The Execution Quality of Corporate Bonds

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Abstract

This paper investigates execution quality issues in corporate bond trading. Using an extensive sample of bond trades by insurance companies, we find that an insurance company entering a trade of similar size and on the same side for the same bond on the same day with the same dealer will receive a better price if it is a more active investor than if it is a less active investor. Trading with the dominant dealer or underwriter worsens these differentials, while greater transparency and smaller trading networks lessens these effects. Our results provide strong evidence of systematic execution quality failures in corporate bond trading.

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Introduction

The U.S. corporate bond market is massive, with more than 40,000 corporate bond issues outstanding with a principal amount of more than $8 trillion dollars. It is also growing, with issuance of U.S corporate bonds in 2015 totaling almost $1.5 trillion.[1] Despite this enormous scale, the trading of corporate bonds remains largely confined to highly decentralized dealer markets where, as noted by SEC Chairman Mary Jo White, the "costs of intermediation are much more difficult to measure than in other, more transparent venues."[2] There is also the problem that many bonds rarely trade, making it difficult to discern how well trade prices reflect "true" values or instead are artifacts of dealer power or other market characteristics. These difficulties have led to concerns by both regulators and industry as to what execution quality is achieved for investors in fixed income securities.[3] As Rick Ketchum, CEO of bond market regulator FINRA, noted "It strikes me as odd that we've spent enormous energy in equity markets to measure and save pennies or just basis points on execution quality, while in the fixed income market it's more a question of nickels, quarters and dollars."[4]

This paper investigates execution quality issues in corporate bond trading. Starting with the seminal paper by Schultz [2001], prior research (see, for example, Bessembinder, Maxell and Venkateramen [2006]; Edwards, Harris and Piwowar [2007]; Goldstein and Hotchkiss [2007]; Feldhutter (2012); Bias and DeClerck [2013]) has found that dispersion of prices for trades of the

[1] Based on data from SIFMA. See http://sifma.org/research/statistics.aspx.
[2] Mary Jo While, Intermediation in the Modern Securities Markets: Putting Technology and Competition to work for Investors" Speech to the Economic Club of New York, June 20, 2014. Available at www.sec.gov/speeches
[3] For an industry perspective, see SIFMA, Best Execution Guidelines for Fixed Income Securities, White Paper, January 2008.
[4] Richard G. Ketchum, "Remarks from the Financial Policy Joint Conference on Market Fragmentation, Fragility, and Fees," September 17, 2014, available at www.finra.org.

same security is common, with bond execution quality differing between small and large trade sizes, between frequently and infrequently traded issues, and between new and seasoned issues.[5] What has been harder to establish is how execution quality differs across essentially the same clientele executing like trades in the same securities at the same time. We overcome this difficulty by using an extensive sample of bond trades by U.S. insurance companies over the period 2002-2011. Our data provide information on all trades identified by issue, trade type, size and date, as well as identifying the specific counter-parties in each trade (i.e. the insurance company and the dealer).

Our analysis focusses on finding out on an *ex-post* basis whether trade execution quality is consistent across like traders executing like trades in the same securities at the same time. SEC regulations impose a duty of best execution on brokers (and broker/dealers) and FINRA rules further limit the mark-ups that dealers can impose on customer trades. As previous research has discussed (see, for example, Macey and O'Hara [1997]), best execution is a well-established principle in securities trading, but its actual implementation has long been problematic. If essentially the same trades are not getting essentially the same execution quality, then what exactly does best execution mean in fixed income trading? Our analysis here is geared towards addressing this question, and the larger issue of what contributes to or ameliorates execution quality differences.

In particular, we examine how trade execution quality differs between insurance companies with larger bond holdings (whom we call more active investors) and insurance companies with

[5] For a sample of investment-grade bonds in Lehman Brother's Bond index between January 1995 and March 1997, Schultz (2001) estimated transaction costs using trade prices and month-end bid quotes from Lehman Brothers and found on average they are lower for the 20 institutions with the largest volume during the sample period. Execution quality differences have also been found in research investigating trading in municipal bonds. See Green, Holifield, and Schurhoff [2007a; 2007b]; Harris and Piwowar [2006]; and Hong and Warga [2004].

smaller bond holdings (denoted less active investors). Controlling for trade type, bond issue, day, and trade size, we find strong evidence that less active investors receive significantly worse execution, paying on average 0.23% more for buys and receiving 0.61% less for sales than do more active investors. Controlling for dealer identity, we find essentially the same results, refuting the hypothesis that more active investors are simply transacting with more skilled dealers. Our results provide strong evidence of execution quality deficiencies in corporate bond trading.

What causes these execution quality differences? We investigate three main factors affecting trade execution quality: liquidity, dealer market structure, and trading networks. We show how a variety of factors that might be expected to affect bond liquidity such as price level, volatility, time to maturity, investor base of the bond, and latent liquidity also affect this differential between more active and less active investor execution quality. None of these, however, is sufficient to remove the execution quality differences between active and less active traders. We do find a strong effect played by trade size, with the execution quality differences between active and less active investors greatest for smaller-sized trades and not statistically different for block trades. These latter trades, however, are only a tiny fraction (0.1%) of insurance company bond trades during our sample period.

Market structure, and in particular the competitiveness of the market, plays an important role in affecting the execution quality differential. We show that market making for corporate bonds is very concentrated, with the top dealer doing on average 69% of the volume and the top 3 dealers having a 92% market share for the average sample bond. We find that more concentrated trading worsens execution quality differentials between trades for more active and less active investors. Interestingly, trading with the top dealer also worsens execution quality for less active investors, as does dealing with the bond's underwriting dealer. We also find that dealers increase price discrimination for issues held by more passive traders (pension and insurance companies) and decrease it for issues held by more aggressive traders (mutual funds). We find that execution quality differences decrease, but remain significant, after the introduction of TRACE reporting. Overall, these data strongly support that dealers' use market power to give some traders worse executions than others.

We also investigate how an insurance company's trading network affects the execution quality it receives. We classify an insurance company as having a small network or a large network of relations with dealers, where we use a variety of cut-off levels to determine this classification. We find that small networks actually reduce the price disparities between active and less active traders, and can completely remove it for buy trades. Large networks, on the other hand, exacerbate these differences in execution quality. As the size of the trading network is endogenous to the insurance company, our results suggest that network selection can play a significant role in counter-balancing dealer power. Hendershott et al [2015], in work completed subsequent to ours, also find network effects to be an important influence in execution quality.

Overall, our results suggest that execution quality differences remain pervasive in corporate bond trading. We believe these results, by highlighting the determinants and extent of *ex post* differential execution quality in corporate bond trading, have particular relevance for the on-going regulatory debate regarding how well investors fare in corporate bond trading. Another paper having similar relevance is Harris [2015], who looks at this issue from *an ex ante* basis by examining the routing decisions of brokers executing fixed income trades for clients in electronic trading venues. He finds that trade-throughs (or executing trades at worse prices than are available elsewhere) are rampant. Whether measured on an *ex-ante* or *ex-post* basis, both papers suggest that execution quality is problematic in fixed income trading.

This paper is organized as follows. Section 2 sets out the data we use and our sample selection criteria. Section 3 illustrates the empirical design of our study, and tests for trade execution quality differences between more active and less active investors, investigating as well the differential impact of dealer identity, offer day effects, and trade size. Section 4 then evaluates what causes execution quality differentials focusing on liquidity factors, dealer market structure, and the trading networks of insurance companies. Section 5 concludes with a discussion of potential solutions for execution quality problems in fixed income dealer markets.

2. Data and Sample Selection

Our primary data are insurance companies' transactions in corporate bonds, obtained from the National Association of Insurance Commissioners (NAIC)[6]. Our sample covers 2001 to 2011. The data provide detailed information on each transaction of corporate bonds by insurance companies, including the identity of the issue and the issuing firm, the execution date, the transaction price, the par value traded, and the direction of the trade, e.g., whether the trade was an insurance company buying from a dealer, or an insurance company selling to a dealer. In addition, the data also provide the identities of the insurance company and the dealer between whom each trade is completed.

To construct our sample, we start with all corporate bond transactions between insurance companies and dealers reported in NAIC from 2001 to 2011. After merging the full sample of 2.2 million bond trades with Mergent Fixed Income Security Database (FISD) to obtain the issue and issuer characteristics, we end up with a sample of 2 million trades. For the ease of comparisons of prices among different types of traders and for different types of bonds, we exclude bonds whose

[6] The NAIC data has been used in many studies, such as Ellul, Jotikasthira, and Lundblad (2011), Ellul et al. (2015), and Becker and Opp (2014).

face value is not equal to $1000. We also exclude issues with total issue size less than $1 million as these issues are very illiquid and hence rarely traded. Applying these two filters together removes about 20 thousand trades (about 1% of our sample).

We classify all insurance companies in our sample into more active and less active bond traders based on their aggregate holdings of corporate bonds. In robustness tests discussed in Section 3 we show that similar results obtain if we segment dealers based on trading volume. Data on corporate bond holdings for insurance companies are obtained from Lipper's eMAXX database for the period from 2001 to 2011. This database reports details of corporate bond holdings for insurance companies based on their regulatory disclosure to the NAIC.[7] If an insurer's aggregate holding of corporate bonds in par amount during the year prior to the transaction date is above (below) the median aggregate bond holding of all insurance companies in that year, it is classified as a more (less) active bond trader. Since we require one year of holding data to identify more/less active bond traders, the sample under study is from 2002 to 2011. Finally, to remove potential price errors, we first exclude trades whose price deviates from trades in surrounding days by more than 20%, and then truncate the sample at 1% and 99% in the distribution of bond trade prices. Our final sample consists of 1,703,237 bond trades. These trades occurred in 33,490 bonds issued by 6,458 corporate firms. They took place between 2,406 insurance companies and 1,025 dealers. The details for constructing our sample are summarized in Table 1.

