The Effects of Transparency on OTC Market-Making*

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Abstract

We examine the effects of post-trade transparency on intermediation in the over-the-counter corporate bond market using the staggered introduction of TRACE as a natural experiment. Post-trade transparency leads to increased trading volume and more connected dealer networks. Transparency reduces dealers' profitability but also their portfolio risk and adverse selection costs. In contrast to prior research suggesting that TRACE benefits customers at the expense of dealers, we show that the net effect on dealer welfare is ambiguous. Bond spreads are less predictive of default in a transparent market, consistent with reduced profitability of informed trade weakening incentives to produce information.

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Many important financial assets, including leveraged loans and credit, currency, and interest rate swaps, trade over-the-counter (OTC) and lack publicly available information on transaction prices and volumes. Regulators have considered proposals to enhance transparency in these markets in the interest of investor protection, but the jury is out on the equilibrium effects of publishing transaction data in OTC markets. This paper examines the effects of post-trade transparency in the corporate bond market using the introduction of the Trade Reporting and Compliance Engine (TRACE) as a natural experiment.

We use newly released data on corporate bond transactions with anonymized dealer identifiers to shed light on how the introduction of post-trade transparency affects informational frictions, search costs, and the economics of market-making. Our analysis exploits the staggered implementation of TRACE to implement a modified difference-in-differences identification strategy that compares bonds with the same credit rating and issue size, traded by the same dealer at the same time, but with different dissemination status, allowing for a causal interpretation of the effects of post-trade transparency.

We begin by showing that when post-trade transparency is introduced, dealers trade with more counterparties and trading volume increases. This is consistent with a reduction of search costs (Duffie, Garleanu, and Pedersen (2005)) due to the improved confidence that a quoted price is close to the outside option that comes from the public dissemination of transaction prices. The resulting expansion of dealer networks likely contributes to the lower customer execution costs observed in prior research (Bessembinder, Maxwell, and Venkataraman (2006), Edwards, Harris, and Piwowar (2007), Goldstein, Hotchkiss, and Sirri (2007), Asquith Covert and Pathak (2019)).

Next, we consider how post-trade transparency affects the profitability of market-making. In line with earlier work, we observe that dealers earn lower average profits trading bonds after the introduction of TRACE. This effect is economically significant, equal to about 24% of the pre-TRACE average. However, dealers are not necessarily worse off in the post-TRACE environment because the risk of market-making decreases commensurately. We find that the covariance between profits on a dealer's individual bond positions and its overall portfolio is significantly reduced by the introduction of TRACE, with a similar magnitude to what we observe for profits. This is consistent with a reduction in search costs and expansion of the dealer network improving dealers' ability to share risk.

Turning to the effects of informational frictions, we find that dealers widen bid-ask spreads when they face imbalanced order flow from customers (i.e., more sales than purchases, or vice versa), in line with the predictions of Copeland and Galai (1983). We show that order imbalance is driven at least in part by informed trading activity, as evidenced by the ability of order imbalance to predict bond returns prior to the introduction of TRACE.[1] Despite the widening of bid-ask spreads in periods of order imbalance, we find that dealers earn significantly lower profits during these episodes.

We estimate that the introduction of TRACE reduces the adverse effect of order imbalance on dealer profits by 74%. This suggests that post-trade transparency reduces the degree of adverse selection that dealers face when trading with informed customers. We show this effect is driven by dealers' ability to adjust the level of prices more quickly when other dealers' trades are published, which reduces the predictive relation between order imbalance and subsequent bond returns.

The overall effect of post-trade transparency on dealer welfare is ambiguous. While the introduction of TRACE reduces the average profits earned by dealers, it also leads to reductions in portfolio risk and adverse selection costs. This casts doubt on the conventional wisdom from earlier studies that focus on customer execution costs and conclude that TRACE benefits customers at the expense of dealers.[2]

Although post-trade transparency reduces execution costs for customers and the risks of

[1] Chordia, Roll, and Subrahmanyam (2002) study the relation between order imbalances and returns in the stock market. They note that order imbalances can be driven by either privately informed trading or random supply-demand imbalances, both of which increase costs for a market-maker.

[2] For example, Asquith, Covert, and Pathak (2019) write, "The sharp pervasive reduction in trading costs may be a consequence of the fact that trading information changes the relative bargaining positions of investors and dealers, allowing investors to benefit at the expense of dealers. Our best estimate is that TRACE transferred about $600 million a year from dealers to customers."

accommodating order flow for dealers, there are potentially adverse consequences. Higher profits for dealers when order flow is imbalanced correspond to lower profits for informed traders, which weakens the incentives for these traders to gather information. Therefore, TRACE may have the unintended effect of reducing overall price informativeness by hindering information production.[3]

To explore this possibility, we develop a novel empirical test of corporate bond price efficiency, exploiting the fact that the payoff of a corporate bond ultimately depends on whether or not the issuer defaults. We show that when bond trades are disseminated, the explanatory power of credit spreads to predict default over a two-year window is significantly worse than when trades are not disseminated. This finding is consistent with post-trade transparency weakening the incentives of informed traders to participate in the market, which leads to reduced information content in prices.

Past research on the TRACE experiment shows that post-trade transparency reduces the effective bid-ask spreads paid by customers (Bessembinder, Maxwell, and Venkataraman (2006), Edwards, Harris, and Piwowar (2007), Goldstein, Hotchkiss, and Sirri (2007)) and the volume of trading activity in risky high-yield bonds (Asquith, Covert and Pathak (2019)). We contribute to the literature by showing that price transparency alters the OTC market structure and the profitability and riskiness of market-making activities. By altering the incentives of market participants, transparency also affects the information content of prices. Our findings provide empirical support for theoretical predictions that both dealers and informed traders prefer an environment without disclosure because dealers are less able to earn profits from uninformed traders through bid-ask spreads and informed traders are less able to hide their information as they trade (Madhavan (1995), Pagano and Roell (1996)).[4]

The identification strategy in this paper builds on prior studies using the same natural ex-

[3]Consistent with this prediction, in an experimental setting Da and Huang (2019) show that amateur equity analysts become less accurate as a group when provided with consensus forecasts.

[4]Most of our findings are inconsistent with the experimental evidence in Bloomfield and O'Hara (1999), who find that trade disclosure widens bid-ask spreads, increases dealer profits, and improves informational efficiency. However, the post-TRACE reduction in return predictability could be interpreted as informational efficiency in their experimental setup.

periment. We improve on these studies by controlling for a bond's time-varying credit quality in addition to the standard control for its time-invariant characteristics. Closest in spirit to our work is Asquith, Covert, and Pathak (2019), who explore a variety of outcomes including price dispersion, volumes, and bid-ask spreads in a bond-level difference-in-differences analysis around the initiation of each phase. In addition to our more stringent controls for credit risk, our use of data with dealer identifiers allows us to study novel outcomes including the structure of dealer networks and the profitability and riskiness of market-making.

Our findings are also related to Chalmers, Liu, and Wang (2020), who study the introduction of the Real-Time Transaction Reporting System (RTRS) in the municipal bond market. In line with our results, these authors find that a reduction in dealer reporting times from 24 hours to 15 minutes leads to a reduction in search costs that is reflected in lower bid-ask spreads, higher trading volume, and more complete dealer networks. Our empirical settings differ in that the TRACE experiment involves a shift from no transparency to full transparency at the bond level, which allows us to use a difference-in-differences identification strategy, whereas the RTRS introduction shortened the reporting time for all bonds in a market that was already transparent. In addition, we provide novel evidence on the profitability and risks of market-making, as well as implications for price informativeness.

Our analysis of dealer-level profits builds on the relatively recent literature that uses transaction-level data with dealer identifiers to understand the structure of OTC markets (e.g., Adrian, Boyarchenko, and Schachar (2017), Di Maggio, Kermani, and Song (2017), Schultz (2017), Bessembinder et al. (2018), Dugalic (2018), O'Hara, Wang, and Zhou (2018), Choi and Huh (2019), Hendershott et al. (2019), Li and Schurhoff (2019), Kakhbod and Song (2020)). In this manner, we contribute to the broader literature on frictions associated with trading corporate bonds (e.g., Schultz (2001), Goldstein and Hotchkiss (2008), Mahanti et al. (2008), Feldhutter (2012), Ederington, Guan, and Yadav (2014), Bao, O'Hara, and Zhou (2018), Brugler, Comerton-Forde, and Martin (2018), Dick-Nielsen and Rossi (2019)) and the relation between dealer inventory costs and trading behavior (e.g., Zitzewitz (2010), Randall (2015), Schultz (2017), Bessembinder et al. (2018)), Choi and Huh (2019)).

Finally, we contribute to the literature on price efficiency in the corporate bond market (e.g., Hotchkiss and Ronen (2002)). Two recent papers are closely related to our finding that price informativeness declines after the introduction of post-trade price transparency. Badoer and Demiroglu (2019) show that the bond market reacts less strongly to ratings changes after dissemination, consistent with ratings containing less incremental information when bond prices more effectively aggregate information from market participants. In a similar vein, Chen and Lu (2019) find that bond prices react more quickly to bond analyst reports but that these analysts issue fewer reports after the introduction of TRACE. The prevailing narrative in these papers is that after price transparency improves, bond prices adjust more quickly when new information is introduced. Our finding that dealers adjust more quickly to the information contained in customer order flows is in line with these studies. However, we argue that new information is less likely to be produced because post-trade transparency reduces the potential profits from informed trade. Consistent with this view, Chen and Lu (2019) report a reduction in analyst coverage and fewer reports generated by analysts after TRACE.[5]

The remainder of the paper is organized as follows. Section 1 describes our data and identification strategy. Section 2 presents our main results on how post-trade transparency affects trading activity and the profitability and riskiness of market-making. Section 3 examines the effects of transparency on price informativeness. Section 4 concludes.

[5]This finding is also consistent with the theoretical result in Banerjee, Davis, and Gondhi (2018) that increased transparency can worsen price efficiency if investors use the new information to learn about other traders instead of asset fundamentals.

1 Empirical Setting and Research Design

1.1 TRACE Transaction Dissemination Program

This study uses a differences-in-differences design based on the staggered implementation of TRACE, which introduced post-trade price transparency in the corporate bond market. Our regression analysis uses variation in outcomes both across time for the same bond before and after its trades are publicly disseminated and at the same time across bonds for which trades are currently subject to dissemination or not. The fact that post-trade transparency was introduced at different times for different bonds allows a causal interpretation of our results. To provide context for our identification strategy, we describe the institutional setting surrounding this natural experiment.

