm and 5:00 pm. Panel B indicates that the percentage of trades for all bonds between 6:00 am and 9:30 am is higher on announcement days (than all days combined), with 16.63% (16.97%) of volume (trades). For top bonds (Panel C), this percentage is higher yet with 32.01% (16.04%) of volume (trades), on announcement days. This last set of numbers is consistent with a large percentage of top bond trade occurring in large amounts during these early morning hours.

We also consider the possibility that announcements occurring closer to normal business hours are followed by greater amounts of bond trading than those released earlier. To test for the relationship between trade propensity and announcement timing, we determine whether the wait time until the first trade after an earnings announcement is invariant to the earnings announcement time with the following Poisson regression:

$$\begin{aligned} WaitTime_i = \alpha + Hour6Dum_{i,j} + Hour7Dum_{i,j} + Hour8Dum_{i,j} \\ + TA_i + LEV_i + CDS_i + SPEC_i + LTM_i + HY_i + FIN_i + \varepsilon_i, \end{aligned} \tag{6}$$

where $WaitTime_i$ is the number of minutes from the earnings announcement to the first trade, and $Hour6Dum_{i,j}$, $Hour7Dum_{i,j}$, and $Hour8Dum_{i,j}$ represent three dummy variables for whether the announcement arrives between 6:00 am and 7:00 am, 7:00am and 8:00 am, or 8:00am and 9:00 am, respectively. The control variables include the total asset (TA) and financial leverage (LEV) of the issuer, and bond characteristics including special dummy ($SPEC$), long-term dummy (LTM), CDS dummy (CDS), HY dummy (HY), and FIN dummy (FIN), which are equal to 1 if the bond has special features attached, if the bond's maturity is greater than 10 years, if the bond has CDS coverage, if the bond is high-yield, or if the bond belongs to the finance industry, respectively, and 0 otherwise.

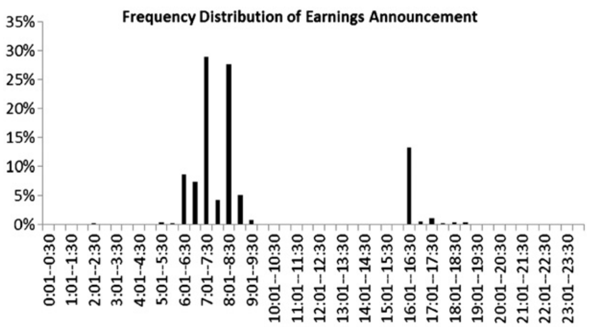

Fig. 2. Distribution of the arrival time of earnings announcements. This figure presents the frequency distribution for the arrival time of the 762 earnings announcements examined in our sample.

Table 10
Intraday distribution of bond trading.

This table presents the average percentage of bond trading, both in terms of volume and number of trades, for each of the 30-minute intervals over a trading day. We calculate the intraday bond trading distribution using All Bonds over all trading days, All Bonds on announcement days, and Top Bonds only on announcement days.

Time Interval	Panel A: All Bonds		Panel B: All Bonds		Panel C: Top Bonds	
	Over all Days		On Announcement Days		on Announcement Days	
	volume	ntrades	volume	ntrades	volume	ntrades
0:01–0:30	0.05%	0.07%	0.02%	0.10%	0.00%	0.05%
0:31–1:00	0.01%	0.00%	0.01%	0.01%	0.00%	0.00%
1:01–1:30	0.02%	0.01%	0.00%	0.01%	0.00%	0.00%
1:31–2:00	0.02%	0.01%	0.00%	0.02%	0.00%	0.01%
2:01–2:30	0.02%	0.01%	0.01%	0.03%	0.00%	0.01%
2:31–3:00	0.03%	0.02%	0.02%	0.02%	0.00%	0.00%
3:01–3:30	0.05%	0.03%	0.03%	0.07%	0.02%	0.02%
3:31–4:00	0.05%	0.03%	0.05%	0.07%	0.00%	0.01%
4:01–4:30	0.07%	0.04%	0.03%	0.08%	0.00%	0.02%
4:31–5:00	0.07%	0.05%	0.05%	0.15%	0.00%	0.02%
5:01–5:30	0.07%	0.05%	0.06%	0.09%	0.02%	0.02%
5:31–6:00	0.07%	0.04%	0.05%	0.08%	0.05%	0.03%
6:01–6:30	0.13%	0.05%	0.09%	0.10%	0.05%	0.03%
6:31–7:00	0.23%	0.07%	0.22%	0.19%	0.25%	0.12%
7:01–7:30	0.50%	0.27%	0.74%	0.77%	1.39%	0.68%
7:31–8:00	0.99%	0.33%	1.59%	1.12%	2.47%	1.11%
8:01–8:30	2.26%	0.97%	3.51%	3.15%	6.23%	3.12%
8:31–9:00	3.33%	1.57%	4.52%	4.65%	9.21%	4.47%
9:01–9:30	4.74%	2.58%	6.06%	7.00%	12.40%	6.51%
9:31–10:00	5.54%	3.70%	6.55%	9.76%	8.05%	5.11%
10:01–10:30	6.58%	5.23%	7.27%	12.55%	7.36%	5.54%
10:31–11:00	6.36%	5.66%	6.68%	13.10%	6.36%	5.09%
11:01–11:30	6.96%	6.69%	6.97%	14.88%	5.84%	5.06%
11:31–12:00	6.19%	6.31%	5.91%	14.28%	4.70%	4.58%
12:01–12:30	6.04%	6.44%	6.28%	14.61%	4.34%	4.54%
12:31–13:00	5.04%	5.74%	4.95%	12.59%	3.81%	3.98%
13:01–13:30	5.16%	6.10%	4.83%	13.64%	3.46%	4.09%
13:31–14:00	4.87%	5.91%	3.92%	12.92%	2.13%	3.78%
14:01–14:30	5.51%	6.74%	5.11%	15.12%	3.10%	4.44%
14:31–15:00	5.32%	6.68%	4.53%	14.30%	2.82%	3.96%
15:01–15:30	6.15%	7.92%	5.10%	17.14%	2.89%	4.69%
15:31–16:00	5.62%	8.27%	4.87%	18.10%	3.21%	5.20%
16:01–16:30	5.49%	6.46%	3.78%	13.46%	2.95%	4.10%
16:31–17:00	3.93%	3.58%	3.56%	7.71%	3.75%	2.86%
17:01–17:30	1.83%	1.28%	2.05%	2.96%	2.54%	1.76%
17:31–18:00	0.42%	0.78%	0.42%	1.83%	0.43%	0.60%
18:01–18:30	0.15%	0.17%	0.10%	0.36%	0.15%	0.14%
18:31–19:00	0.04%	0.07%	0.02%	0.09%	0.00%	0.02%
19:01–19:30	0.04%	0.03%	0.01%	0.09%	0.01%	0.03%
19:31–20:00	0.01%	0.01%	0.00%	0.03%	0.00%	0.00%
20:01–20:30	0.00%	0.01%	0.00%	0.02%	0.00%	0.00%
20:31–21:00	0.01%	0.01%	0.00%	0.01%	0.00%	0.00%
21:01–21:30	0.01%	0.00%	0.00%	0.01%	0.00%	0.00%
21:31–22:00	0.01%	0.00%	0.01%	0.01%	0.00%	0.00%