The NAIC data provide a wealth of data including the identities of both sides of the trades, but these data are not without limitations. For example, the NAIC data do not provide intraday time stamps of the trades, making it impossible to analyze the potential impact of intraday price

[7] Lipper eMAXX database also provide quarterly corporate bond holdings data for mutual funds based on their regulatory discloser to the SEC, and some leading public pension funds based on their voluntary disclosure. For more information on Lipper eMAXX data, refer to Manconi, Massa, and Yasuda (2012) and Becker and Ivashina (2014).

movement of the transaction prices of bonds. Given that most bonds do not have multiple trades per day, we think that the impact of intraday price movement is limited to only a small set of bonds that are actively traded. In subsequent sections we control for the liquidity of bonds which should capture at least part of this impact. Moreover, it is not clear why less active or more active insurance companies would trade bonds at different times or ways during our sample period, particularly if they are trading with the same dealer.[8] Unlike in equities where large orders are routinely chopped into smaller orders, bond orders are generally left intact because large trades receive better trade prices than small trades. Thus, sequence effects of trades are unlikely to be an important factor. We view the impact of any intraday timing issues as contributing noise rather than any systematic bias to our results.

3. Trade Executions for Insurance Companies

3.1. Do Less Active Traders Receive Worse Prices?

We start by examining the differences in execution quality for more active and less active traders after controlling for bond, date, and trade size effects. Specifically, we test whether less active traders receive worse prices from dealers than more active traders by comparing the prices for the two types of traders when both of them execute similar sized trades in the same bond on the same day. Our empirical design is illustrated in Figure 1. Since the implication of more favorable prices varies with the direction of trades, we first divide our sample of trades into buys and sales. Within each subsample, for each trade size category S in bond i on day t, we calculate

[8] Because our sample firms are all insurance companies, accounting rules also gravitate against trading differences across firms related to harvesting capital gains or losses. Insurance companies follow statutory accounting principles which require that any gain or loss on a bond trade be amortized over the remaining maturity of the bond, in contrast to GAAP rules which allow gains and losses to impact the income statement.

separately the average prices for more active traders and less active traders, denoted as $P^{MA}i,t,s$ and $P^{LA}i,t,s$ respectively. Trade size categories are formed based on the dollar amount of the trades: Micro ($1 to $100,000), Odd-lot ($100,000 to $1,000,000), Round-lot ($1,000,000 to $5,000,000), and Block (above $5,000,000).[9]

For each bond *i*, day *t*, and size *s*, we then calculate the difference between $P^{MA}_{i,t,s}$ and $P^{LA}_{i,t,s}$:

$$PriceDiff_{i,t,s} = P^{MA}_{i,t,s} - P^{LA}_{i,t,s}.$$

To be included in this calculation, both types of traders need to trade at least once in bond *i* on day *t* in size category *s*.[10] We end up with 20,682 bond-day-size level estimates, which are calculated from using 263 thousand trades.

If trade execution is similar for more active and less active traders in the bond market, the $PriceDiff_{i,t,s}$ measure should not be significantly different from zero. Results in Table 2 show that this is not the case. The mean $PriceDiff_{i,t,s}$ is -0.23% for buys, and 0.61% for sales, and these differences are highly significant. These numbers suggest that compared with more active traders, less active traders buy at higher prices and sell at lower prices. Therefore, execution quality for less active traders is significantly worse than for more active traders. In addition, these execution quality differentials are stronger for sales than for buys. For a standard $1000 bond, these results show that less active traders on average pay $2.30 more to buy one bond and receive $6.10 less to sell the bond than more active traders.

[9] These cut-off points are consistent with standard industry conventions. Also, see Hendershott and Madhavan (2015) who use the same approach to form trade-size categories to study transaction costs for corporate bond trading.
[10] Because more and less active traders have different tendency to trade, and their trading activities might also differ with respect to bond characteristics, time, size, and direction, the number of trades used to calculate $P^{MA}_{i,t,s}$ can be different from that used to calculate $P^{LA}_{i,t,s}$.

We further examine whether trade execution differentials for the two types of traders vary with trade size. For buys, less active traders received worse executions in small sized trades. The mean *PriceDiff*$_{i,t,s}$ is -0.20% and -0.28% for Micro and Odd-lot trades respectively, and both of them are highly significant. This suggests that the price per bond for a less active trade is $2 ($2.8) higher than for a more active trader when both of the submit a micro (odd-lot) trade in the same bond on the same day.

When less active traders buy larger amounts, their prices are not much different from those for more active traders as the *PriceDiff*$_{i,t,s}$ estimate is not statistically significant for Round-lot and Block trades. For sales, the results are different.. Less active traders receive worst execution in micro trades. The mean *PriceDiff*$_{i,t,s}$ is 0.88% and it is highly significant, suggesting that less active traders received $8.8 less per bond than more active traders when both of them trade a micro lot in the same bond on the same data. The *PriceDiff*$_{i,t,s}$ estimate declines to 0.42 for Odd-lot, and further to 0.29% for Round-lot, but they are still highly significant. There is no significant difference between their prices when both more active and less active traders sell a block.

Earlier researchers, most notably Bessembinder et al [2008], found worse execution prices for the smallest trades, a finding they attributed to retail traders receiving worse execution than institutional traders. All of our traders here are institutions, but as our data show, many small trades are in fact coming from institutions, suggesting caution in linking trade sizes with particular trading clienteles. Our results do reinforce earlier findings that some traders are getting much worse execution quality than others (e.g., Schultz (2001)).

3.2. Controlling for Dealer Identity

The corporate bond market is an OTC market, with multiple dealers making a market in the same bond. One potential explanation for our findings above is that given the size of their portfolio, more active traders are able to trade with more competitive dealers, while less active traders might have to trade with less competitive dealers, who usually charge higher prices to compensate for their higher trading or operating costs. In this case, the price differential for more active and less active traders reflects the competitiveness of different types of dealers, rather than that the same dealer quotes different prices based on the identity of the traders.

To examine whether price differences for the two types of traders reflect the possibility of trading with different types of dealers, we now require that all trades used to calculate the $PriceDiff_{i,t,s}$ measure have to be executed with the same dealer. As illustrated in Figure 2, within the subsamples of buys and sales, for trades in size category s, with dealer d in bond i on day t, we first calculate separately the average prices for more active traders and less active traders, denoted as $P^{MA}_{i,t,s,d}$ and $P^{LA}_{i,t,s,d}$ respectively. Then, for each bond i, day t, size s, and dealer d, we calculate the difference between $P^{MA}_{i,t,s,d}$ and $P^{LA}_{i,t,s,d}$:

$$PriceDiff_{i,t,s,d} = P^{MA}_{i,t,s,d} - P^{LA}_{i,t,s,d}.$$

To be included in this calculation, we require that there is at least one trade from each of the two types of traders, and these trades must be in the same size category s, with the same dealer d, in the same bond i, and on the same day t.

Table 3 shows that the execution differentials between more active and less active traders decline after we control for dealer identity. This finding suggests that trading with less competitive dealers explains part of the poor execution quality for less active traders as documented in Table 2. Nevertheless, the mean $PriceDiff_{i,t,s,d}$ estimate is still negative for buys and positive for sales. And it is statistically highly significant for both buys and sales. On average, compared with more active traders, less active traders pay $2 more per bond in buying, and receive $5.1 less per bond in selling. This is after we control for bond characteristics, date and size effects, and dealer identity.

Further breaking the sample by trade size categories yields results similar to those in Table 2. For both buys and sales, there exist significant execution differentials when less active traders trade a small amount, i.e., Micro and Odd-lot. The execution quality for less active traders is similar to that for more active traders when they trade a Block, no matter whether they buy or sell. In addition, the quality differentials are stronger for sales than for buys. Finally, when selling a bond, less active traders receive the worst execution when they trade an odd-lot.

3.3. Robustness Checks

3.3.1. Offer Day Effects

Our sample includes both trades on the offer day and trades in the secondary market (i.e. trades taking place during the life of the bond). Because many bonds are bought by long-term investors following a buy-and-hold strategy, it can be the case that some bonds never actually trade again before maturity. We examine whether execution quality differentials between the two types of traders exist mainly in the aftermarket trading.[11] To this end, we exclude all trades that occur on the first day following a bond's issuance.[12] Since most of the trades on a bond's offering day are buys, after excluding trades on the offering day from our sample, we lose about 40% of the buys, but almost no sales. The results are given in Panel A of Table 4. For sales, since the sample

[11] Schultz (2012) finds that different investors pay different prices to buy similar amount of new issues of municipal bonds.

[12] Results are very similar when we exclude all trades that occurred within three days, one week or one month of issuance.

barely changes, the results are similar to those in Table 3. For buys, the mean *PriceDiff*$_{i,t,s,d}$ estimate declines to -0.27% and it is highly significant. This suggests that execution quality differentials actually worsen in the aftermarket.

That offer day and aftermarket trading differ may reflect the natural feature of relative scarcity of some bonds in the aftermarket. In particular, while virtually all bonds are plentiful when first offered, their supply is more problematic over time as investors hold bonds and thus reduce the amount actually trading. These aftermarket liquidity effects can explain why the same bond trading on the offer day and in the aftermarket may have different prices, but they do not explain why prices for more active and less active investors trading the same bond on the same day with the same dealer will differ. To understand this puzzle, we have to investigate how features of corporate bond market trading affect best execution, an issue we address in the next section.