Prompted by the Securities and Exchange Commission (SEC) to improve transparency in over-the-counter (OTC) markets, the National Association of Securities Dealers (NASD) introduced the Trade Reporting and Compliance Engine (TRACE) on July 1, 2002. The system assembles OTC bond transactions facilitated by brokers and dealers registered with the NASD and it publicly disseminates those transactions in real time. Most U.S. dollar-denominated corporate debt securities registered with the SEC are TRACE-eligible.

Asquith, Covert, and Pathak (2019) describe in detail the rollout of the TRACE platform. To summarize, TRACE replaced a preexisting platform, the Fixed Income Pricing System (FIPS), which was initiated in 1994 and distributed transaction data for about 50 high-yield bonds. In the late 1990s, the SEC pushed for an expansion of this system citing three main objectives: (i) create a platform to assemble and disseminate information on all secondary market corporate bond trades, (ii) create a database of corporate bond transactions that would allow regulators to supervise market activity, and (iii) establish a surveillance system that would enable detection of misconduct and enhance investor confidence.

TRACE began collecting trade data from dealers in July 2002, but instead of disseminating all of these prices to the public from the start, the NASD chose to roll out dissemination in phases. This decision was motivated by the desire to minimize disruption to existing markets and under the auspices that, should TRACE cause significant negative consequences, the program could be abandoned. The phased implementation allowed the NASD to examine the impact of transparency on market function for highly liquid and large bonds before introducing dissemination for riskier securities for which liquidity could be more sensitive to changes in transaction transparency. Phase 1 was implemented on July 1, 2002 and involved dissemination of transaction information for about 470 investment-grade issues of $1 billion or greater, as well as 50 non-investment-grade bonds that were previously disseminated under FIPS. Phase 2 began on March 3, 2003 and expanded dissemination to include smaller, above-investment-grade bonds with original issue size between $100 million and $1 billion and a rating of A- or above. In April 2003, this phase concluded by adding 120 more investment-grade bonds. Between Phases 1 and 2, post-trade transparency was introduced for 4,650 bonds. Phase 3, the largest of the three, was initiated on April 22, 2004 and expanded dissemination to almost all corporate bonds. This last phase was completed on February 7, 2005, at which point real-time transaction data were publicly available for 99% of corporate bond trades.[6]

Figure 1 depicts the introduction of trade dissemination in our sample of bonds, which we describe below. The staggered rollout of TRACE offers an opportunity to identify the causal effect of post-trade transparency on outcomes in the corporate bond market. However, it is important to note that bonds introduced in different phases have different credit ratings and issue sizes at the time dissemination begins, so without controlling for credit quality and bond characteristics, there may be omitted factors that affect interpretation of the dissemination effect. To address this issue, our main regression specification controls for bond, time-rating-dealer, and time-issue size-dealer fixed effects, going beyond the bond and time fixed effects used in standard difference-in-differences regressions. This means we compare bonds with the same current credit rating and issue size, traded by the same dealer at the same time, but

[6]FINRA provides additional details about the TRACE program in the TRACE fact book: `https://www.finra.org/sites/default/files/AppSupportDoc/p017618.pdf`.

with different dissemination status, while accounting for the bond's time-invariant attributes. We also control for observable factors that could affect the outcomes of interest. Even after taking these measures, we recognize the potential for omitted variable bias and discuss this concern when presenting our empirical results.

1.2 Data Sources

In February 2017, FINRA released a historical database of both disseminated and non-disseminated bond transactions starting from July 1, 2002 with anonymized dealer identifiers for each transaction.[7] These data enable a difference-in-differences approach that exploits the staggered introduction of price dissemination. We clean the data by adapting the algorithm proposed by Jens Dick-Nielsen for the Enhanced TRACE database.[8] We focus on the period from July 2002 to December 2006 to encompass the TRACE rollout period and to include a window when nearly all trades are disseminated. After cleaning the raw Academic TRACE data, our sample contains 34.2 million secondary market corporate bond transactions. Our analysis excludes bonds issued under Rule 144A according to Mergent FISD, which comprise about 4% of the sample, because these bonds are not subject to dissemination during our sample period unless the issuer decides to register them after issuance.

Our computation of monthly dealer profits requires the estimation of mark-to-market returns on bond trades that have not yet been unwound. Since many corporate bonds trade infrequently, this calculation often requires the use of stale prices. For an alternative source of data on the value of bonds that are not currently trading, we augment the TRACE data with quote prices from Bank of America Merrill Lynch (BAML). These quotes form the basis for Bank of America's bond indices and are used by many institutional investors to value their portfolios. We are able to match quotes from the BAML data for 15.0 million out of the 34.2 million transactions in the Academic TRACE data. The requirement that a bond

[7]For information on Academic TRACE, see `http://www.finra.org/industry/trace-historic-academic-data`.

[8]See `https://sf.cbs.dk/jdnielsen/how_to_clean_trace_data`.

is quoted in the BAML data tilts the sample towards larger, more liquid issues.

In addition to these corporate bond data sets, our analysis incorporates stock return data from the Center for Research in Security Prices (CRSP) and credit default swap (CDS) quote data from IHS Markit. We merge the TRACE data with CRSP using the Bond CRSP Link on Wharton Research Data Services. We use these data to identify firms with publicly traded equity and to compute equity volatility as a measure of firm-level risk. We use bond tickers to match our data to the IHS Markit CDS quotes and identify firms with traded credit derivatives.

1.3 Measurement of Dealer Profits

Previous researchers examining the role of dealers in OTC markets have constructed measures of customer transaction costs (e.g., bid-ask spread, price impact) and competitive dynamics (e.g., network centrality). To our knowledge, no prior paper directly measures the profitability of dealers. We propose a new measure that reflects the economics of intermediating trade in an OTC market.

The numerator of our measure is straightforward: the dollar profit that dealer d obtains from its N trades in bond i during month t:

$$\pi^{\$}_{d,i,t} = \sum_{j=1}^{N} p_{d,i,j} * (-q_{d,i,j}) + p^{\text{eom}}_{i,t} \sum_{j=1}^{N} q_{d,i,j}, \tag{1}$$

where $p_{d,i,j}$ is the price for trade j and $p^{\text{eom}}_{i,t}$ is the end-of-month price. Quantities q are positive for dealer purchases and negative for dealer sales.[9] The first term captures the net investment across all j trades and represents the realized profit or loss, while the second term captures the mark-to-market value of the position held by the dealer at the end of the month. $p^{\text{eom}}_{i,t}$ is measured using a bid quote from BAML, which represents the price at which

[9]Note that while participants in the corporate bond market observe truncated trade sizes on the TRACE platform, with investment-grade amounts capped at $5 million and non-investment-grade amounts capped at $1 million, our historical data include the actual amounts traded.

a dealer could sell the bond to another dealer.

Dollar profits do not account for the opportunity cost of capital. All else equal, a dealer would prefer to make the same dollar profit while minimizing the amount of inventory and the time holding that inventory. Therefore, we normalize our dollar profits measure by calculating the time-weighted capital committed throughout the month by the dealer in each bond,

$$CC_{d,i,t} = \frac{1}{T}\left[\sum_{j=1}^{N}\left|\left(t_{j,j+1} * p_{d,i,j}\sum_{k=1}^{j}(-q_{d,i,k})\right)\right|\right], \tag{2}$$

where $t_{j,j+1}$ is the time elapsed between trade j and $j+1$, while $p_{d,i,j}\sum_{k=1}^{j}(-q_{d,i,k})$ captures the total dollar amount invested after completing trade j. Multiplying the two terms gives the time-adjusted dollar investment between trades j and $j+1$, which we sum across all trades in the month. Finally, we define time $N+1$ as the end of the month, so the final summation term captures the time-adjusted capital invested from trade N through the end of the month. We normalize by T, the length of time in the month.

We combine equations (1) and (2) to obtain our scaled measure of profits:

$$\pi_{d,i,t} = \frac{\pi^{\$}_{d,i,t}}{CC_{d,i,t}}. \tag{3}$$

1.4 Sample Characteristics

Table 1 reports summary statistics on dealer profits and the explanatory variables used in our regression analysis. Panel A contains bond-month measures of trading activity and Panel B contains dealer-bond-month measures of profits and other control variables. The Appendix contains definitions of each variable. About two-thirds of the dealer-bond-month observations are subject to public dissemination of trade information, while the other one-third are only observed by the transacting parties.

Our calculations show that trading corporate bonds is profitable on average for the dealers in our sample, before accounting for their overhead costs, but there is substantial variability in profits. In the average bond-month observation with nonzero trade, the dealer earns \$4,450 on 6.5 customer-facing trades prior to dissemination and \$2,410 on 7.4 customer-facing trades after dissemination. The scaled profits measure shows a similar pattern, averaging 38.84 pre-dissemination and 21.86 post-dissemination, in line with the difference in dollar profits. Effective bid-ask spreads, computed as the monthly average of within-bond-day differences between the average prices of sales and purchases by the dealer, also exhibit a similar difference, with an average of \$1.10 per \$100 face value before and \$0.60 after a bond's trades are disseminated on TRACE.

The typical month involves an imbalance of buy and sell orders that amounts to 60% of traded volume on average, with slightly more imbalance when trades are disseminated. We focus on absolute imbalance as an explanatory variable in our empirical tests because the magnitude of imbalance matters more than the sign of imbalance for the dealer's costs of market-making. The concentration of dealers in the typical bond-month is slightly lower with dissemination, with the Herfindahl-Hirschman Index (HHI) averaging 0.33 pre-TRACE and 0.28 post-TRACE. This difference is consistent with dealer competition increasing after the introduction of TRACE. When testing for the effects of dissemination on dealer profitability, we control for these characteristics of the market for each bond to mitigate the effect of changes in market structure on the estimates.

About 40% of the observations involve non-investment-grade bonds, with a higher proportion pre-dissemination because of the later introduction of post-trade transparency for high-yield bonds. About 20% of the observations involve firms without publicly traded equity. We use both of these firm characteristics as proxies for information asymmetry in our examination of the determinants of dealer profits, since high-yield bonds have higher default risk than investment-grade bonds and there is less market-based information available for private firms than for public firms. We are unable to obtain a credit default swap quote from IHS Markit, which could serve as an alternative form of price discovery, for 27% of observations in the sample.