Table 10 (*continued*)

Time Interval	Panel A: All Bonds Over all Days		Panel B: All Bonds On Announcement Days		Panel C: Top Bonds on Announcement Days	
	volume	ntrades	volume	ntrades	volume	ntrades
22:01–22:30	0.01%	0.00%	0.00%	0.01%	0.00%	0.01%
22:31–23:00	0.01%	0.00%	0.00%	0.01%	0.00%	0.01%
23:01–23:30	0.01%	0.00%	0.00%	0.00%	0.00%	0.01%
23:31–24:00	0.01%	0.00%	0.01%	0.01%	0.00%	0.00%

This model is estimated for both the full sample of bonds (Panel A of Table 11), and for the top bonds only sample (Panel B of Table 11). The results for both samples indicate that the earnings announcement time does affect the distribution of time until the first trade. Further, the coefficient on the hour dummy decreases monotonically, consistent with traders being more likely to trade as 'normal business' hours approach, as well as with the timing and depth of general information arrival.

To examine whether the arrival time of the announcement also affects the differential impacts on large and small trades, we re-estimate model (5), separately by hour between 6:00 am and 9:00 am. Table 12 highlights the point made above; as time progresses, the number of trades does increase. However, we know from Table 10 that the number of announcements increases as well. Nevertheless, our inferences regarding the confounding effect of small trades do not change. For example, tests using large trade size prices for the 8:00 am to 9:00 am subsample reveal a more significant reaction to earnings surprises, and provide more explanatory power than using either the small trade size prices or prices from the pool of all trades. While tests on the 6:00 am to 7:00 am and 7:00 am to 8:00 am subsamples are limited due to lower trading activity and hence lower availability of data, distinct reactions from using the different sample (small and large trade prices) are still observed at some intervals.

Partitioning the sample across trade sizes also allows us to conduct cross-sectional tests to examine the effect of issuer characteristics, such as size and leverage, as well as specific bond features, such as complexity, CDS coverage, and term on our results. To determine whether the pattern of information reactions changes once we control for the timing of the announcement as well as for bond- and firm-specific variables, we estimate the following multivariate regression:

$$(\Delta P/P)^{t}_{-close} = \alpha_t + \beta_t S + \sum_{i=1}^{10} \gamma_t ControlVar_i + \varepsilon_t \tag{7}$$

where the control variables include the total asset (*TA*) and financial leverage (*LEV*) of the issuer, and bond characteristics including special dummy (*SPEC*), long-term dummy (*LTM*), CDS dummy (*CDS*), HY dummy (*HY*), FIN dummy (*FIN*), and three dummy variables for the timing of announcements as defined in model (6). Panel A of Table 13 presents the results for the first five minute window following earnings announcements. Even after controlling for the above effects, our conclusions from Table 7 persist. Panel B

Table 11
Effect of timing of earnings announcements on the arrival of bond trades.

This table presents the results from estimating the following Poisson regression:

$$WaitTime_i = \alpha + Hour6Dum_{i,j} + Hour7Dum_{i,j} + Hou8Dum_{i,j} + TA_i + LEV_i + CDS_i + SPEC_i + LTM_i + HY_i + FIN_i + \varepsilon_i,$$

where *WaitTtime* is the number of minutes from the earnings announcement to the first trade, *Hour6Dum, Hour7Dum, and Hour8Dum* represent three dummy variables for whether the announcement arrives between 6:00 am and 7:00 am, 7:00 am and 8:00 am, and 8:00 am and 9:00 am, respectively. The control variables include the total asset (*TA*) and financial leverage (*LEV*) of the issuer, and bond characteristics including special dummy (*SPEC*), long-term dummy (*LTM*), CDS dummy (*CDS*), HY dummy (*HY*), and FIN dummy (*FIN*), which equal 1 if the bond has special features attached, if the bond's maturity is greater than 10 years, if the bond has CDS coverage, if the bond is high-yield, and if the bond belongs to the finance industry, respectively, and 0 otherwise. We estimate this model for the full sample of bonds (All Bonds) and for the Top Bonds only sample. The test is conducted using the All Trades sample, as well as for the subsamples of Large trades and Small trades.

	All Bonds						Top Bonds					
	All trades		Large trades		Small trades		All trades		Large trades		Small trades	
	Est.	*p*-val.	Est.	*p*-val.	Est.	*p*-val.	Est.	*p*-val.	Est.	*p*-val.	Est.	*p*-val.
Intercept	0.406	0.000	0.539	0.000	0.39	0.000	0.168	0.388	0.233	0.228	0.764	0.001
hour6dum	1.86	0.000	1.897	0.000	1.904	0.000	2.099	0.000	2.021	0.000	2.076	0.000
hour7dum	1.804	0.000	1.785	0.000	1.88	0.000	1.696	0.000	1.626	0.000	1.956	0.000
hour8dum	1.663	0.000	1.597	0.000	1.75	0.000	1.071	0.000	1.021	0.000	1.702	0.000
asset	−0.1	0.000	−0.04	0.336	−0.09	0.000	−0.102	0.191	−0.024	0.748	−0.183	0.165
lever	−0.12	0.069	−0.25	0.017	−0.15	0.026	0.117	0.615	0.088	0.700	−0.563	0.046
cdsdum	−0.08	0.000	−0.08	0.002	−0.08	0.000	−0.110	0.053	−0.087	0.119	−0.242	0.006
specialdum	−0.07	0.000	−0.09	0.000	−0.04	0.000	−0.092	0.172	−0.042	0.543	−0.102	0.322
longtermdum	0.026	0.038	−0.02	0.535	0.023	0.086	−0.075	0.189	−0.091	0.113	−0.193	0.024
hydum	0.084	0.000	−0.02	0.556	0.088	0.000	−0.108	0.249	−0.137	0.137	0.075	0.498
findum	0.08	0.000	0.051	0.130	0.066	0.001	−0.132	0.107	−0.139	0.087	0.101	0.355