3.3.2 Trader Classification

We use the size of an insurance firm's bond portfolio to determine whether the insurance firm is a more active or a less active trader in the bond market. This seems sensible because a larger bond portfolio is likely to bring more market making business for the dealer and may facilitate the dealer's future distribution of new bond issues. As an alternative, we also use an insurance firm's aggregate trade volume in corporate bonds over the past year to classify more active and less active traders. Specifically, a bond trader is classified as being more active (less active) if its aggregate bond trade volume over the past year is above (below) the median trade volume of all insurance companies at the same year. Panel B of Table 4 shows that our results hold under this alternative trader-type classification. Price differentials are slightly smaller for both buys and sales, but they are still statistically highly significant. However, using past one year trade volume results in unstable classification of trader types. Therefore, we choose to use bond portfolio size as our main approach to classify bond traders in the paper.

3.3.3 Stress Day Effects

Our study focuses on the sample of bond-days when both more active and less active traders trade similar quantities. Since most insurance company follow a buy-and-hold strategy in their bond investment, trading in a specific bond by both types of traders at the same time are likely to be caused by credit related events. Motivated by Ellul, Jotiskathira, and Lundblad (2011) who find evidence of collective selling of downgraded bonds by insurance companies who are facing regulatory constraints, we study in this sub-section whether excluding trades occurring on stress days affect our results. We obtain from Mergent's Fixed Income Securities Database (FISD) data on historical rating actions by the three largest rating agencies: Standard & Poor's (S&P), Moody's, and Fitch. We follow Ellul, Jotikasthira, and Lundblad (2011) and define the rating change event as the date of downgrade from investment-grade to speculative-grade announced by the first acting rating agency. We then exclude from our sample all trades that occur during the one-month post-downgrade period. Since insurance companies tend to sell following a rating downgrade, the buys sample drops only slightly and the mean $PriceDiff_{i,t,s,d}$ estimate barely changes. The sales sample drops by about 25%. While the $PriceDiff_{i,t,s,d}$ estimate declines to 0.37%, it is still highly significant. This finding suggests that the execution quality differentials we find earlier are not confined to bonds under stress.

4. What Causes Execution Differences?

Why does execution quality differ for like traders making the same trades in the same corporate bond? In a perfect world, we would expect such differences to be zero as traders would be able to identify when they were getting worse prices than other traders. In the dealer market structure characterizing actual bond trading, however, this task is much harder. Many bonds trade rarely, so even in the post-TRACE world of trade reporting, it may not be clear that a price is "worse" than it should be. Dealer markets also do not feature pre-trade transparency so traders have to search across dealers to find the best quote – or hope that the dealer they do trade with is giving them a fair price. Moreover, dealers are not the same in that some hold greater inventories or have better access to particular bond issues – characteristics that may give the trader a better deal or may simply give the dealer greater market power.

In this section, we investigate three possible explanations for execution quality differences: underlying liquidity characteristics, dealer market structure, and trading networks. Our focus is on understanding what factors contribute to some traders getting better execution than others.

4.1. Liquidity Factors

It is well established that corporate bonds are not all alike. Bonds differ in basic characteristics such as issuer, amount outstanding, time to maturity, years outstanding, and credit rating. Bonds also differ with respect to how widely traded they are, whether the issuer has publicly traded equity, the investor base of the bond, and how many dealers trade the bond. All of these factors (and more) can affect the liquidity of the bond, and in particular how willing dealers are to buy and sell particular bonds. In this sub-section we use regression analysis to investigate how factors affecting liquidity (or potential liquidity) affect the differential prices received by more active and less active investors.

4.1.1. Bond Characteristics and Liquidity

Appendix 1 provides the definitions of the variables we use in our multi-variate regressions. The dependent variable is the absolute value of price differences $PriceDiff_{i,t,s,d}$, that is, the magnitude of the difference between prices of more active traders and less active traders when they trade bond *i*, on day *t*, in order size *s*, and with dealer *d*, expressed as a percentage of par. We use absolute values of the price differences to avoid the confusion of opposite signs of the raw price difference in buy and sell trades. Our first regression, reported in Table 5, relates execution quality to bond characteristics given by the following variables: price level (calculated as the volume-weighted average price of all trades in bond *i* on day *t*); volatility (the highest price minus lowest price of all trades in bond *i* on day *t*); credit rating (S&P rating of the bond, translated to a numeric scale: smaller number means better rating); time to maturity; amount outstanding; age (the log of the number of years since issuance); and a public dummy (equal to 1 if the issuer has publicly traded equity, and 0 otherwise). We include in the full sample regression an indicator of trade type, Sell Dummy (which is equal to 1 for sales and 0 for buys) in the full sample regression, and we also report separate regressions for buy trades and sell trades.

For the full sample regression, all variables except for the amount outstanding and the public dummy have statistically significant effects on the price difference variable. Thus, execution quality differences between more active and less active investors are worsened for sell trades and for bonds with lower price, higher volatility, lower credit ratings, longer time to maturity, and longer time since issuance. These results suggest that less active investors receive even worse executions in bonds that feature greater illiquidity.

Looking to the separate buy and sell regressions reveals some major differences between trade types. For buy trades, execution quality differences are influenced by the price level, volatility, time to maturity, and age of the bond, with the other variables now not statistically significant at the 10% level. For sell trades, however, the effects are much stronger with all of the variables except the public dummy being statistically significant. It is worth noting that the coefficient for Amount Outstanding is now negative and statistically significant. Since larger issues tend to be more liquidity, this result suggests again that price differentials are larger in illiquid bonds. The stronger effects found in the subsample of sell trades is particularly striking given that about three quarters of the sample trades are buys, yet it is in the less numerous sell trades that execution quality differences are greater. This may simply reflect the fact, noted earlier, that many bonds are held to maturity and so many buy trades occur only in the relatively liquid offer market. Sell trades, conversely, are virtually all in the aftermarket and, as the results indicate, execution quality differences are rife.

4.1.2. The Investor Base and Latent Liquidity

A recent line of research developed by Mahanti, Naskikkar, Subrahmanyam, Chacko, and Mallik [2008] highlights the role of latent liquidity in influencing bond execution costs. Latent liquidity refers to the ease with which a dealer can find (or trade out of) a bond involved in a customer transaction. As explained by Mahanti et al [2008], a dealer can fill a customer order either by using a bond out of his own inventory or by getting the bond from a buy side client. To the extent that it is easy to get the bond, this "latent liquidity" should affect the transactions costs facing traders in the bond. An interesting question is whether such latent liquidity can also affect the differential execution costs we find between the more active and less active investors.

Measuring latent liquidity is not straightforward as it essentially requires measuring how easy it is for dealers to find a particular bond. Certainly one factor influencing this is how frequently a particular bond issue trades, and this depends upon the investor base in a bond issue.

Bond issues that are held by aggressive investors such as mutual funds or hedge funds, for example, tend to trade more frequently than do bonds issues that are primarily held by passive investors such as insurance companies and pension funds. This suggests that a simple proxy for latent liquidity is the extent to which the bond is held by aggressive or passive investors.

To determine the investor base for each bond in our sample, we collected information on quarterly corporate bond holdings from the Lipper eMAXX database for the period 2001 to 2011. This database includes corporate bond holdings by all insurance companies, over 95% of mutual funds, and the top 250 public pension funds. Holdings by hedge funds, other pension funds, banks, private investors, and foreign entities are not tracked by Lipper. We define aggressive traders to be mutual funds, and insurance companies and pension plans to be passive traders. Given the incompleteness of the Lipper data, these measures should be viewed as noisy proxies for the investor base. Table 6 provides summary information on the investor base of corporate bonds.

For the approximately 33,000 bonds in our sample, we find that on average 12% of a bond's issuance is held by mutual funds, while more passive insurance companies or pension funds are 31% of the investor base. As the data demonstrate, these investor base numbers vary across bonds, with some bond issues entirely held by aggressive investors and others entirely held by passive investors. We add these aggressive and passive holdings to our regression analysis, with the percentage held by different types of investors serving as simple proxies for latent liquidity. As before, the dependent variable is the absolute value of $PriceDiff_{i,t,s,d}$, and the other variables in the regression are the same as in Table 6. The question we ask is how does latent liquidity as captured by the size of the aggressive trader base affect the execution price differential between more active and less active investors?

Table 7 presents our results. For the full sample of bond trades, greater holding by aggressive traders reduces the price differential while greater holding by passive traders increases the price discrimination between trader groups. Both effects are statistically significant. Focusing on buy trades, we find that only holding by aggressive traders is significant with a smaller coefficient, while holding by passive trade is not significant, suggesting a somewhat reduced effect of latent liquidity. Conversely, the sell trade effects are much stronger, consistent with latent liquidity playing a more important role in aftermarket trading in which sells are more prominent. Overall, these results suggest that issues held by passive investors are more likely to result in poorer executions for less active investors.[13] Thus, both liquidity and latent liquidity seem to influence the extent to which less active traders receive poorer execution quality compared to more active traders.

4.2. Dealer Market Structure

The most prominent feature of bond market microstructure is the role played by dealers. Unlike other asset classes in which trading is now largely electronic, the dealer market used to trade corporate bonds has remained remarkably unchanged, with dealers largely intermediating every trade.[14] The lack of pre-trade transparency, and until recently post-trade transparency, as

[13] Mahanti et al. (2008) measure latent liquidity of a bond with the holding-weighted average turnover rate of bond portfolio of each fund that holds this bond. Ideally, we would like to use this same measure in our study. Unfortunately, our bond transaction data only cover insurance companies and we don't have such data for mutual funds and pension funds. Nevertheless, we utilize the Lipper holding data, which cover bond holdings of mutual funds and pension funds, to infer trades of these investors. We then follow the methodology in Mahanti et al. (2008) and calculate the latent liquidity measure. We put this measure in our regressions in place of the active / passive variables, and find the same significant effects in sell trades, although no significant effects in buy trades. Because of the lack of transaction data, we underestimate the turnover rate of active investors, such as mutual funds, and as a result this measure may not really capture the latent liquidity as designed in Mahanti et al. (2008). Hence, in our main analysis, we use our simple active and passive investor holding variables, which can be viewed a simplified version of Mahanti et al. (2008) measure.