Finally, the average equity volatility of the publicly traded firms is 53% before dissemination and 35% after dissemination, primarily due to the early phases of the TRACE rollout having higher marketwide volatility.[10] The sensitivity of bond prices, dealer profits, and trading volumes to macroeconomic factors likely varies by credit quality. Thus, we focus our analysis on specifications where we control by time interacted with rating.

2 Market Structure and Dealer Profitability

We use the data described in the previous section to investigate how post-trade price transparency affects the market structure and allocation of trading surplus in the corporate bond market. First, we investigate the impact of transparency on the network structure of the corporate bond market. We find that the trading network becomes more complete, with disseminated bonds traded by more dealers in both customer-facing and interdealer transactions. This expansion of the trading network is augmented by increased trading volumes for dealers that were already trading a bond prior to dissemination.

Next, we examine the effects of post-trade transparency on the level of dealer profits and their riskiness. We show that the introduction of TRACE has a causal negative effect on dealer profitability. However, the covariance of individual bond profits or losses with the dealer's total portfolio profit or loss is also lower when trades are disseminated, which suggests that transparency reduces the risk borne by dealers. To better understand this finding, we examine the effect of dissemination on dealers' performance in the face of customer order imbalances. We find that dealers earn lower profits when faced with larger order imbalances and that this effect is reduced substantially by the introduction of post-trade transparency. We estimate return predictability regressions that suggest the improvement in dealer performance in the face of imbalance is partially attributable to the ability to adjust prices more quickly to the future level when trades are publicly reported.

[10] For context, the CBOE Volatility Index (VIX) was above 30 during much of the first two years of TRACE (2002-2003), whereas the VIX never moved above 20 during the last two years of our sample (2005-2006).

2.1 Trading Activity and the Dealer Network

We begin our analysis at the bond level by exploring the extent to which post trade dissemination alters the composition of the dealers intermediating bond transactions. We estimate the following regression:

$$Y_{i,t} = \alpha_{i,t} + \beta D_{i,t} + \varepsilon_{i,t}, \tag{4}$$

where $Y_{i,t}$ is a measure of trading activity, $\alpha_{r,t}$ is a vector of fixed effects, and $D_{i,t}$ is an indicator equal to one if trades in bond i are disseminated in month t. We consider various fixed effects specifications to control for unobservable factors that affect trading activity.

Panel A of Table 2 presents estimates of equation (4) where the dependent variable is the number of distinct dealers trading each bond. Column (1) reports a simple regression of dealer count on dissemination status and finds that dissemination raises the number of distinct dealers trading a bond by 4.98, a large increase over the pre-dissemination mean of 9.70 dealers. However, dissemination status is correlated with credit quality and issue size, which are associated with better liquidity, so this estimate is likely biased upward.

To address this endogeneity concern, column (2) adds bond fixed effects to control for time-invariant bond characteristics and year-month fixed effects interacted with the bond's current credit rating and issue size quintile to account for trends in trading activity that correlate with the TRACE rollout. The estimated coefficient drops to 1.61, but remains statistically significant at the 1% level. This is an economically significant effect, representing an increase of 17% over the average number of dealers trading non-disseminated bonds.

Next, we investigate the manner in which the dealer network expands. Column (3) focuses on customer-facing trades under the hypothesis that after bonds are disseminated, private information about order flow available to active dealers is less important, encouraging entry by dealers who are not active in a given bond. We find TRACE causes the number of customer-facing dealers to increase by 1.16 (16% of the pre-TRACE mean). Column (4) shows an increase of 1.46 (23%) in the number of dealers participating in the interdealer market. Thus, the introduction of post-trade transparency induces new dealers to trade with customers and use the interdealer market to offload inventory.

We hypothesize that entry to the interdealer market should increase the number of connections in the interdealer network. Column (5) regresses the number of distinct dealer pairs trading in a bond-month on dissemination status using the same fixed effects specification as columns (2) through (4). Introducing TRACE leads to 2.66 more distinct dealer-to-dealer links in the typical bond-month, approximately 19% larger than the average number of links before dissemination. However, this result is statistically insignificant.

This broadening of the dealer network could have at least two potential effects on trading volume: i) total trading activity increases as a result of dissemination or ii) total volume is unchanged but entrants take market share from incumbents. Theoretically, Kakhbod and Song (2020) show that improving transparency leads to more gains from trade and higher trading volume. Prior studies on the TRACE experiment report mixed results on trading volume based on different sample selection criteria and identification strategies, with Goldstein, Hotchkiss, and Sirri (2007) finding no effect in a sample of BBB-rated bonds, while Asquith, Covert, and Pathak (2019) find a reduction in the number of trades in high-yield bonds and no effect for investment-grade bonds.[11]

Panel B of Table 2 presents estimates of equation (4) where the dependent variable is the logarithm of trading volume. Column (1) shows a positive and statistically significant coefficient in a simple regression that indicates a 41% increase in volume after TRACE. Column (2) adds bond, year-month-rating, and year-month-issue size fixed effects to account for the endogeneity problem discussed above. The coefficient becomes statistically insignificant and close to zero after adding these control variables. We find a similar null effect in column (3), which focuses on customer-facing transactions. However, column (4) shows a positive and statistically significant effect of TRACE on volume in the interdealer market. Overall, these

[11] Asquith, Covert, and Pathak (2019) use a difference-in-differences approach that focuses on a narrow window around the initiation of each phase. Their regression specification fails to account for time-varying credit quality, which could confound their estimates and contribute to differences in our results.

results suggest that customer-facing activity was unaffected by the introduction of post-trade transparency, but trading among dealers increased.

Finally, we estimate the effect of transparency on the intensive margin of trading activity by restricting the sample to dealers that trade the bond both before and after dissemination. If the effects of dissemination on trading volume were driven by expansion of the dealer network, then we would expect to find no effect of dissemination. Column (5) reports a positive and statistically significant coefficient, which suggests that active dealers increased their trading volume after TRACE. However, this estimate is statistically indistinguishable from the full sample coefficient, leading us to conclude that the introduction of post-trade transparency leads to weakly higher trading volume both across and within dealers.

2.2 Dealer Profits

Next, we turn our attention to effects of post-trade transparency on the profitability of market-making. For this analysis, we require a dealer to trade a bond at least twice in a month to compute the profit or loss for that bond.[12] We explore the determinants of dealer profits with regressions of the following form:

$$\pi_{d,i,t} = \alpha_{d,i,t} + \beta D_{i,t} + \gamma \mathbf{X}_{d,i,t} + \varepsilon_{d,i,t}, \tag{5}$$

where $\pi_{d,i,t}$ is a measure of dealer profits, $\alpha_{d,i,t}$ is a vector of fixed effects, $D_{i,t}$ is an indicator equal to one if trades in bond i are disseminated in month t, and $\mathbf{X}_{d,i,t}$ is a vector of variables that are expected to correlate with the profitability of market-making, including absolute order imbalance and the dealer's lagged share of trading volume at the dealer-bond-month level; the logarithm of trading volume, the Amihud (2002) price impact measure of illiquidity, the HHI measure of dealer concentration at the bond-month level; and an indicator for private

[12] The Internet Appendix reports similar results when attention is restricted to the most active dealers in the market, which mitigates concerns about the sparsity of trading and the quality of reporting by smaller dealers.

firms and contemporaneous realized equity volatility for public firms at the issuer-month level. We consider various fixed effects specifications to control for unobservable factors that affect dealer profits. We also include the effective bid-ask spread in one specification to test whether the effects of dissemination on profits are driven by changes in bid-ask spreads.

Panel A of Table 3 reports estimates of equation 5 with dollar profits as the dependent variable. Column (1) includes no fixed effects to offer a basis of comparison for the fixed effects specifications. It shows that dealer profits are unconditionally lower by $2,043 per bond-month when trades are disseminated, equivalent to a reduction of 46% relative to the pre-dissemination mean.

As described above, the earlier introduction of TRACE for higher-rated and larger bond issues creates a potential endogeneity bias. Column (2) addresses this concern by adding bond and year-month fixed effects interacted with the bond's current credit rating and issue size quintile, which control for time-invariant bond characteristics and time-varying market conditions in each rating and size category. The inclusion of these controls reduces the estimated coefficient, but it remains statistically significant at the 1% level. Column (3) interacts the year-month-rating and year-month-issue size fixed effects with dealer fixed effects, comparing bonds of the same credit quality and issue size, traded by the same dealer at the same time, but with different dissemination status. The coefficient is quantitatively similar to column (2) and corresponds to a reduction in profits of $1,058 per bond-month, or 24% of the pre-dissemination average.

The addition of controls in column (4) sheds further light on the determinants of dealer profits. The coefficient on the disseminated indicator is similar, with a slightly larger magnitude, which suggests that omitted variables are not driving our estimates and provides support for our identification strategy. The added control variables have intuitive coefficients, with dealers earning higher profits in bonds that have a lower magnitude of order imbalance and higher trading volume, and bonds issued by firms with high equity volatility. The coefficients on the concentration of dealer activity in the bond and the dealer's lagged share of trade in the bond are more difficult to interpret under the interacted fixed effects structure. Finally, column (5) shows that dealer profits are positively correlated with effective bid-ask spreads, as theory would predict. The effects of dissemination is reduced by one-quarter, which suggests that changes in bid-ask spreads account for part but not all of the reduction in dealer profits after TRACE.

To better understand the relation between bid-ask spreads and dealer profits, Panel B of Table 3 reports estimates of the same regression specifications with bid-ask spread as the dependent variable. These results also replicate the findings of earlier research on customer transaction costs (Bessembinder, Maxwell, and Venkataraman (2006), Edwards, Harris, and Piwowar (2007), Goldstein, Hotchkiss, and Sirri (2007)). Bid-ask spreads are computed at the bond-month level, but we maintain the dealer-bond-month data structure in these regressions so we can control for each dealer's selection of bonds over time. Column (3) of Panel B shows that dissemination reduces bid-ask spreads by \$0.134 per \$100 face value, relative to an unconditional mean of \$1.10 prior to dissemination. This is in line with the effect of dissemination on dealer profits, as higher bid-ask spreads allow dealers to earn higher near-term profits by buying low and selling high within a trading day.

In contrast to the findings on dealer profits, bid-ask spreads are higher when the dealer faces a higher magnitude of order imbalance. This is consistent with dealers responding to order flow by widening bid-ask spreads to account for potential adverse selection, as in models of market-making in the face of information asymmetry (e.g., Copeland and Galai (1983), Glosten and Milgrom (1985)). However, the negative relation between dealer profits and order imbalance suggests that dealers are unable to set bid-ask spreads wide enough to make up for the presence of correlated and potentially informed trade by customers. In Section 2.3.2, we show that dissemination mitigates the negative effect of trade imbalance on dealer profits by helping dealers to adjust the level of prices, rather than the spread between bid and offer prices, in response to informed trading activity.