demonstrates similar patterns for wider time windows. Two control variables present significant coefficients, the CDS dummy and timing dummy corresponding to the 6:00 am–7:00 am announcement arrival time window.

6.3. The effect of embedded credit risk on information sensitivity

In this section we examine how embedded credit risk affects information sensitivity to earnings announcements. We partition the large trade sample by credit rating (as of the announcement date) and re-estimate model (5). Table 14 confirms that credit rating is a significant factor in determining bond price reactions to firm-specific information. While overall, investment-grade bonds do not display significant price reactions, high-yield bonds do, including significant coefficients at the five-minute window. However, when we further partition investment-grade bonds, we find that the BBB-rated sample does present significant coefficients, potentially reflecting investor anticipation of the firm's deteriorating financial condition and increased probability of downgrade. To test for the possibility that this 'anticipation propensity' serves as a proxy for the information inherent in the future (potentially stale) announcements, we examine 'fallen angels' with downgrades occurring either imminently (within one year) or farther out in the future. BBB bonds are now partitioned into three finer categories: bonds that have never been downgraded during our sample period, bonds that were subsequently downgraded within the year, and those whose downgrade occurred more than one year later.[28] Table 14 documents a clear pattern of increasing information sensitivity as time-remaining-to-downgrade shrinks.[29] For bonds subsequently downgraded within the year, prices react swiftly to information. The positive coefficients represent a positive relationship between the sign of the earnings surprise and the magnitude of reaction. However, BBB-rated bonds with subsequent downgrade announcements made more than one year out and those without subsequent downgrades do not exhibit significant reaction to information within the five-minute window. These distinct reactions to information across the different rating groups persist both at the 15- and 30-minute windows and disappear when we further increase the examination windows.[30]

We also consider whether information sensitivity differs on good and bad news days. We define earnings announcement as constituting good (bad) news if actual earnings are higher (lower) than the median analyst forecast. The results in Table 15 can be interpreted

[28]A similar analysis for the impact of upgrades is not possible here since only 4 bonds were upgraded from BBB to A, and 15 from BB to BBB during our sample period. Similarly, we cannot replicate the tests for more finely partitioned downgrade credit rating groups, since the number of bonds with identifiable downgrades for each rating group over our period is: 9 AAA, 3 AA, 7 A, 231 BBB, 43 BB, 1 B, and 0 bonds CCC or lower rated bonds. Finally, small sample size issues also prevent us from conducting the tests in Tables 12–14 on the Top Bond-Only sample.

[29]We exclude a total of 10 observations for which credit ratings could not be identified, resulting in a total of is 1,715 bond quarters (1564 investment grade bonds and 151 high yield bonds), out of the 1,725 total bond quarters with institutional sized trades.

[30]These results could potentially be confounded if bond ratings affect earnings announcement release times. That is, if firms with high yield bonds tend to release information immediately before equity market open and those with investment grade bonds tend to do so earlier, then the observed significant reactions of high yield bonds to information at short time windows may simply reflect such differences in the timing of announcement. However, we find that for high-yield (investment grade) bonds, approximately 75% (84%) of announcements in our sample were released from 6:00 am to 9:30 am, with over 28% (30%) released after 8:00 am. For BBB rated bonds, the corresponding numbers are 82% and 30%, respectively.

Table 12
Timing of announcements and effect of trade size on response inferences.

This table presents the results for the following model, estimated for earnings announcements released during 6 am–7 am, 7 am–8 am, and 8 am–9 am periods separately. The results are presented in panels A–C respectively:

$$(\Delta P/P)_t = \alpha + \beta S + \varepsilon,$$

where the dependent variable is the price change from the previous day's close until t minutes after the announcement, and S is the surprise component in the earnings announcement. Within each panel, we estimate this model at the 5-minute, 15-minute, 30 minutes, 1-hour, 2-hour, and 3-hour windows. In addition, this estimation is conducted using the All Trade sample, as well as the Large and Small trade size subsamples.. For each test, we report the estimate and the t-statistics for the coefficient of the earnings surprises, as well as the number of observations used and the adjusted R-square.

	Using All Trades				Using Large Trades Only				Using Small Trades Only			
	Est.	t-stat	N	AdjR^2	Est.	t-stat	N	AdjR^2	Est.	t-stat	N	AdjR^2
Panel A: 6 am–7 am												
5-minute window	−0.361	−0.851	135	−0.55	−0.241	−0.517	25	−3.11	−0.422	−1.066	111	−0.68
15-minute window	−0.389	−0.905	141	−0.49	−0.219	−0.477	27	−3.01	−0.455	−1.118	117	−0.6
30-minute window	−0.441	−1.137	154	−0.33	−0.221	−0.485	28	−2.83	−0.492	−1.321	130	−0.42
1-hour window	0.060	0.123	211	−0.47	−0.733	−1.039	41	6.39	0.103	0.172	176	−0.56
2−hour window	−0.543	−1.436	467	0.23	0.060	0.082	120	−0.83	−0.579	−1.362	375	0.17
3-hour window	−0.302	−1.445	1109	0.05	0.352	1.091	290	0.42	−0.352	−1.531	923	0.05
Panel B: 7 am–8 am												
5-minute window	0.140	0.385	160	−0.54	0.431	0.696	42	−0.96	−0.258	−0.598	128	−0.47
15-minute window	0.057	0.159	175	−0.56	0.673	1.204	50	2.34	−0.322	−0.768	137	−0.24
30-minute window	0.157	0.596	222	−0.33	0.969	2.170	71	7.34	−0.154	−0.493	166	−0.49
1-hour window	0.430	2.035	378	1.27	0.587	3.144	150	9.94	0.122	0.649	264	−0.25
2-hour window	0.430	3.784	1028	1.55	0.374	2.704	361	3.7	0.333	3.529	791	0.76
3-hour window	0.286	3.370	1984	0.61	0.327	2.434	636	2.39	0.257	3.137	1635	0.45
Panel C: 8 am–9 am												
5-minute window	0.518	3.238	198	1.41	0.893	10.313	69	38.1	0.304	1.659	145	−0.26
15-minute window	0.558	2.841	252	2.08	0.839	7.290	92	30.62	0.366	1.921	187	0.38
30-minute window	0.499	3.619	353	1.84	0.803	6.799	123	21.35	0.358	2.839	270	0.62
1-hour window	0.284	2.745	548	0.46	0.685	4.319	186	8.15	0.265	1.892	429	0.3
2-hour window	0.281	3.905	1205	0.56	0.658	3.718	335	5.25	0.270	3.011	1024	0.48
3-hour window	0.470	6.773	1945	1.7	0.612	4.303	491	3.24	0.477	6.136	1747	1.69