[14] Electronic platforms have emerged in corporate bond trading with MarketAxess and Tradeweb being among the best known. These electronic platforms generally use a RFQ (or request for quote) structure in which dealers provide indicative bids and offers. For more discussion of corporate bond electronic trading see Harris [2015].

well as the basic illiquidity characterizing many bond issues, provides opportunities for dealers to exert substantial market power. A natural question is whether the competitiveness of the market affects the differential execution quality we find for more active and less active investors.

For each of the 33,490 bond issues in our sample, we calculated the number of distinct dealers with some trading volume in any bond year. We then computed the market share of each dealer based on their trades over the annual trade volume in the bond. This allowed us to calculate a Herfindahl index, a standard measure of market competitiveness, for each bond issue by squaring the market share of dealer trading in the bond, and then summing the resulting numbers. Our results are given in Table 8.

The data show that the markets for commercial bond trading are remarkably concentrated. For the average issue in our sample, the largest dealer does 69% of all trading volume, with the top three dealers executing 92% of all volume. Bonds in the lower quartile of the distribution are somewhat less concentrated, with a top dealer market share of 46% and top 3 market share of 87%, while bonds in the top quartile are concentrated in a single dealer who handles 100% of the volume. The average bond issue has 4 dealers, with the most actively traded issue having 49 and the least actively traded having a single dealer. Overall, the average issue has a Herfindahl index of 61% indicating a highly concentrated market structure.[15]

We included the Herfindahl index in our regression analysis to examine whether the competitiveness of the market affected the dealers ability to exercise price discrimination between the more active and less active insurance companies. Table 9 presents these results. For sell trades, greater concentration worsens the execution differential between traders, but it has no effect on

[15] The US. Department of Justice uses Herfindahl indices (also known as the Herfindahl Hirshfeld Index or HHI) to evaluate the impact on competition of potential merger activity, with anything above 0.25 viewed as being "highly concentrated".

execution differences for buy trades. Overall, this results in a weak effect for the entire sample. Given that even the lowest quartile of bond issues have concentrated markets, perhaps these results suggest that above some concentration level, variations in concentration are not a major factor in affecting dealer behavior.

4.2.1. Transparency and Dealer Market Power

One factor that might be expected to affect competitive behavior is transparency. Traditionally, commercial bond trading was opaque, unlike trading in equity markets where a consolidated tape allowed investors to see how their trade price compared with that of similar trades. Starting in 2002, FINRA introduce the Trade Reporting and Compliance Engine (TRACE) system to disseminate real-time execution data on secondary trades in large investment grade bond issues and 50 high-yield bond issues. Subsequently, TRACE used a three-stage implementation process to incorporate smaller and less liquid issues. In February 2005, TRACE began to cover almost all secondary bond trades. We use the staggered introduction of TRACE reporting to investigate how greater transparency affected dealers' ability to exercise market power. We capture this by including a Post-TRACE dummy variable for each bond issue to determine the effect of trade reporting on price discrimination between more active and less insurance companies.

The results in Table 10 show that transparency reduces execution quality differences. For buys, sells, and trades as a whole, TRACE reporting reduced the trade quality execution differentials. While this result is particularly strong for sell trades, it is also statistically significant for buy trades. That TRACE affected the overall competitiveness of bond trading has been found by several researchers (e.g., Bessembinder, Maxwell and Venkateramen, [2006], Edwards, Harris and Piwowar [2007], Goldstein, Hotchkiss and Sirri [2007] and more recently Asquity, Covert, and Pathak [2013]).[16] Our findings here show that it also reduced the ability of dealers to price discriminate between institutional investor groups.

Earlier we found that the top dealer played a large role in trade executions, trading on average 69% of overall volume in the average bond issue. A large market share is consistent with large market power for the dealer, so a natural conjecture is that greater market power can lead to greater execution quality differentials across traders. We test this conjecture by adding a top dealer dummy to our regressions, with the results reported in Table 11. We find strong evidence in support of this hypothesis. Trading with the top dealer actually worsens the execution quality differential between more active and less active insurance company bond investors.

Bond issues also have a lead underwriter who brings the issue to market, and that underwriter often continues to play an important market making role in the issue. We tested whether dealing with the underwriter dealer could benefit less active insurance companies in terms of reduced execution differences. As the results in Table 11 indicate, this is not the case: the data show that execution quality differences widen between clientele classes trading with the underwriter.

Overall, our results are consistent with dealer market power playing a significant role in worsening execution quality differentials between more active and less active insurance company clienteles.

4.3. The Trading Networks of Insurance Companies

[16] Recently, dealers have complained that illiquidity problems in bond trading are being exacerbated by the required transparency of TRACE. As reported by Reuters "Investors and traders said real-time reporting of large trades to [TRACE] caused some dealers to shy away from buying large blocks from corporate bond customers". See Richard Leong, Delayed Reporting seen boosting U.S. bond liquidity" July 7, 2015

Insurance companies have to trade with dealers to buy and sell corporate bonds, but which dealers and how many to trade with is up to the company. We demonstrated above that dealing with the top dealer or underwriter worsened trade quality differentials between more active and less active traders. We now consider how the trading network, in particular the number of dealers an insurance company transacts with in a given year, affects these trading quality differences. We conjecture that trade execution quality for less active traders can be improved when they concentrate their trades with a small number of dealers since dealers are more likely to improve prices in order to win their repeat business.

As a useful preliminary, we look at the corporate bond trading activities of insurance companies during our sample period from 2002 to 2011. This summary information is given in Table 12. As is apparent, the typical insurance company does not trade an individual bond frequently. The average number of times an insurance company trades a given bond in a year is one. Over our entire sample period, an insurance company trades a given bond only three times on average. This is also captured by the trade gap variable which refers to the number of days between two consecutive trades by an insurance company in a given bond. The mean and median of the trade gap is 436 days and 266 days, respectively, consistent with many bonds being bought and held.

There is, of course, more trading by the insurance company across its entire portfolio of bonds, with the mean (median) company entering 698 (67) trades over the sample period and 70 (7) trades in a given year. The divergence between means and medians suggests the presence of large outliers and that is confirmed by the maximum numbers. Some bond issues are heavily traded (the most active traded 282 times during the sample and 94 times in a given year) and some insurance companies are active traders (the most active trading 63,251 times during the sample for an average of 6,325 times a year). These active traders, however, are a relatively small part of the sample as even the third quintile insurance companies are trading only 26 times a year.

How they trade is a function of the network of dealers they use. Table 13 provides summary information on the trading networks of insurance companies. We define the number of dealer relationships per bond to be the number of distinct dealers with whom the insurance company trades in a given bond in a given year. We define the number of dealer relationships per firm to be the number of distinct dealers with whom an insurance company trades any bond in a given year. The data reveal an interesting divergence in these two measures. For all of its trading in a given bond, an insurance company generally deals with only one dealer, and this singularity holds on average across the quartiles of insurance companies in our sample. Across all their bond trades in a year, insurance companies rely on a larger network of dealers, with the mean (median) insurance company dealing with 11 (5) dealers.

To examine whether trade quality differences between more and less active traders reflect the effects of trading with different sized networks, we now further sub-divide our data into two additional groups: one for traders with small networks and one for traders with large networks. Delineating large from small networks is not straightforward as the divergence between the median number of dealers (5) and the average number of dealers (11) suggests a skewed distribution. Consequently, we used three definitions corresponding to the median (5), the mean (11) and the top quartile (16) to delineate these groups, with small networks having less than 5 (11 or 16, variously) dealers and large networks having greater than that number of dealers. Figure 3 illustrates our empirical design where, as before, we create trade buckets that group trades by buys or sales, bond issue, dealer, day, size, and now by whether the trader has a large network (LN) or a small network (SN). Then, for each bond i, day t, size s, and dealer d, we calculate the difference between $P^{MA}_{i,t,s,d}$ and $P^{LA}_{i,t,s,d}$ for small and large networks separately:

$$PriceDiff_{i,t,s,d,LN} = P^{MA}_{i,t,s,d,LN} - P^{LA}_{i,t,s,d,LN},$$

$$PriceDiff_{i,t,s,d,SN} = P^{MA}_{i,t,s,d,SN} - P^{LA}_{i,t,s,d,SN}.$$

Panels A-C of Table 14 show the trade execution differentials between active and less active insurance companies with small networks and large networks, after controlling for trade type, issue, size, day, and dealer identity. The results show that network size has a large effect on trade execution outcomes. Less active firms trading in small networks fare much better relative to more active firms than they do when trading in large networks. For all three network size cut-offs, small network results show no statistically significant difference between more active and less active traders for buy trades in execution quality. Sell trades do show significantly worse executions overall between more active and less active firm, but these differentials are minimized in the smallest networks (i.e. using the median 5 as the cut-off point). Conversely, less active trades in large networks receive poorer executions for both buys and sells, with these differences being strongly statistically significant. These results suggest that network structure can exert significant effects on execution quality, and less active traders can benefit from having a more concentrated trading network.

As a further test of this effect, we now return to our empirical design and control explicitly for network size. In particular, as depicted in Figure 4, we create trade buckets that group trades by buys or sales, bond issue, dealer, day, size and now we also require that the more active and less active traders have exactly the same number of relation dealers. Then, for each bond i, day t, size s, dealer d, and network n, we calculate the difference between $P^{MA}_{i,t,s,d,n}$ and $P^{LA}_{i,t,s,d,n}$ for small and large networks separately:

$$PriceDiff_{i,t,s,d,n} = P^{MA}_{i,t,s,d,n} - P^{LA}_{i,t,s,d,n}.$$

Panel D of Table 14 shows that controlling for the trading network seems to dramatically counteract the dealers' market power. There is no execution differential between more active and less active traders for buy trades, and for sell trades, while still statistically significant, it is greatly reduced. Earlier in Table 3 we found that less active traders received \$5.1 less than more active traders for a sell trade, and paid \$2more for a buy trade. Controlling for the trading network, we find that less active sellers receive \$3.2 less than more active sellers, and they pay the same price for buy trades.