Panel C of Table 3 reports analogous regressions using the scaled measure of dealer profits from equation (3). The estimates are consistent with the regressions using dollar profits, with the reduction in scaled profit in column (4) equivalent to 9% of the pre-dissemination average. The correlation with trading volume is statistically insignificant, which suggests that scaling by capital commitment has the intended effect on the measurement of profits. The Internet Appendix shows that the time-weighted capital commitment from equation (2) increases slightly after the introduction of TRACE, explaining the smaller effect of dissemination on scaled profits relative to dollar profits. In sum, Table 3 shows that the introduction of post-trade transparency has a negative impact on dealer profitability, regardless of whether profits are measured in dollars or scaled by the dealer's capital commitment.

2.3 Risks of Market-Making

The previous section shows that the introduction of TRACE reduced the profitability of market-making in corporate bonds, despite an uptick the volume of both customer-facing and interdealer transactions. However, the profit calculations above do not account for the risks borne by dealers. In theory, the significant expansion of the interdealer network shown in Section 2.1 should improve risk-sharing across dealers. This section explores this issue by estimating the impact of post-trade transparency on the covariance between individual bond profits and the dealer's bond portfolio and the ability of dealer's to respond to imbalanced order flow. Overall, the results in this section indicate that post-trade transparency reduces the riskiness of market-making activities, casting doubt on the conventional wisdom that TRACE benefited customers at the expense of dealers.

2.3.1 Portfolio Risk

Market-making involves risk when price movements are uncertain and bonds must be held in inventory during the search for counterparties. This section pursues this general view of risk by examining time variation in total profits at the dealer level and the contribution of individual trades to portfolio risk before and after the introduction of post-trade transparency.

The next section focuses on the potential for adverse selection, a specific type of risk faced by market-makers.

We begin by constructing a measure of total dealer profits across all bonds traded for each month as:

$$\Pi_{d,t} = \sum_{i=1}^{N_{d,t}} \pi_{d,i,t}, \quad (6)$$

where i indexes bonds and $N_{d,t}$ is the total number of positions traded by dealer d in month t. Figure 2 presents the total profits over time for the top 30 dealers by number of bonds traded. Total profits exhibit significant time-series and cross-sectional variation, with the maximum monthly profit exceeding $20 million and the worst monthly loss around $6 million. Consistent with the evidence in Table 3, mean profitability falls over time as TRACE covers more of the market. However, the variance of profits also declines as post-trade transparency is introduced.

To examine how bond-level profits relate to the dealer's total profitability, we estimate the following regression:

$$\pi_{d,i,t} = \alpha_{d,i,t} + \beta_1 D_{i,t} + \beta_2 \Pi_{d,t} + \beta_3 D_{i,t} \times \Pi_{d,t} + \gamma \mathbf{X}_{d,i,t} + \varepsilon_{d,i,t}, \quad (7)$$

where $\pi_{d,i,t}$ is dollar profits[13] , $\alpha_{d,i,t}$ is a vector of fixed effects, $D_{i,t}$ is an indicator equal to one if trades in bond i are disseminated in month t, $\Pi_{d,t}$ is the total profit of dealer d in month t, and $\mathbf{X}_{d,i,t}$ contains the same set of control variables described in Section 2.2. The coefficients β_2 and β_3 reflect the covariance between the bond-level and portfolio-level profits of a dealer, or the contribution of an individual bond to the dealer's portfolio risk, before and after the introduction of TRACE.

One concern about this approach is that individual bonds may have an outsize effect on total profits, leading to a mechanical relation. To address this issue, we restrict the sample to dealers that trade more than 500 different bonds per month on average. In the Internet

[13] We restrict attention to dollar profits in this analysis because the scaled profits measure does not aggregate naturally to the dealer level.

Appendix, we report qualitatively similar estimates without this sample restriction, albeit with lower statistical precision.

Table 4 presents estimates of equation (7). The positive and significant coefficient on total dealer profit in column (1) indicates that, on average, individual positions in a dealer's portfolio are positively correlated. This is natural given that corporate bonds are exposed to many of the same risk factors.

The negative and significant coefficient on the interaction term shows that the covariance of individual bonds with the dealer's portfolio falls after the introduction of dissemination. In terms of economic magnitude, this corresponds to a reduction of 25% relative to the pre-dissemination covariance. The remaining columns report similar coefficients with alternative fixed effects and control variables, which demonstrates that the estimated effect is not driven by time-varying market conditions or dealer characteristics.

This reduction in portfolio risk is strikingly similar in magnitude to the 20% reduction in dealer profits estimated in Table 3. If dealers price the risk of a bond's covariance with the rest of their trading book in a linear manner, as would be expected in a mean-variance optimization, then the dealer's risk-adjusted profit is approximately unchanged by the introduction of TRACE. Thus, the effect of post-trade transparency on dealers is ambiguous, as they earn lower profits but also bear less risk. This casts doubt on the conclusions of prior research that TRACE benefits customers at the expense of dealers.

2.3.2 Adverse Selection

To understand whether post-trade transparency affects the exposure of dealers to adverse selection by informed traders, we study dealer performance in the face of order imbalance using the following regression:

$$\pi_{d,i,t} = \alpha_{d,i,t} + \beta_1 D_{i,t} + \beta_2 |OI_{d,i,t}| + \beta_3 D_{i,t} \times |OI_{d,i,t}| + \gamma \mathbf{X}_{d,i,t} + \varepsilon_{d,i,t}, \tag{8}$$

where $\pi_{d,i,t}$ is a measure of dealer profits, $\alpha_{d,i,t}$ is a vector of fixed effects, $D_{i,t}$ is an indicator equal to one if trades in bond i are disseminated in month t, $|OI_{d,i,t}|$ is the absolute order imbalance faced by dealer d trading bond i in month t, and $\mathbf{X}_{d,i,t}$ contains the same set of control variables described in Section 2.2.

Table 5 reports estimates of these regressions, using dollar profits in Panel A and scaled profits in Panel B. The first column of Panel A confirms that dealer profits are lower after dissemination and when the magnitude of order imbalance is larger. The interaction coefficient is positive, which means that dissemination reduces the negative effect of order imbalance on dealer profits. The magnitude of this coefficient indicates that 74% of the imbalance effect is eliminated by introducing post-trade transparency.

The next three columns add interaction effects to examine heterogeneity across issuer and dealer types and to assess the influence of information asymmetry and alternative price signals. These regressions show that the negative effect of imbalance on dealer profits is more severe for non-investment-grade bonds and bonds issued by private firms or firms that are not referenced by credit default swaps. This is consistent with some of the order imbalances reflecting the activity of informed traders on one side of the market and dealers being at a larger disadvantage when there is greater scope for information asymmetry or a lack of alternative price signals. The triple interactions with absolute imbalance and the dissemination indicator shows that only a small, statistically insignificant fraction of these incremental effects are offset by dissemination.

Panel B reveals similar patterns for scaled profits, with a larger estimated effect of post-trade transparency on the ability of dealers to face imbalanced order flow in bonds with more scope for information asymmetry, as evidenced by the statistically significant triple-interaction coefficients in the last two columns. These regressions suggest that most of the incremental effect of imbalance on profits for these bonds is offset by the introduction of TRACE. Overall, the results in Table 5 suggest that post-trade transparency reduces the adverse selection costs borne by dealers when there are more buyers than sellers or vice versa.

One mechanism that could explain this effect is that post-trade transparency allows dealers to incorporate new information into their quoted prices more quickly. This improves the ability of dealers to trade with informed investors by reducing the ability of these investors to transact at attractive prices before dealers realize the market has moved. Table 6 tests this hypothesis using return predictability regressions of the following form:

$$r_{i,[t,t+s]} = \alpha_{i,t} + \beta_1 D_{i,t} + \beta_2 OI_{i,t} + \beta_3 D_{i,t} \times OI_{i,t} + \varepsilon_{i,t}, \tag{9}$$

where $r_{i,[t,t+s]}$ is the bond's return from the current date t to a future date $t+s$, $\alpha_{i,t}$ is a vector of fixed effects, $D_{i,t}$ is an indicator equal to one if trades in bond i are disseminated in month t, and $OI_{i,t}$ is the order imbalance faced by all dealers trading bond i on date t. We estimate returns over the week after each trade date using bid quote prices from BAML to avoid potential selection on trading activity, which depends on dissemination status (Table 2). We use the signed order imbalance instead of the absolute value because the sign of imbalance offers a prediction about where customers believe the bond price is moving in the future. For example, an excess of buyers implies a positive prediction about the bond return.

Table 6 reports estimates of these regressions. The first column shows that a larger positive order imbalance, which means that customers are selling more bonds than they are buying, corresponds to a lower return on the bond over the next week. This is consistent with some of the order imbalance coming from informed customers or correlated trade among uninformed customers that predicts future movements in the bond's value. The interaction coefficient between order imbalance and the disseminated indicator shows that post-trade transparency eliminates more than half of this effect, so that imbalance has less predictive power when trades are disseminated.

The next three columns incorporate interaction effects to account for information asymmetry and alternative price signals from the equity and credit derivatives markets. The pre-TRACE association between order imbalance and future returns is stronger for non-investment-grade bonds. The effect of dissemination remains in the split sample, though there is a smaller reduction in predictability for non-investment-grade bonds, suggesting that there is still potential for informed investors to earn near-term profits in the riskier segment of the market.

The pre-TRACE relation between imbalance and future returns is also larger for bonds issued by private firms and firms without credit default swaps, again consistent with at least part of the imbalance reflecting the trading activity of informed investors and the absence of alternative market signals about a bond's quality. The triple interactions with dissemination are statistically insignificant, indicating that order imbalance continues to predict returns for private firm bonds and bonds without CDS even after the introduction of TRACE. This is consistent with the finding in Table 5 that the negative effects of imbalance on dealer profits for these bonds are not fully eliminated by post-trade transparency.