as consistent with institutional traders capitalizing on comparative advantages in information gathering and trade: On average (across all ratings), retail investors pay more to acquire bonds on good news days, evidenced by significantly negative price level differences for institutional- and retail-sized trades. Likewise, on bad news days, the

Table 13
Multi-varaiate analysis.

This table provides the results from estimating the following multi-variate regression:

$$(\Delta P/P)^{t}_{-close} = \alpha_t + \beta_t S + \sum_{i=1}^{10} \gamma_t ControlVar_i + \varepsilon_t,$$

where the dependent variable is the price change from the previous day's close until t minutes after the announcement. We present the estimate and the t-stat for earnings surprises (S), and the control variables, including total asset of the issuer (TA) and financial leverage (LEV) of the issuer, special dummy (SPEC), long-term dummy (LTM), CDS dummy (CDS), HY dummy (HY), and FIN dummy (FIN), and three dummy variables, $AM6$, $AM7$, and $AM8$, which are created based on whether the earnings announcement is released during one of the three hours immediately before market open. Panel A includes the full estimation results of using different trade size groups at one window (5 minutes). Panel B provides the estimates on the earnings surprise variable (S) for different window choices. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

	Int.	*S*	*TA*	*LEV*	*CDS*	*SPEC*	*LTM*	*HY*	*FIN*	*AM6*	*AM7*	*AM8*
Using Large Trades Only:												
Est.	−0.30	0.35	0.10	0.15	0.16	0.01	0.09	0.14	−0.11	0.15	−0.09	0.07
t-stat	−1.93	1.79*	1.28	0.90	2.83***	0.24	1.40	1.34	−1.12	1.86*	−0.74	1.23
Adj R^2	13.36	13.36	13.36	13.36	13.36	13.36	13.36	13.36	13.36	13.36	13.36	13.36
Using Small Trades Only:												
Est.	0.09	0.04	0.10	0.00	−0.10	−0.03	0.14	−0.30	−0.01	−0.01	−0.05	−0.07
t-stat	0.43	0.25	1.07	−0.02	−0.92	−0.58	0.96	−1.33	−0.08	−0.07	−0.17	−0.43
Adj R^2	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
Using All Trades:												
Est.	0.11	0.21	0.12	−0.12	−0.07	0.00	−0.01	−0.05	0.06	−0.02	−0.22	−0.05
t-stat	0.46	1.16	1.12	−0.33	−0.65	0.05	−0.11	−0.39	0.47	−0.21	−0.73	−0.46
Adj R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

	15 minutes	30 minutes	1 hour	2 hours	3 hours
Using Large Trades Only					
Est.	0.39	0.43	0.42	0.31	0.31
t-stat	1.87*	2.25**	3.94***	3.63***	4.19***
Adj R^2	10.31	11.58	7.73	4.53	3.24
Using Small Trades Only					
Est.	0.02	0.15	0.14	0.24	0.32
t-stat	0.16	1.12	1.09	2.77***	3.44***
Adj R^2	−0.18	0.16	0.60	1.09	1.50
Using All Trades					
Est.	0.17	0.25	0.22	0.26	0.30
t-stat	1.19	2.36**	1.63	2.23**	3.47***
Adj R^2	0.05	0.35	0.82	1.32	1.56

Table 14
Effect of credit ratings on earnings surprise reactions.

This table presents the results from estimating the following model on bonds with different credit ratings using institutional-sized trades:

$$(\Delta P/P)_t = \alpha + \beta S + \varepsilon,$$

where the dependent variable is the price change from the previous day's close until t minutes after the announcement, and S is the surprise component in the earnings announcement. The sample consists of 151 high yield bond quarters and 1,564 investment grade bond quarters. Ten bond quarters without ratings are excluded from our credit rating partitions. We further divide the trades in investment grade bonds into several groups (i.e., A and higher, BBB downgraded within one year, BBB downgraded more than one year out, and BBB rated bonds not downgraded within our sample period). The results are reported in Panel B. Institutional-sized trades are defined as those with $500,000 par value or more. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Minutes	5	15	30	60	120	180
Panel A: High-yield vs. Investment-grade						
All High-yield						
Est.	0.66**	0.67**	0.58**	0.40***	0.27**	0.22***
N	28	32	44	69	103	151
All Investment-grade						
Est.	0.04	0.1	0.24	0.39*	0.34**	0.40**
N	397	429	474	607	1,011	1,564
Panel B: BBB-rated bond sample						
All BBB-rated						
Est.	0.22*	0.30*	0.51**	0.83**	0.70**	0.85***
N	152	172	199	262	413	555
Not Downgraded						
Est.	0.08	0.08	0.15	0.71	0.74	0.6
N	104	106	121	148	236	324
Downgraded						
≤ 1 year						
Est.	0.75**	0.79***	1.09***	0.93***	0.61***	0.91***
N	27	35	41	54	81	114
>1 year						
Est.	−0.45	−0.23	0.24	0.78***	0.77***	1.35***
N	21	31	37	60	96	117

difference is positive and significant, indicating that retail investors again receive worse prices.[31]

Comparing BBB with other investment-grade and high-yield bond price reactions on good and bad news days proves revealing in terms of potential information-based activity. The BBB-rated bond sample exhibits greater differences between large- and small-sized trade price levels on good news days than bad news days (Table 16). While bad news is potentially consistent with general anticipation of a shift to low grade status, good news may be associated with a larger surprise component, implying that the bond might not be further downgraded (with implications driven by portfolio inclusion restrictions). Unlike the BBB-rated sample, high-yield bonds display the greatest divergences after bad news,

[31] Since buy/sell indicators are not available to us, we are basing this analysis upon the assumption that transactions on bad news days are sells and those on good news days are buys.