That the trading network may serve to counteract (to at least some degree) the dealers' market power is a new, and we believe potentially important, result. Earlier literature in equities (see Bernhardt [2004]) argued that dealers gave their best, repeat customers better prices, suggesting an important role for on-going relationships. Less active insurance companies do not trade very much, but interacting with a smaller network of dealers may make the firm more important to those dealers and hence elicit more favorable executions.

5. Conclusions

Execution quality is an important dimension of market quality. In the U.S, there are a variety of regulations designed to insure that traders receive high quality executions. In fixed income trading, for example, FINRA regulations limit the size of dealer markups, a rule structure designed to allow traders, and not dealers, to capture the benefits of bond trading.[17] For all securities, there are best execution requirements, with the SEC dictating that "brokers are legally

[17] FINRA limits dealer markups on bonds to "acceptable" levels, where acceptable markups are a function of market conditions and the specific security but in no case should exceed 5%.

required to seek the best execution reasonably available for their customers' orders."[18] In equity markets, market structure and regulatory changes, abetted by new technologies, have dramatically lowered trading costs for investors. Whether such improvements have occurred in fixed income trading has remained an open, and important, question.

In this research, we demonstrated that execution quality falters in the fixed income markets. While marginal differences in execution quality may be expected even between like investors trading identical fixed income securities, we find systemic differences resulting in large and statistically significantly worse execution quality experienced by particular subsets of institutional traders. Our findings that these differences are reduced by greater transparency and can be partially ameliorated by trading network structure support our contention that these differences arise primarily from dealer power.

Improving execution quality in fixed income trading is likely to require a variety of changes. With greater awareness of the problem, institutional traders can adapt their trading networks to better counteract these anti-competitive forces. The gravitation of fixed income trading to electronic venues may also help by improving both pre- and post-trade transparency. Harris's [2015] results on execution in electronic bond trading venues, however, suggest that such improvements in execution quality are not guaranteed. Harris, Kyle, and Sirri [2015] suggest that introducing a public limit order display facility might be one step to reduce trading costs for public investors.

Regulatory change may also have to play a role both by clarifying, and enhancing executions requirements in fixed income trading. In Europe, the currently proposed Markets in Financial Instruments Directive (Mifid 2) will require investment firms to establish best execution

[18] Cited from http://www.sec.gov/answers/bestex.htm

policies throughout the trading process for all asset classes. One aspect of this proposal will require investment firms to establish the fairness of prices based on market data and comparison with similar instruments.[19] Our analysis here of bond trading execution differentials is an example of such a comparison, but it highlights that the data needed to do so are not currently available to bond market investors. FINRA's recent proposal to require disclosure on retail-sized trade confirmations of the price of dealer's same day principal trades in the security is an excellent start.[20] It would also be useful to require dealers to disclose trade prices for similar-sized same-day trades on trade confirmations. This could facilitate both transaction cost analysis and allow for the development of meaningful execution benchmark prices. The SEC's increased focus on markups in dealer riskless principal trading is also well-founded. As our research here suggests, it is not just retail traders who are paying the price in corporate bond trading.

[19] For discussion, see H. Yegerman, "Why Should Best Execution Matter to Global Bond Managers?" Traders Magazine Online News, October 8, 2015.

[20] Similar efforts at greater disclosure are also taking place in the municipal bond market. See MSRB Regulatory Notice 2014-20, "Request for Comment on Draft Rule Amendments to Require Dealers to Provide Pricing Reference Information on Retail Customer Confirmations;" available at http://www.msrb.org/~/media/Files/Regulatory-Notices/RFCs/2014-20.ashx?n=1%5bmsrb.org%5d.

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Appendix 1: Variable Definition

This appendix provides the definition of all variables used in the multivariate regressions conducted in Section 4.

Variable Name	Variable Definition
$PriceDiff_{i,t,s,d}$	Price for more active traders minus price for less active traders when they trade bond *i* on the day *t* in size category *s* with dealer *d*. This variable is computed at the bond-day-trade size-dealer level, and it is expressed as a percentage of the par.
Sell Dummy	An indicator variable which takes the value of 1 for sales, and 0 for buys.
Price Level	Daily average price of the traded bond, calculated as the volume-weighted average price of all trades of the bond on the day.
Volatility	Daily price volatility, which is equal to the highest price minus the lowest price of all trades of the bond on the day.
Credit Rating	S&P's numerical credit rating of the bond issue, with 1, 2, 3, 4, … denoting AAA, AA+, AA, AA-, …, respectively.
Time to Maturity	The log of the number of years for the bond to mature.
Amount Outstanding	The log of the total amount outstanding of the bond.
Age	The log of the number of years since the issuance of the bond.
Public Dummy	A dummy variable which takes the value of 1 if the bond issuer has publicly traded equity, and 0 otherwise.
% by Mutual Funds	The percentage of total outstanding par amount held by mutual funds.
% by Pension & Insurers	The percentage of total outstanding par amount held by pension funds and insurance companies.
Herf in Market Making	Herfindahl index, calculated as the sum of the squared market share of each dealer in handling all trades of the bond in the previous year.
Post-TRACE Dummy	A dummy variable which takes the value of 1 for days when the bond is subject to TRACE dissemination, and 0 otherwise.
Top Dealer Dummy	A dummy variable which takes the value of 1 if the dealer has the largest market share in the bond over the previous year, and 0 otherwise.
Underwriter Dummy	A dummy variable which takes the value of 1 if the dealer is the underwriter of the bond, and 0 otherwise.

Figure 1: **Calculating Differences in Prices for More Active and Less Active Traders after Controlling for Trade Type, Bond, Day, and Trade Size**

Our sample includes all corporate bond trades by insurance companies during the period 2002-2011. A bond trader is classified as being more active/less active if its average quarterly holding in corporate bonds in the previous year is above/below the median corporate bond holding of all insurance companies in that year. We first separate the full sample of trades into insurers' buys and sells. Within the subsamples of buys and sell, we then create trade buckets by including all trades in bond *i* on day *t* within a trade size category *s* into one bucket. Consistent with standard industry conventions, bond trades are classified into four size categories based on their dollar value: Micro (\$1 to \$100,000), Odd-lot (\$100,000 to \$1,000,000), Round-lot (\$1,000,000 to \$5,000,000), and Block (above \$5,000,000). Finally, within each trade bucket, we calculate the average prices for trades by more active and less active bond traders separately, and they are denoted as $P^{MA}_{i,t,s}$ and $P^{LA}_{i,t,s}$ respectively. Only those trade buckets with at least one trade by each of the two types of traders are included in our calculation.

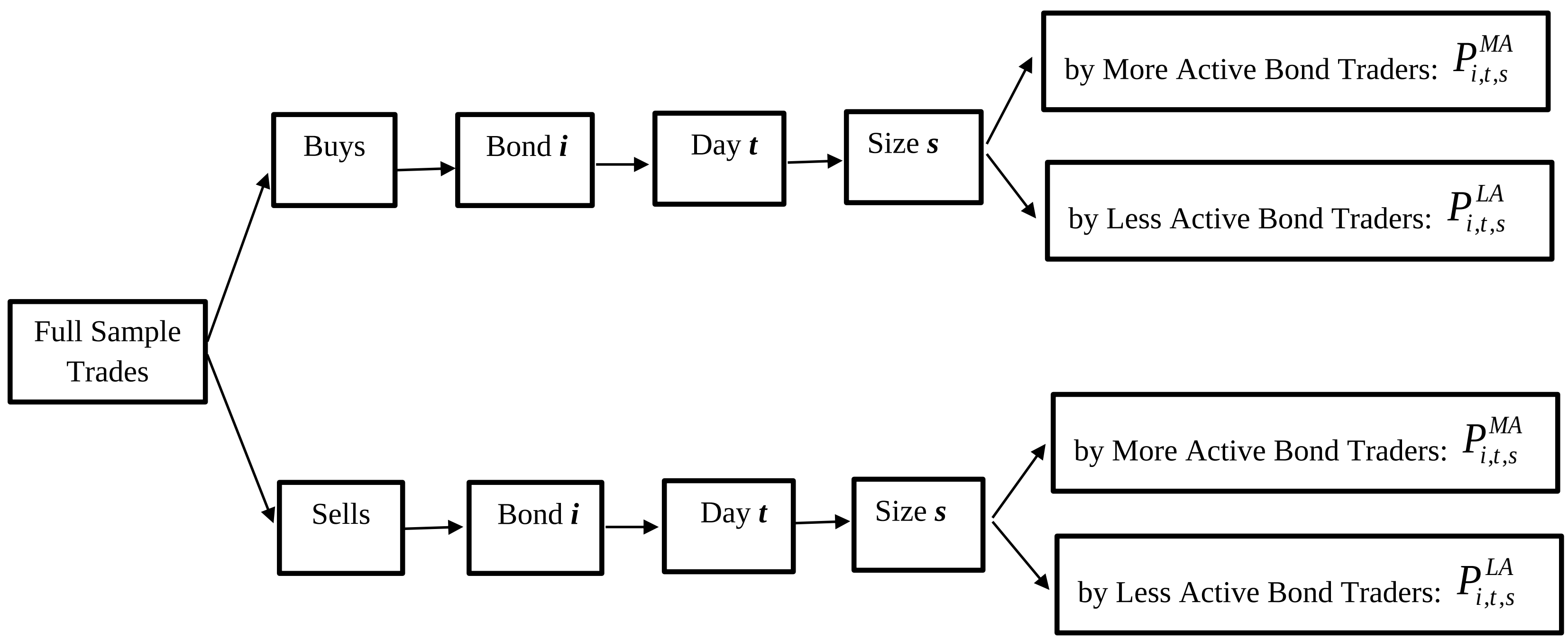

Figure 2: **Calculating Differences in Prices for More Active and Less Active Traders after Controlling for Trade Type, Bond, Day, Trade Size, and Dealer**

Our sample includes all corporate bond trades by insurance companies during the period 2002-2011. A bond trader is classified as being more active/less active if its average quarterly holding in corporate bonds during the previous year is above/below the median corporate bond holding of all insurance companies in that year. We first separate the full sample of trades into insurers' buys and sells. Within the subsamples of buys and sell, we then create trade buckets by including all trades in bond *i* with dealer *d* on day *t* within a trade size category *s* into one bucket. Consistent with standard industry conventions, bond trades are classified into four size categories based on their dollar value: Micro ($1 to $100,000), Odd-lot ($100,000 to $1,000,000), Round-lot ($1,000,000 to $5,000,000), and Block (above $5,000,000). Finally, within each trade bucket, we calculate the average prices for trades by more active and less active bond traders separately, and they are denoted as $P^{MA}{}_{i,t,s,d}$ and $P^{LA}{}_{i,t,s,d}$ respectively. Only those trade buckets with at least one trade by each of the two types of traders are included in our calculation.