Overall, these results support the narrative that post-trade transparency improves the ability of dealers to respond to informed and correlated trading activity by moving their price quotes to the appropriate level more quickly. Our conversations with market participants confirm that post-trade reporting by other dealers is a valuable source of information about market movements that supplements the information in a dealer's own order flow. One implication of these findings is that informed investors may find it less attractive to incorporate their information by trading corporate bonds. Although the regression analyses in Tables 5 and 6 indicate that dissemination partially offsets the effects of order imbalance on dealer profits for the typical bond, there remain attractive opportunities for informed investors to trade against dealers in bonds that are subject to more severe information asymmetry. In the next section, we explore the ramifications of the changing incentives for informed investors on the informativeness of prices in the corporate bond market.

3 Price Informativeness

After post-trade transparency is introduced, we see fewer episodes of imbalance and higher profits for dealers during such episodes. This corresponds to lower profits for customers when order flow is imbalanced and suggests that the profits to informed trading are lower following the introduction of TRACE. In such an environment, investors should be less willing to incur the costs of acquiring information and incorporating it into prices. Thus, we hypothesize that the introduction of post-trade transparency could have a detrimental effect on the information content of bond prices.

We examine the effects of post-trade transparency on price informativeness by comparing the ability of disseminated and non-disseminated bond credit spreads to predict future default. The mark-to-market value of a corporate bond is affected by a variety of factors, but its fundamental value depends only on whether the fixed payments specified by the contract are made on schedule. Therefore, price efficiency in the corporate bond market is the degree to which prices reflect the likelihood of default and the states of nature in which it occurs, holding fixed other factors that affect the present value of cash flows (e.g., maturity, coupon rate). We use this view of corporate bond price informativeness to assess whether the introduction of post-trade transparency affects the information content of prices.

To test our prediction that dissemination reduces price informativeness, we compare the ability of bond credit spreads to predict future default in monthly cross-sections of disseminated and non-disseminated bonds. By focusing on credit spreads, we isolate the market's assessment of the bond's risk-neutral expected loss rate (Duffie and Singleton (1999)) from other factors that affect prices. Nevertheless, in our regressions we control for bond characteristics interacted with rating indicators to ensure comparability between the underlying risks of disseminated and non-disseminated bonds in a given month.

To sharpen our analysis, we restrict the sample in three ways. First, we mitigate the bias associated with disseminated bonds being of higher quality, especially in the early phases of TRACE, by only considering bonds rated BBB+ or lower. Second, we focus on the period July 2003 to January 2005 so that each month has at least 25 bonds in each of the disseminated and non-disseminated samples. Finally, we limit the sample to bonds issued by firms with at least one bond maturing over the next three years, which focuses our analysis on firms with near-term rollover risk that could result in a payment default.[14]

For each month of our sample period, we estimate the following regression separately for disseminated and non-disseminated bonds:

$$1\left(\text{Default}\right)_i = \sum_{k\in\{\text{B,C}\}} 1\left(\text{Rating} = k\right)\left[\alpha_k + \beta \text{Spread}_i + \gamma \mathbf{X}_i\right] + \varepsilon_i, \tag{10}$$

where $1\left(\text{Default}\right)_i$ is an indicator equal to one if bond i defaults over the next two years, Spread_i is the bond's current option-adjusted credit spread over the swap curve, and $\mathbf{X}_i$ is a vector of controls. We allow each broad rating group (i.e., "B" ratings from BBB+ to B- and "C" ratings from CCC+ to C) to have distinct intercept and slope coefficients, allowing for a flexible relation between credit spreads and default risk. We estimate equation (10) each month for the disseminated and non-disseminated bonds in the restricted sample, then compute the incremental R^2 from bond spreads relative to a regression that contains only rating dummies and interactions with log issue size and time to maturity.

Panel A of Figure 3 shows that the incremental R^2 of credit spreads for predicting default is higher for non-disseminated bonds throughout second half of the restricted sample period. In the early part of the sample, both disseminated and non-disseminated bond spreads explain about 10% of the variation in future defaults. The explanatory power of disseminated and non-disseminated bonds diverges in early 2004 and continues through the start of Phase 3A of TRACE, which introduced dissemination for all bonds rated BBB- and higher in October 2004. The mean difference between the R^2 coefficients of disseminated and non-disseminated bonds is 6.6%.

[14] In the Internet Appendix, we remove the maturity restriction and find qualitatively similar results. While default rates are similar in the broader sample, the power of bond spreads to predict default is lower. This suggests that market participants are better able to infer default probabilities for firms with near-term rollover risk.

For long-term bonds issued by firms near default, price may convey information about default likelihood above what is contained in spreads, which amortize expected losses over the bond's life. Panel B of Figure 3 adds log price as an explanatory variable and shows similar patterns, with greater ability to predict default in both groups of bonds. When price is included in the regression, the difference in incremental R^2 between non-disseminated and disseminated bonds increases to 8.5%.

We address concerns over identification, such as the possibility that selection of bonds into the disseminated and non-disseminated groups drives the difference in explanatory power, in two ways. First, we plot the two-year default rates in the two groups of bonds in each panel of Figure 3. The default rates are almost identical until the last few months of the sample period, so the difference in incremental R^2 is not driven by different default probabilities (i.e., variation in our dependent variable). Second, in Panel C of Figure 3 we consider a placebo test in which we use the first spread in our sample for each bond instead of the current market spread. Here we see no difference in explanatory power between the two groups, with a difference in incremental R^2 of 0.04%, which suggests that time-invariant differences among the two groups of bonds cannot explain our findings. This supports the notion that changes in the information content of prices are behind the differences in explanatory power in Panels A and B of Figure 3.

Under the assumption that monthly observations are independent, we find that the R^2 estimates in the disseminated and non-disseminated samples are significantly different at the 1% level. However, given that the composition of issuers the monthly samples is fairly stable, the independence assumption is unlikely to be satisfied. Complicating matters is the fact that TRACE was introduced during an economic expansion with few corporate defaults. Specifically, in July 2003 there are three issuers with disseminated bonds (Delta Air Lines, Delphi Automotive Systems, and Dana Corp.) and 11 issuers without disseminated bonds that default over the following two years. By the start of Phase 3A in October 2004, the proportions switch so there are 12 issuers with disseminated bonds and 7 issuers with non-disseminated bonds that default over the two-year window.

As an alternative approach to evaluating the statistical significance of the difference in predictive power, we bootstrap each monthly regression by drawing firms with replacement, which allows for correlation in errors across bonds issued by the same firm. We estimate the standard error of the R^2 based on 100 bootstrapped samples and use it for a difference-in-means t-test. Given the limited amount of statistical power, we do not find a statistically significant difference in R^2 in any month at conventional levels of significance, with the closest month being July 2004 ($t = 1.61$). Ultimately, the evidence in this section is consistent with the hypothesis that price transparency can lead to reduced price efficiency, but the empirical setting does not offer enough statistical power to reject the null hypothesis of no effect.

The findings in this section are consistent with the hypothesis that the introduction of post-trade transparency has an adverse effect on the information content of prices by reducing incentives for informed traders to participate in the market. Consistent with these effects, Green (2007) notes that some large traders migrated to the credit derivatives market after TRACE began disseminating transaction prices.

Nevertheless, we should emphasize the limitations of our analysis. To obtain causal inference, our analysis is restricted to the period of the TRACE experiment, which happens to be an economic expansion. As noted above, a consequence of this environment is that there are few corporate defaults, so our default prediction test has low statistical power. It is possible that we would find different results if price transparency were instead implemented during an economic downturn.

Our findings on price efficiency are at odds with the claim in Badoer and Demiroglu (2019) that credit spreads, as well as ratings, are better able to predict corporate defaults after the introduction of TRACE. These divergent results can be explained by differences in methodology. Although Badoer and Demiroglu (2019) estimate a similar predictive regression to ours, their conclusions are based on increases in the magnitude of regression coefficients instead of increases in the explanatory power of the regression. In other words, they find that a given increase in credit spread corresponds to a larger increase in default probability when trades are disseminated. However, this does not imply that the prediction errors are smaller in the transparent environment. In fact, we find that prediction errors are larger after TRACE is introduced, as evidenced by the R^2 estimates in Figure 3.[15]

We conclude that an improvement in post-trade transparency has nuanced effects on price efficiency. After transparency improves, bond prices adjust more quickly to the announcement of new information, as documented by Chen and Lu (2019) and Badoer and Demiroglu (2019). However, the information content of bond prices, as measured by their ability to explain future fundamentals, is worse in the transparent environment. This can be explained by the reduced incentives of traders to produce information when the profits from transacting on that information are lower. In line with this view, Chen and Lu (2019) find a reduction in the production of bond analyst reports after the introduction of TRACE.

4 Conclusion

This paper provides novel evidence on the effects of price transparency on the economics of market-making and the information content of prices in over-the-counter markets. We show that trading activity increases and dealer networks become more complete after the introduction of TRACE, consistent with a reduction in search costs due to market participants being able to assess their outside option more easily.

In line with prior evidence on customer execution costs, we find that the profitability of dealers is lower when trade information is disseminated. However, we find that the risk of market-making is also reduced by TRACE, as evidenced by lower covariance risk and higher profits in the face of order imbalance. The latter effect is consistent with a reduction in

[15]In addition to this difference in methodology, there are important conceptual differences between the present analysis and Badoer and Demiroglu (2019). First, credit rating agencies may use information from disseminated bond prices as an input to their decisions, which would lead to endogeneity bias. It is less likely that managers use secondary market bond prices as an input to corporate default decisions. Second, rating downgrades are reflective of default risk but generally do not correspond to a change in the cash flows paid to bondholders. By definition, default represents a change in a bond's cash flow profile.

information asymmetry regarding bond valuations, which lowers the costs of adverse selection from trading with informed investors. The overall impact of post-trade transparency on dealer welfare is ambiguous, as it leads to offsetting effects on profitability and risk. These findings cast doubt on the conclusions of prior research suggesting that TRACE benefited customers at the expense of dealers.

Although trade dissemination offers clear benefits for customers and has an ambiguous impact on market-makers, an adverse consequence is that informed traders have weaker incentives to participate in the market. We present evidence consistent with these weaker incentives leading to reduced price efficiency in the corporate bond market. In sum, our findings highlight the trade-offs regulators must balance when considering changes to the information environment of opaque markets, such as the markets for leveraged loans and credit, currency, and interest rate swaps.

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Figure 1: Staggered Introduction of Post-Trade Transparency

This figure reports the fraction of disseminated bonds by rating category in each month from the beginning of the TRACE rollout in July 2002 to the end of our sample in December 2006.