Table 15
Institutional/Retail price behavior on good and bad news days.

This table reports the results from tests on the null hypothesis that institutional and retail bond trades do not react differently to good versus bad information. We define an earnings announcement as good (bad) news if the actual earnings are higher (lower) than the median forecast of final analysts. We keep all trades within one day following each earnings announcement, and calculate for each bond/date, the average price levels for institutional- and retail-sized trades, respectively. We then conduct t-tests on whether the distance between the average price for large trades in bonds (*Plarge*) and that for small trades (*Psmall*) (normalized by the average price level) is significantly different from zero following good news and bad news. The sample is comprised of 532 good news days and 208 bad news days. The 93 remaining event days are classified as no news days (the surprise is zero). *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

	Good News					Bad News				
	T-test on H0: E(Plarge-Psmall)=0		*Lower Quartile Mean* (%)	*Upper Quartile Mean* (%)	*obs.*	*T-test on H0: E(Plarge-Psmall)=0*		*Lower Quartile Mean* (%)	*Upper Quartile Mean* (%)	*obs.*
	Mean (%)	*p-value*				*Mean* (%)	*p-value*			
Panel A: Using All Bonds										
Full Sample	−0.07	(0.002)***	−0.36	0.26	1,798	0.09	(0.031)**	−0.21	0.46	531
Investment-grade	−0.10	(<0.0001)***	−0.35	0.23	1,579	0.02	(0.660)	−0.20	0.22	341
BBB	−0.27	(<0.0001)***	−0.75	0.26	551	0.07	(0.445)	−0.43	0.42	105
A and Higher	−0.01	(0.648)	−0.21	0.21	1,028	−0.004	(0.935)	−0.18	0.2	236
High-Yield	0.12	(0.165)	−0.48	0.77	223	0.21	(0.019)**	−0.27	0.9	187
Panel B: Using Top Bonds										
Full Sample	−0.10	(<0.0001)***	−0.39	0.26	1,498	0.11	(0.013)**	−0.21	0.49	453
Investment-grade	−0.14	(<0.0001)***	−0.38	0.21	1,301	0.02	(0.670)	−0.21	0.22	283
BBB	−0.34	(<0.0001)***	−0.81	0.21	493	0.09	(0.343)	−0.41	0.43	94
A and Higher	−0.02	(0.447)	−0.22	0.21	808	−0.01	(0.788)	−0.20	0.17	189
High-Yield	0.12	(0.184)	−0.45	0.78	191	0.26	(0.004)***	−0.21	0.9	169

with minimal divergence on good news days. For top bonds, similar results are observed (Panel B).

We consider the possibility that firms release earnings announcements strategically, withholding bad news as late as possible.[32] We estimate the following logistic regression:

$$ATDUM = \alpha + \beta * \Delta P + \varepsilon, \tag{8}$$

where $ATDUM$ is a dummy variable for whether the announcement time is close to market open (after 8 am), and ΔP represents the price change from the previous day's close until three hours after the announcement. Table 16 documents a statistically significant negative coefficient for ΔP, suggesting that bonds with post announcement negative returns more likely follow announcements released close to market open. We account for the fact that the non-constant number of bonds issued by different firms can potentially bias the results towards those more heavily represented in the corporate bond market in two ways. First, we replace individual returns with averaged returns across all bonds for each issuer, and second, we estimate the model on top bonds only. Table 16 documents consistent results, with statistically significant negative coefficients for both specifications.

6.4. Improving retail investor welfare: reporting time changes

The notably favorable terms of trades for institutional investors in the corporate bond market have been documented in several recent papers. Goldstein and Hotchkiss (2007) and JNS (2008) find higher trading costs for retail-sized trades than large-sized trades. Similar results have been found in Schultz (2001), Saunders, Srinivasan, and Walter (2002), Bessembinder, Maxwell, and Venkataraman (2006), Edwards, Harris, and Piwowar (2007), and Goldstein, Hotchkiss, and Sirri (2007) among others for the corporate bond market, and Green, Hollifield, and Schürhoff (2007a) for the municipal bond market. Consistent with these studies, we find an inverse relationship between price volatility and trade size. See Panel A of Table 17, which shows retail volatility and price ranges to be nearly five times greater (significant at the 1% level) than those of large trades. Further, these results persist across both high yield and investment grade categories. The relative terms to trade for institutional and retail trades bear on the informational efficiency of the market as a whole, and should potentially receive more policy attention.

Within the initial TRACE years, a gradual decline in mandatory reporting time windows for dealers was enforced. Specifically, transaction reporting-time for NASD members decreased from 75 minutes to 45 minutes on October 1, 2003, was further reduced to 30 minutes on October 1, 2004, and finally to 15 minutes on July 1, 2005. Of special interest is whether small trades benefit from these changes, particularly in terms of informational efficiency, and if so, whether the benefit is sufficient to reduce any comparative disadvantages retail investors may face. To the extent that quicker reporting mandates create faster dissemination of information to the market, resulting retail welfare improvements would bear on the growing transparency debate.[33]

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[32] We would like to thank the referee for this suggestion.