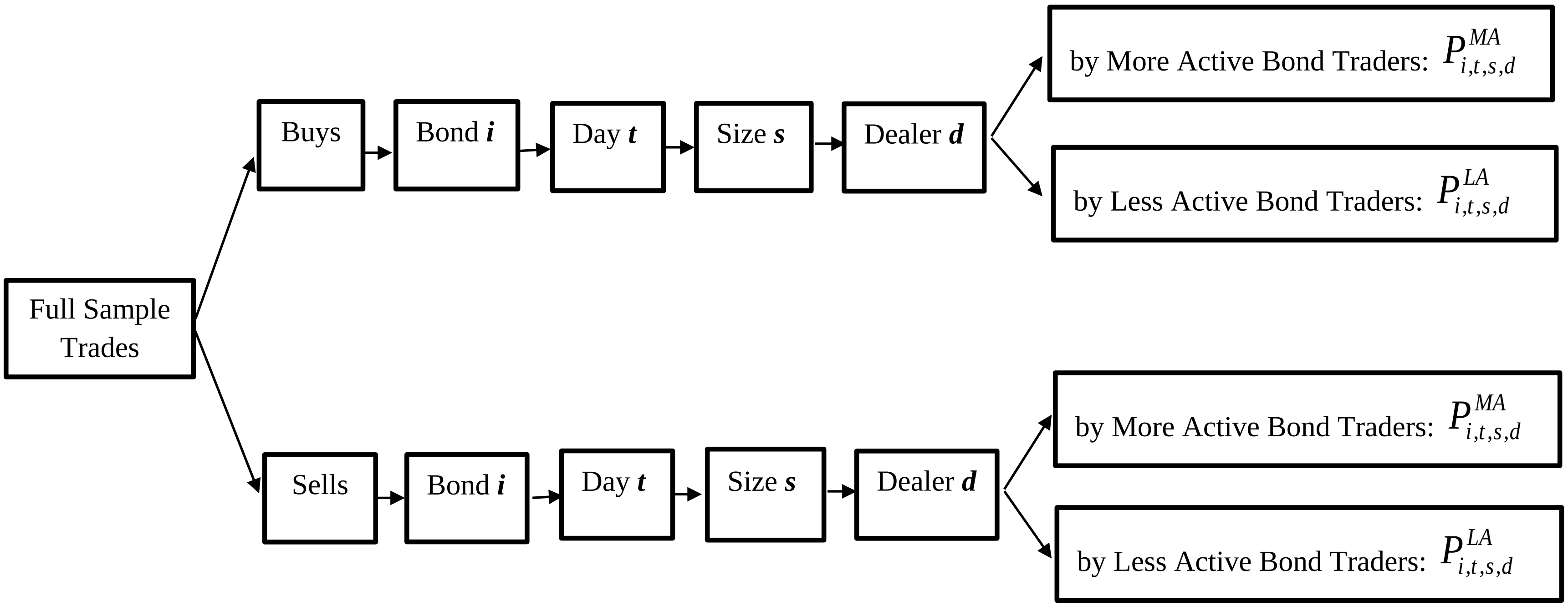

Figure 3: **Calculating Differences in Prices for More Active and Less Active Traders after Controlling for Trade Type, Bond, Day, Trade Size, Dealer, and Trader Network Category**

Our sample includes all corporate bond trades by insurance companies during the period 2002-2011. A bond trader is classified as being more active/less active if its average quarterly holding in corporate bonds during the previous year is above/below the median corporate bond holding of all insurance companies in that year. A bond trader is classified as one with large network if the number of distinct dealers it trades with is greater than the median of our sample. We first separate the full sample of trades into insurers' buys and sells. Within the subsamples of buys and sell, we then create trade buckets by including all trades in bond *i* with dealer *d* on day *t* within a trade size category *S* into one bucket. Consistent with standard industry conventions, bond trades are classified into four size categories based on their dollar value: Micro ($1 to $100,000), Odd-lot ($100,000 to $1,000,000), Round-lot ($1,000,000 to $5,000,000), and Block (above $5,000,000). We further divide the trades within each bucket into two groups: one for traders with small network and one for traders with large network. Finally, within each group, we calculate the average prices for trades by more active and less active bond traders separately. Only those trade groups with at least one trade by each of the two types of traders are included in our calculation.

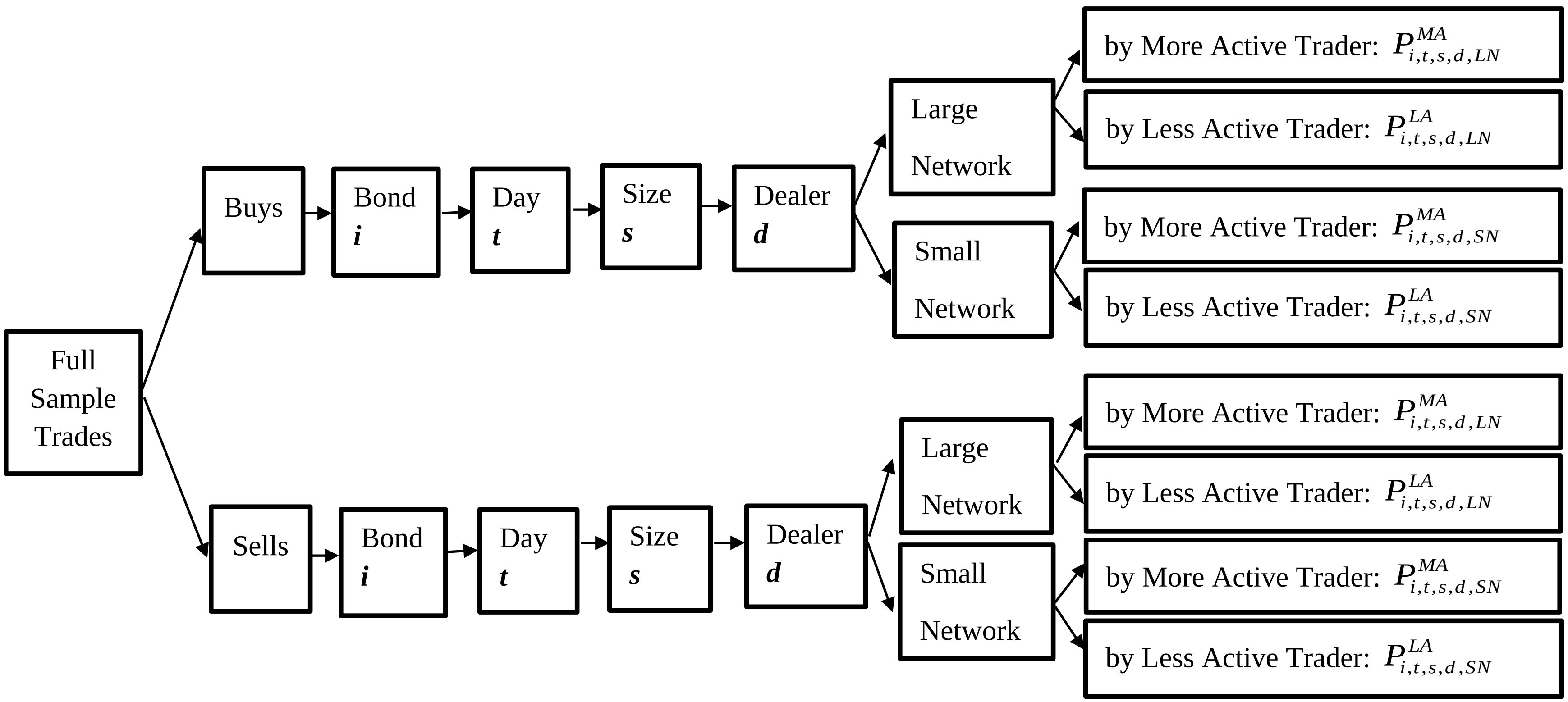

Figure 4: **Calculating Differences in Prices for More Active and Less Active Traders after Controlling for Trade Type, Bond, Day, Trade Size, Dealer, and Trader Network**

Our sample includes all corporate bond trades by insurance companies during the period 2002-2011. A bond trader is classified as being more active/less active if its aggregate holding in corporate bonds during the previous year is above/below the median aggregate bond holding of all insurance companies in that year. We first separate the full sample of trades into insurers' buys and sells. Within the subsamples of buys and sell, we then create trade buckets by including all trades in bond *i* with dealer *d* on day *t* within a trade size category *s* and by a trader with a network size *n* into one bucket. Consistent with standard industry conventions, bond trades are classified into four size categories based on their dollar value: Micro ($1 to $100,000), Odd-lot ($100,000 to $1,000,000), Round-lot ($1,000,000 to $5,000,000), and Block (above $5,000,000). We further divide the trades within each bucket into two groups: one for traders with small network and one for traders with large network. Finally, within each trade bucket, we calculate the average prices for trades by large and small bond traders separately, and they are denoted as $P^{MA}_{i,t,s,d,n}$ and $P^{LA}_{i,t,s,d,n}$ respectively. Only those trade buckets with at least one trade by each of the two types of traders are included in our study.