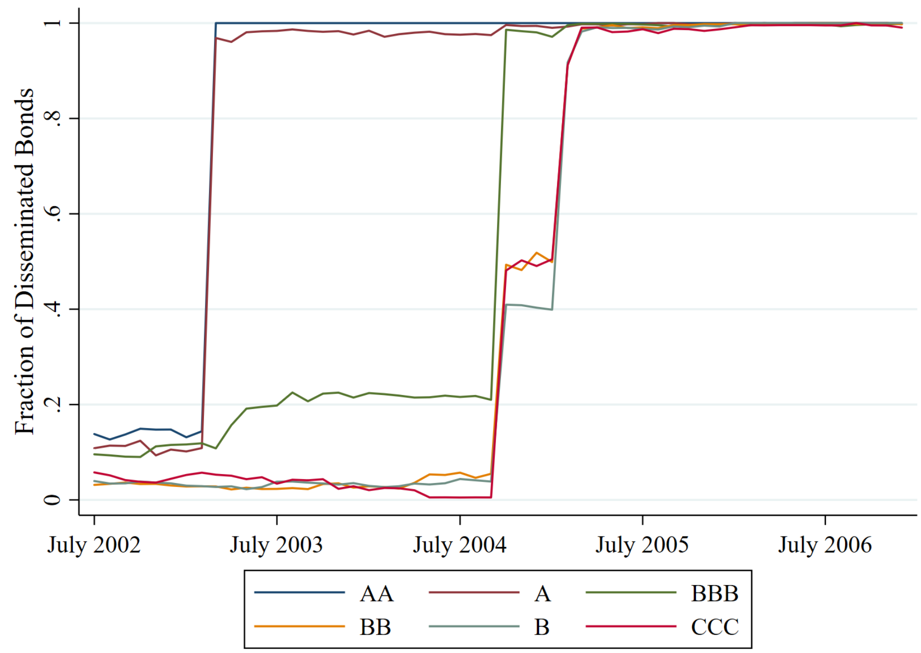


Figure 2: Total Dealer Profits over Time

This figure reports monthly dollar profits by dealer (dots) and average profits in each month (line) for the 30 top dealers by the number of distinct bonds traded. These dealers account for 60% of the total trading volume in our sample.

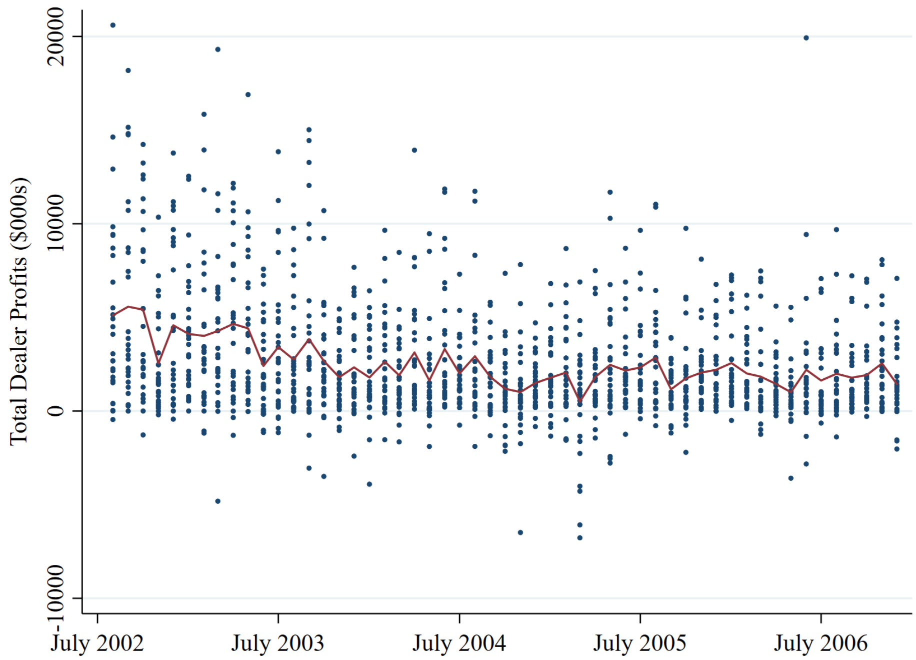
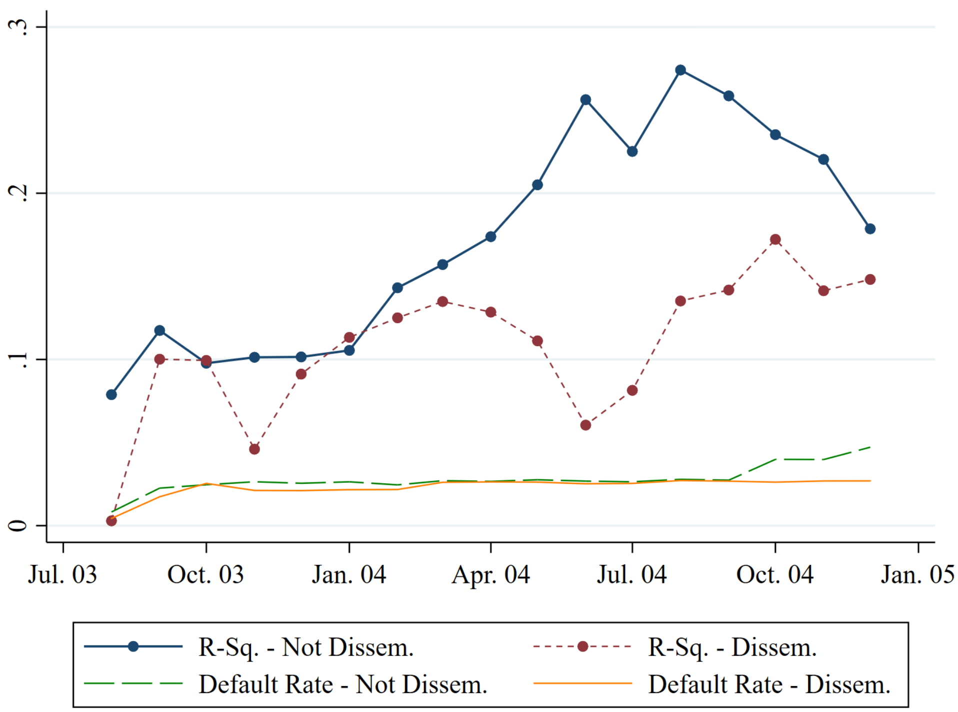


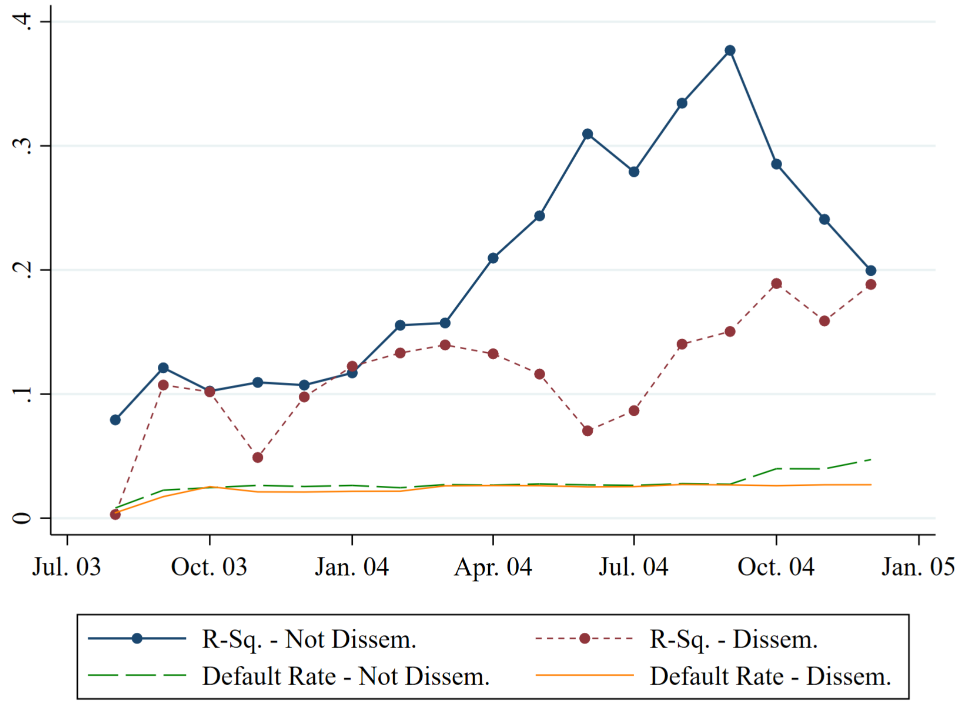
Figure 3: Credit Spreads and Default Prediction

This figure reports R^2 coefficients from cross-sectional default prediction regressions. R^2 coefficients are obtained from separate monthly regressions from July 2003 to January 2005 for disseminated (dashed maroon line) and non-disseminated bonds (solid navy line). The regression is specified in equation (10). Observations in each regression are at the bond-month level. The sample is restricted to bonds rated BBB+ or lower and issued by firms with at least one bond maturing over the next three years. The dependent variable is an indicator that equals one if the bond defaults over the next two years. The solid orange and dashed green lines in each panel report the average forward two-year default rate from each month for disseminated and non-disseminated bonds, respectively. R^2 is computed after controlling for the bond's time to maturity and log issue size interacted with its broad rating category. Panel A considers the ability of credit spreads to explain default. Panel B adds the log price of the bond as an explanatory variable. Panel C is a placebo test that uses the bond's first credit spread in our sample period as the explanatory variable.