[33] In terms of the effect on trading costs, several studies have documented declining costs for certain bonds when transparency was first introduced through the TRACE system. Using a proprietary data set, Edwards, Harris, and Piwowar (2007) find that TRACE transparent bonds have lower transaction costs than opaque ones, and that transaction costs drop when the bonds become transparent. The largest decreases are shown for small trades. This is consistent with Bessembinder, Maxwell, and Venkataraman (2006) and Bessembinder and Maxwell (2008) who

Table 16
Timing of announcement release and post-announcement price changes.
This table provides the results from estimating the following logistic regression:

$$ATDUM = \alpha + \beta * \Delta P + \varepsilon.$$

The dependent variable is a dummy variable for whether the announcement time is close to market open (after 8 am), and the independent variable represents post-announcement price movements, estimated using price changes from the previous day's close until three hours after the announcement. We choose three different approaches to measure the post-announcement price movements. First, we calculate the price changes at the firm level by averaging the price changes across bonds by the same issuer. Second, we use the price change for the top bond for each firm. Lastly, we use the price changes for each individual bond.

	Firm Level				Bond Level	
	Average across Bonds by the Same Issuer		Top Bonds		Individual Bonds	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Intercept	−0.875	<0.0001	−1.241	<0.0001	−0.909	<0.0001
Post-announcement Price Change	−25.312	0.039	−34.548	0.032	−16.716	0.015

Panel B of Table 17 indicates that both the price dispersions and ranges for small and large trades decline monotonically and significantly with each reporting window improvement (1% significance level for the 75-minute vs. 15-minute windows). Further, the distance between the average price levels for institutional and retail trades also shrinks significantly (from 0.68% to 0.37%, at the 1% significance level). Specifically, the difference between the small–large price level distance measure during the 75-minute reporting time regime and the 15 minutes regime is 0.31% (significant at the 1% level).

The above results combined paint a consistent picture in which retail investors appear to benefit from the decreased reporting time windows regulated (and imposed upon dealers). Speedier transmission of institutional-sized trade information to retail customers significantly decreases their price dispersions and ranges.[34]

7. Concluding remarks

Corporate bond market liquidity has been a subject of great interest lately, and the shifting liquidity across bonds proves to be instrumental in the ability to detect informational advantages of certain type of investors, and at certain times of day. For example, low equity market liquidity periods prove to be advantageous for institutional traders entering the market immediately after announcement releases.

(*footnote continued*)
find that insurance company transaction costs declined for bonds upon inclusion on TRACE system, while for their sample of BBB rated bonds, Goldstein, Hotchkiss, and Sirri (2007) show that increased transparency has either a neutral or positive effect on liquidity. In terms of transaction costs, they do document significant decreases for trade sizes between 21 and 250 bonds.

[34] Since anecdotal evidence suggests that dealers reduced their reporting times significantly with the first regulation change, we consider the periods before and after July 1, 2005, representing the final reduction to a 15-minute reporting lag. While these results could potentially be driven by inter-temporal volume changes, Fig. 3 indicates relatively stable volume and trading frequency across reporting lag periods.

Table 17

TRACE reporting time changes and effect on bond price behavior.

This table presents summary statistics for price volatility and average price levels for large and small bond trades. For each bond/day, the average price levels, price range (difference between the highest and lowest prices within that day, divided by the average price level), and price dispersions (standard deviations of the intraday prices, normalized by the average price level) are calculated for the small and large bond trades, respectively. There are a total of 103,236 bond/days included in the sample. In the third set of columns, we conduct a *t*-test on the difference between average large and small trade price levels and the *p*-values are recorded. Panel A documents summary statistics for the price volatility measures and for average price level differences over the entire sample period by credit rating category. Panel B presents the results across reporting time window regimes for the 593 bonds that trade during both the 75-minute and 15-minute reporting time regimes. The bottom two rows present the estimates and *p*-values, respectively, for *t*-tests conducted on the difference in means (of price dispersions, price ranges, and average price level differences between large and small trades) between the two regimes.

	Large						*Small*						*Price Level Difference between Large and Small Trades*		
	Price Dispersions (%)			*Price Range* (%)			*Price Dispersions* (%)			*Price Range* (%)					
	Mean	*Median*	*STDEV*	*Mean*	*Median*	*STDEV*	*Mean*	*Median*	*STDEV*	*Mean*	*Median*	*STDEV*	*Est.*(%)	*p-value*	*N*
Panel A: Whole Sample Period (January 1, 2003–December 31, 2006)															
Full Sample	0.40	0.17	0.83	0.17	0.08	0.34	2.45	1.82	2.26	0.71	0.57	0.59	0.47	<0.0001	103,236
Investment-grade	0.15	0.07	0.34	0.36	0.15	0.79	0.67	0.52	0.58	2.26	1.65	2.10	0.47	<0.0001	93,617
High-yield	0.30	0.22	0.33	0.85	0.55	1.05	1.06	0.99	0.56	4.34	3.92	2.78	0.95	<0.0001	9,618
Panel B: Different Reporting Time Periods															
75-Minute Reporting Time Period (January 1st, 2003–September 30th, 2003)															
	0.25	0.16	0.38	0.62	0.35	0.99	0.93	0.81	0.68	3.16	2.63	2.50	0.68	<0.0001	23,374
45-Minute Reporting Time Period (October 2nd, 2003–September 30th, 2004)															
	0.15	0.08	0.26	0.34	0.17	0.65	0.74	0.61	0.58	2.44	1.95	2.05	0.47	<0.0001	30,059
30-Minute Reporting Time Period (October 2nd, 2004–June 30th, 2005)															
	0.15	0.07	0.27	0.37	0.13	0.77	0.63	0.47	0.55	2.24	1.56	2.29	0.39	<0.0001	20,325
15-Minute Reporting Time Period (July 2nd, 2005–December 30th, 2006)															
	0.13	0.05	0.42	0.31	0.10	0.87	0.56	0.41	0.50	2.04	1.34	2.10	0.37	<0.0001	29,186
T-test on Differences between 75-Minute and 15-Minute Reporting Time Periods															
estimate	0.12			0.32			0.37			1.12			0.31		
p-value	<0.0001			<0.0001			<0.0001			<0.0001			<0.0001		

Notably, the liquidity of an issuer's bonds tends to shift across time, rendering the notion of 'more liquid' and 'less liquid' bonds a dynamic concept. We find common characteristics for the top bonds after information events, facilitating the a priori identification of the most trade-intensive bonds.