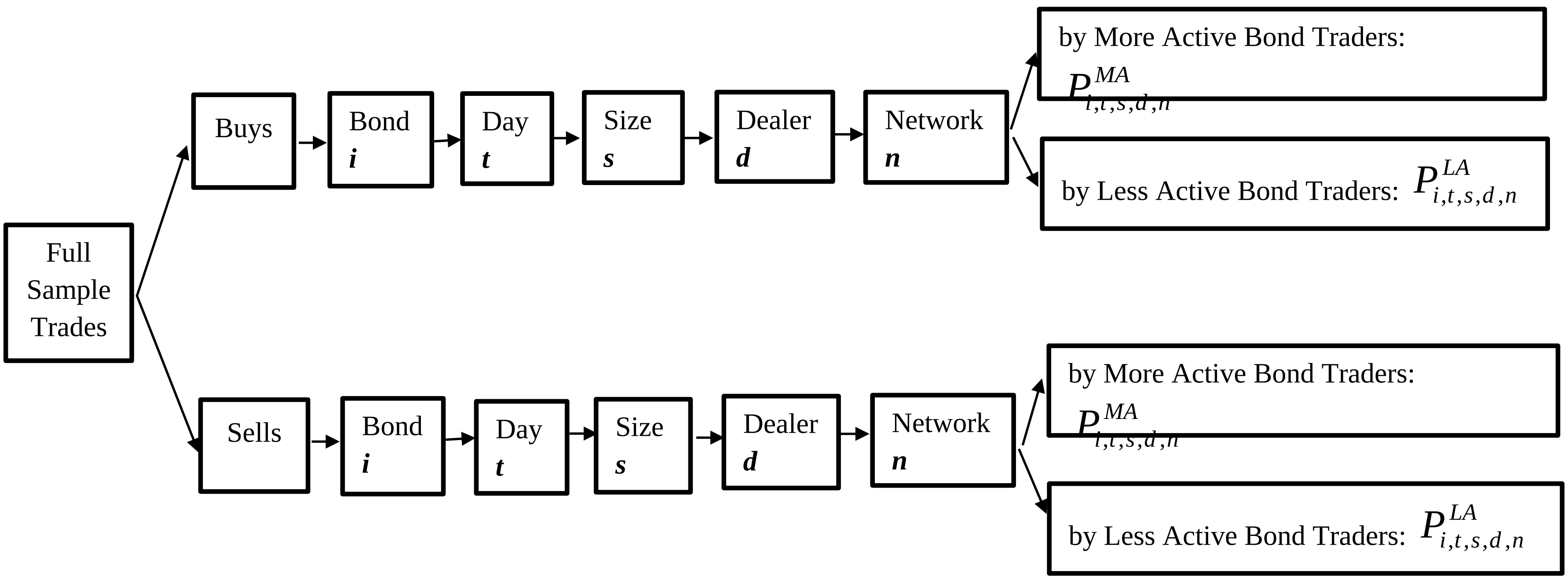

Table 1: Sample Selection

This table describes the procedures we use to construct our sample. Our data of corporate bond transaction is from the National Association of Insurance Commissioners (NAIC). It provides detailed information of all corporate bond trades by insurance companies from 2001 to 2011, including the date and price of trades, par valued traded, identity of the insurer and the dealer (or counterparty) of the trade, and the direction of the trade (whether the insurance company is buying from the dealer or selling to the dealer). Characteristics of the issue and the issuer of the traded bond are obtained from the Fixed Income Security Database (FISD).

Data Filters	Nobs
All NAIC dealer-client trades for 2001-2011	2,225,932
After merging with FISD data for issue and issuer characteristics	2,007,081
After excluding bonds whose face value is not $1000	1,984,972
After excluding bonds with issue size less than $1 million	1,983,733
After excluding 2001 trades (since we use 2001 data to classify insurance companies)	1,767,792
After excluding trades whose price deviates from trades in surrounding days by more than 20% (to remove potential price errors)	1,741,359
After truncating the distribution of prices at 1% and 99% (to remove potential price errors)	1,703,237
Number of bond issues	33,490
Number of bond issuers	6,458
Number of insurance companies	2,406
Number of bond dealers	1,025

Table 2: Tests on the Differences in Prices for More Active and Less Active Traders

This table presents the average prices and the differences in prices of trades involving more active and less active traders. A bond trader is classified as being more active (less active) if its average quarterly holdings of all corporate bonds in the previous year is above (below) the median corporate bond holding of all insurance companies at the same year. Insurance companies' quarterly holdings of corporate bonds are from Lipper eMAXX database and cover the period of 2001-2011. As illustrated in Figure 1, we first separate our full sample of bond trades into two subsamples of insurers' buys and sells. Within each subsample, we then classify each trade into four size categories based on its dollar transaction value: Micro ($1 to $100,000), Odd-lot ($100,000 to $1,000,000), Round-lot ($1,000,000 to $5,000,000), and Block (above $5,000,000). Then for each bond i, trading day t, and size category s, we calculate the average price (as a percentage of the par) for more active traders ($P^{MA}_{i,t,s}$), that for less active traders ($P^{LA}_{i,t,s}$), and the difference of the two average prices ($PriceDiff_{i,t,s}$). To be included in the calculation, a bond needs to be traded at least once by *each* group of traders in the same size category and on the same day. We report the mean of $P^{MA}_{i,t,s}$, $P^{LA}_{i,t,s}$, and $PriceDiff_{i,t,s}$ across all bonds and all days for both the full sample, and by trade size category. We also report *t*-statistics from testing whether the mean price difference is significantly different from zero and the number of the observations in the sample.

	Buys					Sells				
	$P^{MA}_{i,t,s}$	$P^{LA}_{i,t,s}$	$PriceDiff_{i,t,s}$	*t*-test	Nobs	$P^{MA}_{i,t,s}$	$P^{LA}_{i,t,s}$	$PriceDiff_{i,t,s}$	*t*-test	Nobs
Full Sample										
	101.79%	102.02%	-0.23%	-4.384	14,939	99.77%	99.16%	0.61%	6.120	5,743
by Trade Size Category										
Micro	101.71%	101.91%	-0.20%	-3.659	5,853	100.38%	99.50%	0.88%	5.134	2,637
Odd-lot	101.94%	102.22%	-0.28%	-6.093	7,451	99.23%	98.81%	0.42%	4.987	2,475
Round-lot	101.48%	101.57%	-0.09%	-1.148	1,349	99.35%	99.06%	0.29%	2.730	542
Block	101.11%	101.14%	-0.03%	-0.324	286	99.14%	99.15%	-0.01%	0.873	89

Table 3: Tests on the Differences in Prices for More Active and Less Active Traders when They Trade with the Same Dealer

This table presents the average prices and the differences in prices of trades involving more active and less active traders. A bond trader is classified as being more active (less active) if its average quarterly holdings of all corporate bonds in the previous year is above (below) the median corporate bond holding of all insurance companies at the same year. Data on insurance companies' quarterly holdings of corporate bonds are from Lipper eMAXX database and cover the period of 2001-2011. As illustrated in Figure 2, we first separate our full sample of bond trades into two subsamples of insurers' buys and sells. Within each subsample, we then classify each trade into four size categories based on its dollar transaction value: Micro ($1 to $100,000), Odd-lot ($100,000 to $1,000,000), Round-lot ($1,000,000 to $5,000,000), and Block (above $5,000,000). Then for each bond i, trading day t, size category s, and each dealer d, we calculate the average price (as a percentage of the par) for more active traders ($P^{MA}_{i,t,s,d}$), that for less active traders ($P^{LA}_{i,t,s,d}$), and the difference of the two average prices ($PriceDiff_{i,t,s,d}$). To be included in the calculation, a bond needs to be traded at least once by *each* group of traders in the same size category, with the same dealer, and on the same day. We report the mean of $P^{MA}_{i,t,s,d}$, $P^{LA}_{i,t,s,d}$, and $PriceDiff_{i,t,s,d}$ across all bonds, all days, and all dealers, for both the full sample, and by trade size category. We also report t-statistics from testing whether the mean price difference is significantly different from zero and the number of observations in the sample.