Panel A: Predictive Power of Credit Spreads



Panel B: Predictive Power of Credit Spreads and Log Prices



Panel C: Placebo Test Based on Initial Credit Spreads

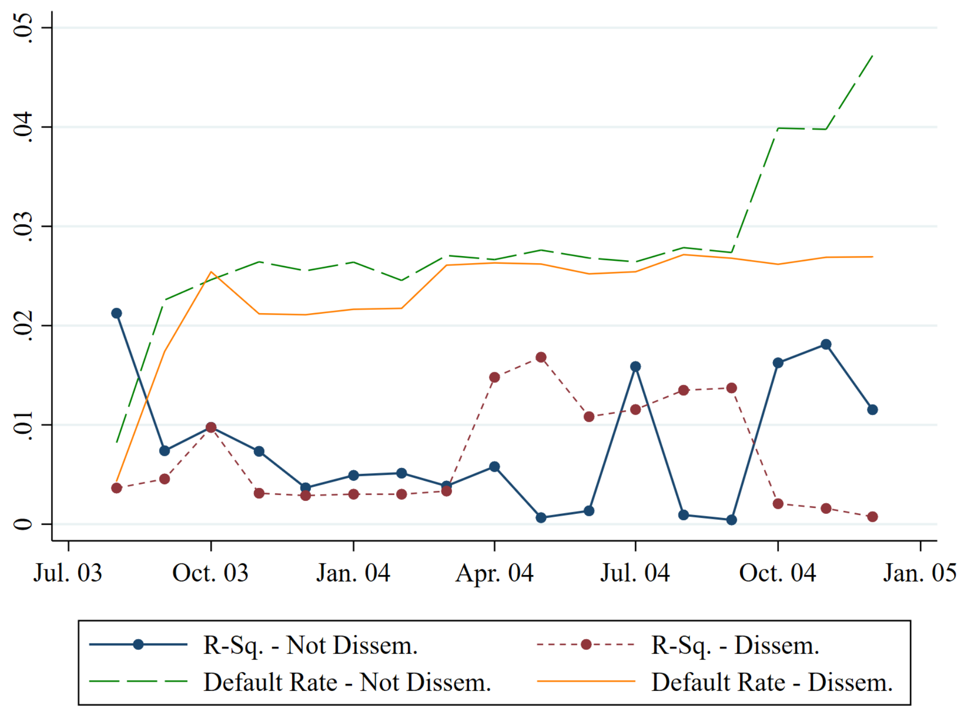


Table 1: Summary Statistics

This table reports statistics on variables used in our analysis. Panels A and B are based on observations at the bond-month and dealer-bond-month levels, respectively. Variables are defined in the Appendix.

Panel A: Bond-Month Observations of Trading Activity

	All			***Disseminated***			***Not Disseminated***		
	Mean	Std.Dev.	Obs.	Mean	Std.Dev.	Obs.	Mean	Std.Dev.	Obs.
1(Disseminated)	0.57	0.49	180,924	1.00	0.00	103,509	0.00	0.00	77,415
Log(Total Volume)	2.58	1.99	169,914	2.75	1.99	98,217	2.34	1.97	71,697
Log(Customer Volume)	2.35	1.99	169,451	2.48	1.99	97,955	2.17	1.97	71,496
Log(Interdealer Volume)	0.79	2.40	132,630	1.03	2.42	82,587	0.41	2.33	50,043
Log(Volume (Intensive))	2.05	2.14	116,976	1.99	2.13	66,592	2.12	2.15	50,384
Dealer Count	12.54	13.62	180,924	14.66	14.98	103,509	9.70	10.93	77,415
Dealer Count (Customer)	9.64	10.71	180,924	11.28	11.98	103,509	7.44	8.24	77,415
Dealer Count (Interdealer)	9.13	12.41	180,924	11.22	13.84	103,509	6.34	9.50	77,415
Dealer Pair Count	22.98	47.62	169,973	29.53	56.63	98,217	14.01	29.05	71,756

Panel B: Dealer-Bond-Month Observations of Profits and Control Variables

	All			***Disseminated***			***Not Disseminated***		
	Mean	Std.Dev.	Obs.	Mean	Std.Dev.	Obs.	Mean	Std.Dev.	Obs.
Disseminated	0.67	0.47	1,451,448	1.00	0.00	966,723	0.00	0.00	484,725
Dealer Profit ($000s)	2.85	42.36	1,547,700	2.41	41.60	966,723	4.45	45.97	484,725
Dealer Profit (Scaled)	25.88	126.49	1,547,700	21.86	114.14	966,723	38.84	157.24	484,725
Bid-Ask Spread	0.76	0.78	1,465,718	0.60	0.57	927,852	1.10	1.01	447,661
Customer-Facing Trades	7.12	21.57	1,031,108	7.43	23.80	685,613	6.49	16.25	345,495
1(Non-IG)	0.40	0.49	1,547,700	0.33	0.47	966,723	0.54	0.50	484,725
1(Private)	0.20	0.40	1,547,700	0.20	0.40	966,723	0.20	0.40	484,725
1(No CDS)	0.27	0.44	1,547,700	0.23	0.42	966,723	0.35	0.48	484,725
|Order Imbalance|	0.60	0.25	1,546,566	0.62	0.25	966,296	0.57	0.26	484,428
Log(Volume)	3.94	1.61	1,451,448	4.15	1.63	966,723	3.55	1.50	484,725
Dealer HHI	0.30	0.20	1,546,566	0.28	0.19	966,296	0.33	0.22	484,428
Equity Volatility (%)	40.71	35.37	1,237,120	34.78	27.73	773,399	53.17	45.24	384,799

Table 2: Trading Activity and the Dealer Network

This table reports monthly regressions of trading volume and the number of distinct dealers trading a bond on the bond's dissemination status. The sample consists of bond-month observations from July 2002 to December 2006. The dependent variables in Panels A and B are the number of active dealers (or the number of distinct dealer pairs that trade the security, column (5)) and log trading volume, respectively. In both panels, column (3) counts only customer-facing transactions and (4) restricts the sample to the interdealer market. In Panel A, column (5) restricts the sample to the interdealer market. In Panel B, column (5) excludes dealers that do not trade the bond both before and after dissemination. t-statistics based on standard errors clustered by firm and month are reported in parentheses. * and ** denote p-values less than 0.05 and 0.01, respectively.

Panel A: Number of Active Dealers

	Number of Dealers				Num. of Pairs
	(1)	(2)	(3)	(4)	(5)
Disseminated	4.984***	1.607***	1.158***	1.459***	2.656
	(6.63)	(3.48)	(3.15)	(3.40)	(1.04)
Sample	All	All	Customer	Interdealer	Interdealer
Bond FE	N	Y	Y	Y	Y
Month-Rating FE	N	Y	Y	Y	Y
Month-Size Quintile FE	N	Y	Y	Y	Y
R^2	0.032	0.860	0.863	0.839	0.802
Observations	169,973	168,500	168,500	168,500	168,500

Panel B: Log(Trading Volume)

	(1)	(2)	(3)	(4)	(5)
Disseminated	0.406***	0.044	0.032	0.135***	0.127**
	(6.24)	(1.23)	(0.89)	(2.69)	(2.09)
Sample	All	All	Customer	Interdealer	Intensive
Bond FE	N	Y	Y	Y	Y
Month-Rating FE	N	Y	Y	Y	Y
Month-Size Quintile FE	N	Y	Y	Y	Y
R^2	0.010	0.567	0.541	0.537	0.580
Observations	169,914	168,445	167,984	131,581	116,296

Table 3: Determinants of Dealer Profits

This table reports regressions of monthly profits in thousands of dollars (Panel A), effective bid-ask spreads (Panel B), and profits scaled by time-weighted capital committed (Panel C) on a bond's dissemination status, absolute order imbalance, and other characteristics. The sample consists of dealer-bond-month observations from July 2002 to December 2006. All explanatory variables, excluding indicator variables, are standardized for ease of interpretation. *Dealer Profit* is the mark-to-market profit or loss, in dollars or scaled by the dealer's time-weighted capital commitment (see equation (3)). *Bid-Ask Spread* is computed as the monthly average of daily differences between average dealer purchase and sale prices. |*Order Imbalance*| is the absolute difference between the volume of dealer purchases and sales divided by total trading volume. Other variables are defined in the Appendix. t-statistics based on standard errors clustered by firm and month are reported in parentheses. * and ** denote p-values less than 0.05 and 0.01, respectively.

Panel A: Dealer Profit ($000s)

	(1)	(2)	(3)	(4)	(5)
1(Disseminated)	-2.043***	-0.937***	-1.058***	-1.074***	-0.820**
	(-4.59)	(-3.00)	(-3.28)	(-3.36)	(-2.66)
|Order Imbalance|				-0.808***	-0.815***
				(-5.02)	(-4.93)
Log(Volume)				1.501***	1.453***
				(6.68)	(7.18)
Amihud Illiquidity				0.143*	0.046
				(1.83)	(0.62)
Dealer HHI				0.741***	0.653***
				(2.92)	(2.74)
Equity Volatility				0.285**	0.258**
				(2.25)	(2.07)
Bid-Ask Spread					1.378***
					(6.59)
Bond FE	N	Y	Y	Y	N
Month-Rating FE	N	Y	N	N	N
Month-Size Quintile FE	N	Y	N	N	N
Month-Rating-Dealer FE	N	N	Y	Y	Y
Month-Size Quintile-Dealer FE	N	N	Y	Y	Y
R^2	0.000	0.010	0.064	0.066	0.066
Observations	1,451,448	1,451,384	1,401,956	1,352,377	1,286,653

Panel B: Bid-Ask Spread

	(1)	(2)	(3)	(4)
1(Disseminated)	-0.500***	-0.138***	-0.134***	-0.128***
	(-9.93)	(-5.25)	(-5.45)	(-5.58)
|Order Imbalance|				0.028***
				(8.51)
Log(Volume)				-0.046***
				(-7.07)
Amihud Illiquidity				0.037***
				(8.93)
Dealer HHI				0.013***
				(3.67)
Equity Volatility				0.062***
				(4.27)
Bond FE	N	Y	Y	Y
Month-Rating FE	N	Y	N	N
Month-Size Quintile FE	N	Y	N	N
Month-Rating-Dealer FE	N	N	Y	Y
Month-Size Quintile-Dealer FE	N	N	Y	Y
R^2	0.091	0.601	0.633	0.643
Observations	1,375,513	1,375,471	1,327,143	1,286,653

Panel C: Dealer Profit (Scaled)

	(1)	(2)	(3)	(4)	(5)
1(Disseminated)	-16.984***	-2.866***	-3.475***	-3.430***	-3.004***
	(-5.91)	(-3.64)	(-5.06)	(-4.68)	(-4.61)
|Order Imbalance|				-8.230***	-7.326***
				(-5.50)	(-5.39)
Log(Volume)				-0.154	0.188
				(-0.15)	(0.19)
Amihud Illiquidity				-3.051***	-2.932***
				(-5.43)	(-5.40)
Dealer HHI				-1.176***	-1.088***
				(-3.25)	(-2.68)
Equity Volatility				0.983***	0.874***
				(3.33)	(3.36)
Bid-Ask Spread					2.847***
					(7.53)
Bond FE	N	Y	Y	Y	N
Month-Rating FE	N	Y	N	N	N
Month-Size Quintile FE	N	Y	N	N	N
Month-Rating-Dealer FE	N	N	Y	Y	Y
Month-Size Quintile-Dealer FE	N	N	Y	Y	Y
R^2	0.004	0.048	0.269	0.277	0.281
Observations	1,451,448	1,451,384	1,401,956	1,352,377	1,286,653

Table 4: Dealers' Portfolio Risk

This table reports regressions of monthly profits on a bond's dissemination status, total dealer profits, and their interaction. The sample consists of dealer-bond-month observations, restricting to dealers that trade at least 500 bonds per month on average, over the period July 2002 to December 2006. All explanatory variables, excluding indicator variables, are standardized for ease of interpretation. *Dealer Profit* is the mark-to-market profit or loss in thousands of dollars. *Total Dealer Profit* is the sum of profits across all dealer positions in each month. Controls include log trading volume, the Amihud (2002) price impact measure of illiquidity, the HHI measure of dealer concentration, the share of volume traded by that dealer in the previous month, and the volatility of daily stock returns. These variables are defined in the Appendix. t-statistics based on standard errors clustered by firm and month are reported in parentheses. * and ** denote p-values less than 0.05 and 0.01, respectively.