Recognizing the predominantly institutional investor base of the corporate bond market as well as the liquidity and timing of trades yields compelling results regarding the informational efficiency of the market as a whole, and its relative informational efficiency with the equity or potentially other markets. Moreover, the difficulties associated with

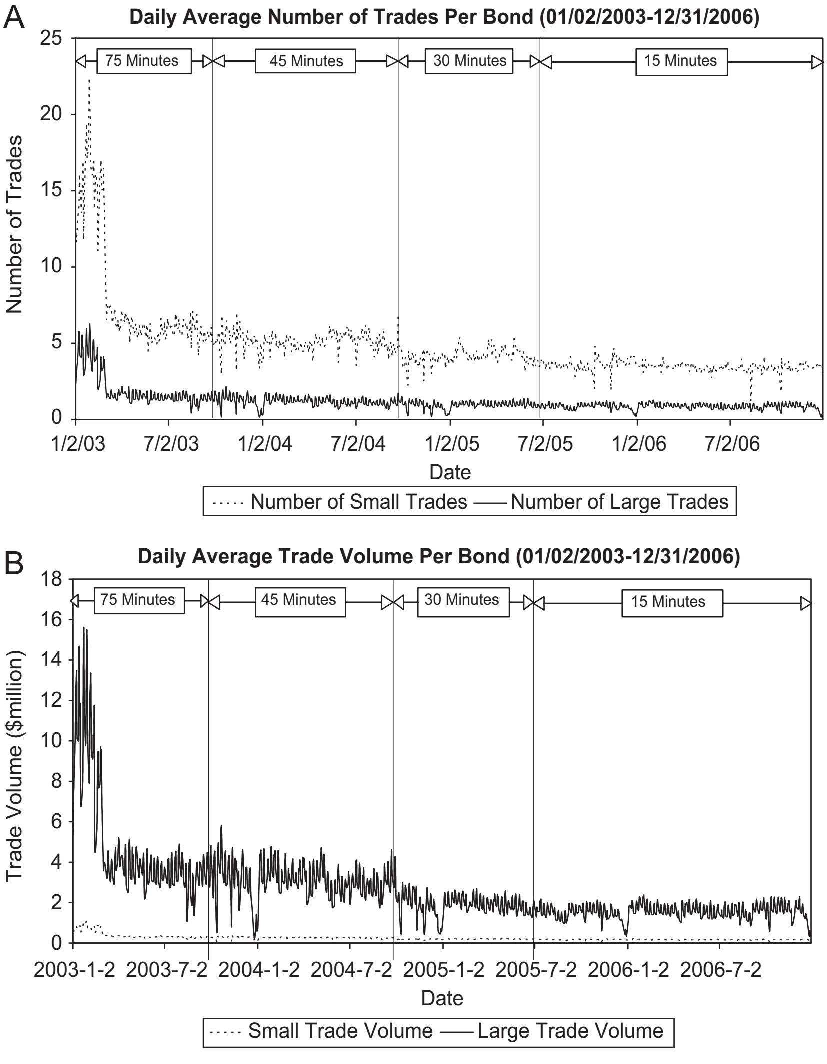

Fig. 3. Average daily trading frequency and volume per bond. This figure presents average daily number of trades (Panel A) and average daily trading volume (Panel B) for all bonds over the sample period (2003–2006). During this period, transaction reporting time for NASD (FINRA) members decreased from 75 minutes to 45 minutes on October 1, 2003, further reduced to 30 minutes on October 1, 2004, and finally to 15 minutes in July 1, 2005. The early drop in (per bond) volume corresponds to the TRACE phase-in inclusion of less liquid bonds.

testing the relative informational efficiency across markets in general are highlighted. Certain cautionary steps must be taken to adequately incorporate shifting liquidity effects, trade size, and information arrival patterns into tests. For example, we demonstrate that the VAR approach is inadequate in addressing the informational efficiency of corporate bonds without proper considerations. Further research involves the implications of these findings for the design of tests of information incorporation in other financial assets.

One main focus of this paper is documenting the importance of recognizing the dominance of the institutional trading sector in the corporate bond market. The large number of noisier retail trades (relatively small in overall volume) tends to obscure statistical testing and resulting inferences. We show that in terms of the response to news surprises, large trades are most informative around earnings announcements. Notably, the distinct reactions of large and small trades persist even after we account for timing patterns in announcement arrivals. Credit quality is shown to affect the sensitivity of bond trades to firm-specific information, with lower-rated bonds exhibiting stronger reactions, particularly on bad news days. We also find that the relative terms to trade between large and small trades improve as dealers are forced to report within shorter periods of time following execution.

This paper can be seen as carrying important implications for regulators, academics, capital structure arbitrageurs, and other investors alike. While our results are consistent with Green (2007), who models retail investors as having less access to information and similar acquisition costs, they should also bear on the growing debate on transparency.[35] In contrast to the prediction that bond market transparency can worsen terms for efficiency, Spatt (2004) argues that it can be optimal for risk sharing (unlike in the equity markets, where transparency may hamper liquidity to large traders), and Naik, Neuberger, and Viswanathan (1999) assume that market makers need not scale back the size of trades since the informational content should already be reflected in the marketplace. Our results, combined with extant evidence of low trading costs for larger bond trades imply that the relatively larger information content of institutional trades does not negatively affect dealer participation terms, in terms of either speed or cost.

Certain policy questions remain open. If optimal trading structures are those that protect retail investors as fully as their institutional counterparts, our results related to reporting time changes and resulting retail investor welfare improvements indicate that retail investors may be best served by continued scrutiny. Further, if markets are information-integrated (and if liquidity in one market affects trade in another), regulation-based efforts should be directed towards all markets simultaneously to be ultimately effective.

References

Alexander, G.J., Edwards, A.K., Ferri, M.G., 2000. The determinants of trading volume of high-yield corporate bonds. Journal of Financial Markets 3, 177–204.

Amihud, Y., Mendelson, H., 1991. Liquidity, maturity, and the yields on U.S. Treasury securities. Journal of Finance 46, 1411–1425.

[35] Green (2007) models differential search costs of retail investors in new issues with limited secondary market transparency. He finds that retail search costs result in more disperse pricing in the secondary market, with a different outcome for institutional trades. Our results are also consistent with Green, Hollifield, and Schürhoff (2007a) in which an uninformed retail sector cannot properly monitor dealer rent seeking.

Barclay, M.J., Hendershott, T., 2003. Price discovery and trading after hours. The Review of Financial Studies 16, 1041–1073.