	(1)	(2)	(3)
1(Disseminated)	-231.358	133.703	136.869
	(-0.52)	(0.23)	(0.23)
Total Dealer Profit($000s)	1.156***		
	(17.59)		
1(Disseminated) ×	-0.284***	-0.365**	-0.358**
Total Dealer Profit ($000s)	(-3.45)	(-2.36)	(-2.38)
Controls	N	N	Y
Bond FE	Y	Y	Y
Bond-Dealer FE	N	N	N
Month-Rating FE	Y	N	N
Month-Size Quintile FE	Y	N	N
Month-Rating-Dealer FE	N	Y	Y
Month-Size Quintile-Dealer FE	N	Y	Y
R^2	0.018	0.052	0.054
Observations	877,988	876,555	844,039

Table 5: Order Imbalance and Dealer Profits

This table reports regressions of monthly dealer profits, in dollars (Panel A) and scaled by time-weighted capital committed (Panel B), on a bond's dissemination status and absolute order imbalance interacted with proxies for information asymmetry. The sample consists of dealer-bond-month observations from July 2002 to December 2006. All explanatory variables, excluding indicator variables, are standardized for ease of interpretation. *Dealer Profit* is the mark-to-market profit or loss scaled by the dealer's time-weighted capital commitment. |*Order Imbalance*| is the absolute difference between the volume of dealer purchases and sales divided by total trading volume. *1(Non-IG)* is absorbed by the month-rating-dealer fixed effects. Controls include log trading volume, the Amihud (2002) price impact measure of illiquidity, the HHI measure of dealer concentration, the share of volume traded by that dealer in the previous month, and the volatility of daily stock returns. These variables are defined in the Appendix. t-statistics based on standard errors clustered by firm and month are reported in parentheses. * and ** denote p-values less than 0.05 and 0.01, respectively.

Panel A: Dealer Profit ($000s)

		Interaction Variable (Z)		
		1(Non-IG)	1(Private)	1(No CDS)
1(Disseminated)	-0.609**	-0.794*	-0.496*	-0.454
	(-2.79)	(-2.19)	(-2.36)	(-1.87)
|Order Imbalance|	-1.068**	-0.821**	-0.936**	-0.864**
	(-5.08)	(-4.38)	(-4.89)	(-4.25)
1(Disseminated) × |Imbalance|	0.793**	0.602**	0.697**	0.566**
	(4.25)	(3.33)	(4.19)	(2.82)
Interaction Variable (Z)		0.000	0.239	0.896*
		(0.00)	(0.76)	(2.54)
Z × |Imbalance|		-0.522*	-0.477*	-0.564**
		(-2.36)	(-2.20)	(-2.84)
Z × 1(Disseminated)		0.566	-0.688*	-0.537
		(1.14)	(-2.02)	(-1.76)
Z × 1(Disseminated) × |Imbalance|		0.357	0.269	0.611*
		(1.99)	(1.15)	(2.57)
Controls	Y	Y	Y	Y
Bond FE	Y	Y	Y	Y
Month-Rating-Dealer FE	Y	Y	Y	Y
Month-Size Quintile-Dealer FE	Y	Y	Y	Y
R^2	0.051	0.051	0.051	0.051
Observations	2,075,104	2,075,104	2,075,104	2,075,104

Panel B: Dealer Profit (Scaled)

		Interaction Variable (Z)		
		1(Non-IG)	1(Private)	1(No CDS)
1(Disseminated)	-3.254**	-3.682**	-2.958**	-3.549**
	(-4.43)	(-3.85)	(-4.05)	(-4.77)
|Order Imbalance|	-10.298**	-8.167**	-8.823**	-8.227**
	(-6.55)	(-6.15)	(-6.34)	(-6.37)
1(Disseminated) × |Imbalance|	6.843**	5.675**	5.851**	5.245**
	(6.93)	(6.02)	(6.34)	(6.29)
Interaction Variable (Z)		0.000	2.775*	-4.610**
		(0.00)	(2.33)	(-4.81)
Z × |Imbalance|		-4.474**	-5.509**	-6.025**
		(-2.85)	(-4.12)	(-4.20)
Z × 1(Disseminated)		1.583	-1.516	1.671
		(1.20)	(-1.19)	(1.91)
Z × 1(Disseminated) × |Imbalance|		1.509	2.830**	4.043**
		(1.43)	(2.75)	(4.09)
Controls	Y	Y	Y	Y
Bond FE	Y	Y	Y	Y
Month-Rating-Dealer FE	Y	Y	Y	Y
Month-Size Quintile-Dealer FE	Y	Y	Y	Y
R^2	0.252	0.252	0.252	0.252
Observations	2,075,104	2,075,104	2,075,104	2,075,104

Table 6: Order Imbalance and Return Predictability

This table reports regressions of bond returns on order imbalance interacted with dissemination status and bond characteristics. The sample consists of bond-date observations with at least five transactions in TRACE from July 2002 to December 2006. All explanatory variables, excluding indicator variables, are standardized for ease of interpretation. *Bond Return* $[0, 5]$ is the return over the next five trading days relative to the date of trade imbalance using the volume-weighted average prices on each trade date. Returns are calculated using BAML bid quotes to avoid selection bias from non-traded bonds. *Order Imbalance* is the difference between the volume of dealer purchases and sales divided by total trading volume from the TRACE data. Other variables are defined in the Appendix. *1(Non-IG)* is absorbed by the date-rating fixed effects. *t*-statistics based on standard errors clustered by firm and date are reported in parentheses. * and ** denote *p*-values less than 0.05 and 0.01, respectively.

		Interaction Variable (Z)		
Bond Return $[0, 5]$		1(Non-IG)	1(Private)	1(No CDS)
1(Disseminated)	0.010	0.000	0.025	0.022
	(0.62)	(0.02)	(1.45)	(1.29)
Order Imbalance	-0.079***	-0.032***	-0.071***	-0.070***
	(-13.75)	(-5.88)	(-10.60)	(-10.49)
1(Disseminated) × Imbalance	0.043***	0.016***	0.038***	0.038***
	(7.52)	(2.73)	(5.92)	(5.89)
Interaction Variable (Z)		0.000	0.075	0.015
		(0.00)	(1.63)	(0.93)
Z × Imbalance		-0.092***	-0.039***	-0.026***
		(-9.45)	(-3.46)	(-2.63)
Z × 1(Disseminated)		0.026	-0.108***	-0.044**
		(0.78)	(-2.77)	(-2.51)
Z × 1(Disseminated) × Imbalance		0.015	0.013	0.008
		(1.35)	(1.07)	(0.76)
Bond FE	Y	Y	Y	Y
Trade Date-Rating FE	Y	Y	Y	Y
R^2	0.367	0.368	0.367	0.367
Observations	725,028	725,028	725,028	725,028

Appendix – Variable Definitions

Amihud Illiquidity: Average price impact per dollar traded at the bond-month level, defined as $Amihud_{i,t} = \frac{1}{N}\sum_{d=1}^{N}\frac{|r_{i,d}|}{vol_{i,d}}$, where N is the number of trading days in period t for bond i and $vol_{i,d}$ is the daily volume of trade. This calculation uses all trade types.

Bid-Ask Spread: Bid-ask spread from the WRDS Bond Returns Database.

Bond Return: Return from the current date over a future window using volume-weighted average prices from TRACE. This calculation uses all trade types.

Dealer Count: Number of distinct dealer identifiers that either buy or sell a security in a bond-month. *Dealer Count (Customer)* and *Dealer Count (Interdealer)* refer to customer-facing and interdealer trades, respectively.

Dealer HHI: Concentration of dealer trading by bond-month, defined as $HHI_{i,t} = \sum_{j=1}^{M}(\frac{vol_{i,j,t}}{vol_{i,t}})^2$. This calculation uses only customer-facing trades.

Dealer Pair Count: Number of distinct pairs of dealer identifiers that trade a security in the interdealer market in a bond-month.

Dealer Profit: Mark-to-market profits at the dealer-bond-month level, scaled by the dealer's time-weighted capital commitment. Refer to Section 1.3 for a detailed definition. This calculation uses all trade types.

Dealer Share: Fraction of volume in the bond of interest traded by the dealer. This calculation uses only customer-facing trades.

1(Disseminated): Indicator equal to one if more than half of trades in the bond were publicly disseminated over the observation window. This calculation uses all trade types.

Equity Volatility: Annualized standard deviation of the bond issuer's stock returns over the trading month using data from CRSP.

1(No CDS): Indicator equal to one if the bond's ticker symbol cannot be matched with a CDS quote in IHS Markit's credit default swap database.

1(Non-IG): Indicator equal to one if the bond is not investment-grade rated.

Order Imbalance: Difference between the volume of dealer purchases and sales divided by total trading volume during the month. This calculation uses only customer-facing trades.

1(Private): Indicator equal to one if the bond issuer is not publicly listed. We proxy for listing status using inclusion in the CRSP database.

1(Rule 144A): Indicator equal to one if the bond was issued under Rule 144A according to Mergent FISD.

Total Dealer Profits: Sum of *Dealer Profits* for all bonds traded by a dealer in a month.

Trade Count (Customer): Number of customer-facing trades in a dealer-bond-month.

(Log) Volume: Dollar volume of transactions in a bond-month, counting only one side of interdealer transactions. *Customer Volume* and *Interdealer Volume* refer to customer-facing and interdealer trades, respectively. *Intensive Margin Volume* refers to total volume involving dealers that trade a bond both before and after dissemination.