Barclay, M.J., Hendershott, T., 2008. A comparison of trading and non-trading mechanisms for price discovery. Journal of Empirical Finance 15, 839–849.

Barclay, M.J., Hendershott, T., McCormick, T.D., 2003. Information and trading on electronic communications networks. Journal of Finance 58, 2637–2666.

Barclay, M.J., Warner, J.B., 1993. Stealth trading and learning during the pre-opening period in the Paris Bourse. Journal of Political Economy 107, 1218–1248.

Bao, J., Pan, J., Wang, J., 2011. The illiquidity of corporate bonds. Journal of Finance 66, 911–945.

Bessembinder, H., Maxwell, W.F., 2008. Transparency and the corporate bond market. Journal of Economic Perspectives 22, 217–234.

Bessembinder, H., Maxwell, W.F., Venkataraman, K., 2006. Market transparency, liquidity externalities, and institutional trading costs in corporate bonds. Journal of Financial Economics 82, 251–288.

Biais, B., Green, R., 2007. The microstructure of the bond market in the 20th century. IDEI working paper no. 482.

Boehmer, E., Kelley, E., 2009. Institutional investors and the informational efficiency of prices. Review of Financial Studies 22, 3563–3594.

Chakravarty, S., Sarkar, A., 2003. A comparison of trading costs in the U.S. corporate, municipal and treasury markets. Journal of Fixed Income 13, 39–48.

Crabbe, L.E., Turner, C.M., 1995. Does the liquidity of a debt issue increase with its size? Evidence from the corporate bond and medium-term note markets. Journal of Finance 50, 1719–1734.

Dick-Nielsen, J., Feldhutter, P., Lando, D., 2011. Corporate bond liquidity before and after the onset of the subprime crisis. Journal of Financial Economics 103, 471–492.

Downing, C., Underwood, S., Xing, Y., 2009. The relative informational efficiency of stocks and bonds: an intraday analysis. Journal of Financial and Quantitative Analysis 44, 1081–1102.

Edwards, A.K., Harris, L., Piwowar, M.S., 2007. Corporate bond market transaction costs and transparency. The Journal of Finance 62, 1421–1451.

Edwards, A.K., Nimalendran, M., 2007. Corporate bond market transparency: liquidity concentration, informational efficiency, and competition. Securities Exchange Commission working paper.

Fabozzi, F.J., 1996. Bond Markets, Analysis and Strategies. Prentice-Hall, Upper Saddle River, NJ.

Goldstein, M.A., Hotchkiss, E.S., 2007. Dealer behavior and the trading of newly issued corporate bonds. Boston College working paper.

Goldstein, M.A., Hotchkiss, E.S., Sirri, E.R., 2007. Transparency and liquidity: a controlled experiment on corporate bonds. Review of Financial Studies 20, 235–273.

Green, R.C., 2007. Presidential address: issuers, underwriter syndicates, and after-market transparency. The Journal of Finance 62, 1529–1550.

Green, R.C., Hollifield, B., Schürhoff, N., 2007a. Financial intermediation and the costs of trading in an opaque market. Review of Financial Studies 20, 275–314.

Green, R.C., Hollifield, B., Schürhoff, N., 2007b. Dealer intermediation and price behavior in the aftermarket for new bond issues. Journal of Financial Economics 86, 643–682.

Guo, R., Sarkar, A., Schuermann, T., 2007. Liquidity, returns and investor heterogeneity in the corporate bond markets. Federal Reserve Bank working paper.

Gurun, U., Johnston, R., Markov, S., 2008. The effects of sell-side debt research on debt and equity markets. University of Texas at Dallas working paper.

Hong, G., Warga, A.D., 2000. An empirical study of bond market transactions. Financial Analysts Journal 56, 32–46.

Hotchkiss, E.S., Ronen, T., 2002. The informational efficiency of the corporate bond market: an intraday analysis. Review of Financial Studies 15, 1325–1354.

Hotchkiss, E.S., Jostova, G., 2007. Determinants of corporate bond trading: a comprehensive analysis. Boston College working paper.

Jankowitsch, R., Nashikkar, A., Subrahmanyam, M.G., 2008, Price dispersion in OTC markets: a new measure of liquidity. New York University working paper.

Kwan, S.H., 1996. Firm-specific information and the correlation between individual stocks and bonds. Journal of Financial Economics 40, 63–80.

Madhavan, A., Richardson, M., Roomans, M., 1997. Why do security prices change? A transaction-level analysis of NYSE stocks. Review of Financial Studies 10, 1035–1064.

Mahanti, S., Nashikkar, A., Subrahmanyam, M.G., Chacko, G., Mallik, G., 2008. Latent liquidity: a new measure of liquidity, with an application to corporate bonds. Journal of Financial Economics 88, 272–298.
McInish, T.H., Van Ness, B., Van Ness, R.A., 2002. After-hours trading of NYSE stocks on the regional exchanges. Review of Financial Economics 11, 287–297.
Naik, N.Y., Neuberger, A., Viswanathan, S., 1999. Trade disclosure regulation in markets with negotiated trades. Review of Financial Studies 12, 873–900.
Saunders, A., Srinivasan, A., Walter, I., 2002. Price formation in the OTC corporate bond markets: a field study of the inter-dealer market. Journal of Economics and Business 54, 95–113.
Sarig, O., Warga, A.D., 1989. Bond price data and bond market liquidity. Journal of Financial Quantitative Analysis 24, 367–378.
Schultz, P.H., 2001. Corporate bond trading costs and practices: a peek behind the curtain. Journal of Finance 56, 677–698.
Spatt, C.S., 2004. Frictions in the bond market. Keynote address at the second MTS conference on financial markets: The organization and performance of fixed-income markets, Vienna, December 16, 2004.
Thompson, S.B., 2011. Simple formulas for standard errors that cluster by both firm and time. Journal of Financial Economics 99, 1–10.
Warga, A.D., 1992. Bond Returns. Liquidity, and Missing data. Journal of Financial Quantitative Analysis 27, 605–617.
Warga, A.D., 2004. An Overview of the Regulation of the Bond Markets. Report to the Senate Banking Committee.
Zhou, X., 2009. Information-based trading in the junk bond market. Cornell University working paper.