	Buys					Sells				
	$P^{MA}_{i,t,s.d}$	$P^{LA}_{i,t,s,d}$	$PriceDiff_{i,t,s,d}$	t-test	Nobs	$P^{MA}_{i,t,s,d}$	$P^{LA}_{i,t,s,d}$	$PriceDiff_{i,t,s,d}$	t-test	Nobs
Full Sample	101.63%	101.83%	-0.20%	-5.128	12,024	99.69%	99.19%	0.51%	5.876	4,167
by Trade Size Category										
Micro	101.65%	101.86%	-0.21%	-3.011	4,622	99.44%	98.76%	0.68%	4.043	1,852
Odd-lot	101.72%	101.95%	-0.24%	-5.734	5,967	99.95%	99.56%	0.39%	5.173	1,810
Round-lot	101.26%	101.31%	-0.05%	-0.879	1,175	99.69%	99.36%	0.33%	3.015	437
Block	101.06%	101.04%	0.02%	0.134	260	99.80%	99.82%	-0.02%	0.934	68

Table 4: Tests on the Differences in Prices for More Active and Less Active Traders when They Trade with the Same Dealer: Robustness Checks

This table presents the robustness checks of the analysis in Table 3 by excluding all Odd-lot trades (Panel A), offer day trades (Panel B), or using a different approach to classify more/less active traders. In Panels A and B, a bond trader is classified as being more active (less active) if its average quarterly holdings of all corporate bonds in the previous year is above (below) the median corporate bond holding of all insurance companies at the same year. Data on insurance companies' quarterly holdings of corporate bonds are from Lipper eMAXX database and cover the period of 2001-2011. As illustrated in Figure 2, we first separate our full sample of bond trades into two subsamples of insurers' buys and sells. Within each subsample, we then classify each trade into four size categories based on its dollar transaction value: Micro ($1 to $100,000), Odd-lot ($100,000 to $1,000,000), Round-lot ($1,000,000 to $5,000,000), and Block (above $5,000,000). Then for each bond *i*, trading day *t*, size category *s*, and each dealer *d*, we calculate the average price (as a percentage of the par) for more active traders ($P^{MA}_{i,t,s,d}$), that for less active traders ($P^{LA}_{i,t,s,d}$), and the difference of the two average prices ($PriceDiff_{i,t,s,d}$). To be included in the calculation, a bond needs to be traded at least once by *each* group of traders in the same size category, with the same dealer, and on the same day. In Panel A, we exclude all Odd-lot trades. In Panel B, we exclude all trades taking place on the bond's offering day. In Panel C, a bond trader is classified as being more active (less active) if its aggregate trade volume over the past year is above (below) the median trade volume of all insurance companies at the same year. We then report the mean across all bonds, all days, all trade size categories, and all dealers. We also report *t*-statistics from testing whether the mean price difference is significantly different from zero and the number of observations in the sample.

Buys					Sells				
$P^{MA}_{i,t,s.d}$	$P^{LA}_{i,t,s,d}$	$PriceDiff_{i,t,s,d}$	*t*-test	Nobs	$P^{MA}_{i,t,s.d}$	$P^{LA}_{i,t,s,d}$	$PriceDiff_{i,t,s,d}$	*t*-test	Nobs
Panel A. Excluding Offer Day Trades									
101.59%	101.86%	-0.27%	-3.891	7,289	99.72%	99.20%	0.52%	5.913	4,133
Panel B. Using Past Trade Volume to Classify More/Less Active Traders									
101.72%	101.90%	-0.18%	-3.672	15,023	97.88%	97.45%	0.43%	4.328	6,455
Panel C. Excluding the One-Month following Rating Downgrade									
101.71%	101.92%	-0.21%	-4.324	11,876	100.24%	99.87%	0.37%	4.134	3,089

Table 5: Differences in Best Execution and Bond Characteristics

This table presents regressions of best execution differences on bond characteristics. The dependent variable is the absolute value of price difference between more active and less active traders when they trade the same bond *i* on day *t* in size category *s* with dealer *d* (i.e., $PriceDiff_{i,t,s,d}$). All independent variables are defined in Appendix 1. The regressions are run in the full sample and separately in buy and sells subsamples. Heteroscedasticity adjusted robust *p*-values are provided next to each estimate.

	Full Sample		Buys		Sells	
	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value
Intercept	6.835	0.000	3.606	0.004	4.998	0.009
Sell Dummy	0.513	0.000				
Price Level	-5.584	0.003	-2.795	0.017	-5.734	0.004
Volatility	7.329	0.000	1.567	0.075	8.542	0.001
Credit Rating	0.085	0.001	0.002	0.827	0.531	0.000
Time to Maturity	0.679	0.005	0.638	0.001	0.770	0.037
Amount Outstanding	-0.106	0.259	-0.034	0.511	-0.427	0.000
Age	0.189	0.004	0.232	0.005	0.153	0.002
Public Dummy	-0.240	0.250	-0.089	0.437	-0.267	0.178
Nobs	16,191		12,024		4,167	
Adj_Rsq	0.307		0.092		0.311	

Table 6: Summary Statistics of the Investor Base of Corporate Bonds

This table provides summary information on the percentage of a bond's total amount outstanding held by different types of institutional investors. Quarterly corporate bond holdings data are obtained from the Lipper eMAXX database for the period of 2001 to 2011. This database includes corporate bond holdings by all insurance companies, over 95% of the existing mutual funds, and the top 250 public pension funds.

	Min	Q1	Median	Q3	Max	Mean	Std Dev
% held by mutual funds	0%	3%	8%	16%	100%	12%	12%
% held by pension funds and insurers	0%	12%	27%	46%	100%	31%	22%

Table 7: Differences in Best Execution and Latent Liquidity

This table reports coefficient estimates of regressions of differences in best execution on latent liquidity measures. The dependent variable is the absolute value of price difference between more active and less active traders when they trade the same bond *i* on day *t* in size category *s* with dealer *d* (i.e., $PriceDiff_{i,t,s,d}$). Latent liquidity is measured as the total amount held by active institutional investors, i.e., mutual funds. Other independent variables are defined in Appendix 1. The regressions are run in the full sample and also separately in buys and sells subsamples. Standard errors are clustered at the dealer level. Heteroscedasticity adjusted robust *p*-values are provided next to each estimate.

	Full Sample		Buys		Sells	
	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value
Intercept	7.024	0.000	3.448	0.007	4.717	0.013
Sell Dummy	0.507	0.000				
Price Level	-5.614	0.003	-2.589	0.028	-5.741	0.003
Volatility	7.189	0.000	1.553	0.089	7.941	0.001
Credit Rating	0.083	0.001	0.003	0.752	0.547	0.000
Time to Maturity	0.683	0.003	0.655	0.000	0.722	0.041
Amount Outstanding	-0.134	0.230	-0.037	0.484	-0.416	0.000
Age	0.172	0.008	0.228	0.009	0.149	0.003
Public Dummy	-0.184	0.357	-0.089	0.436	-0.273	0.143
% by Mutual Fund	-0.507	0.002	-0.255	0.023	-1.319	0.010
% by Pension & Insurers	0.295	0.029	0.083	0.864	0.902	0.016
Nobs	16,191		12,024		4,167	
Adj_Rsq	0.307		0.093		0.313	

Table 8: Competitiveness of Market Making in Corporate Bonds

This table provides summary statistics on the competitiveness of market making business in corporate bonds. All the statistics are calculated at the bond-year level. Number of Dealers per Bond refers to the number of distinct dealers that participate in market making in the bond-year. Market share of a dealer is calculated as the dealer's share of annual trade volume in a bond. Herf in Market Making is calculated as the sum of the squared market share of each dealer in handling all trades of the bond in the year.

	Min	Q1	Median	Q3	Max	Mean	Std Dev
Number of Dealers per Bond	1	1	3	6	49	4	5
Market Share of Top 1 Dealer	10%	46%	69%	100%	100%	69%	26%
Market Share of Top 2 Dealers	19%	73%	94%	100%	100%	85%	18%
Market Share of Top 3 Dealers	26%	87%	100%	100%	100%	92%	13%
Herf in Market Making	5%	33%	54%	100%	100%	61%	31%

Table 9: Differences in Best Execution and Dealer Competitiveness

This table reports coefficient estimates of regressions of differences in best execution on the dealer competitiveness measure. The dependent variable is the absolute value of price difference between more active and less active traders when they trade the same bond *i* on day *t* in size category *s* with dealer *d* (i.e., $PriceDiff_{i,t,s,d}$). All independent variables are defined in Appendix 1. The regressions are run in the full sample and separately in buys and sells subsamples. Standard errors are clustered at the dealer level. Heteroscedasticity adjusted robust *p*-values are provided next to each estimate.

Full Sample	Buys		Sells			
	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value
Intercept	6.887	0.000	3.715	0.003	4.148	0.036
Sell Dummy	0.522	0.000				
Price Level	-5.782	0.002	-2.369	0.036	-5.773	0.002
Volatility	7.355	0.000	1.564	0.079	8.011	0.001
Credit Rating	0.081	0.002	0.003	0.749	0.544	0.000
Time to Maturity	0.677	0.005	0.658	0.000	0.725	0.039
Amount Outstanding	-0.151	0.207	-0.041	0.426	-0.409	0.000
Age	0.187	0.005	0.231	0.005	0.152	0.002
Public Dummy	-0.192	0.278	-0.091	0.418	-0.269	0.176
% by Mutual Funds	-0.520	0.001	-0.259	0.021	-1.322	0.008
% by Pension & Insurers	0.310	0.017	0.083	0.866	0.951	0.014
Herf in Market Making	0.693	0.053	-0.121	0.552	3.576	0.004
Nobs	16,191		12,024		4,167	
Adj_Rsq	0.308		0.093		0.314	

Table 10: Differences in Best Execution and Market Transparency

This table examines the effect of the transparency of the corporate bond market on the differences in best execution. We include "Post-TRACE Dummy" to indicate if the date is after the bond issue is subject to TRACE dissemination. Upon its initiation in July 2002, TRACE only disseminated trade information on large investiment-grade issues and 50 high-yield issues. Subsequently, TRACE experienced three stages of implementation when the dissemination was expanded to include smaller and less liquid issues. In February 2005, TRACE began to cover almost all secondary market bond trades. The dependent variable is the absolute value of price difference between more active and less active traders when they trade the same bond i on day t in size category s with dealer d (i.e., $PriceDiff_{i,t,s,d}$). All independent variables are defined in Appendix. The regressions are run in the full sample and separately in buys and sells subsamples. Standard errors are clustered at the dealer level. Heteroscedasticity adjusted robust *p*-values are provided next to each estimate.

	Full Sample		Buys		Sells	
	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value
Intercept	7.133	0.000	3.822	0.002	4.662	0.017
Sell Dummy	0.589	0.000				
Price Level	-5.668	0.003	-2.442	0.038	-5.801	0.001
Volatility	7.321	0.000	1.576	0.079	7.971	0.001
Credit Rating	0.079	0.007	0.003	0.758	0.548	0.000
Time to Maturity	0.681	0.004	0.649	0.000	0.731	0.038
Amount Outstanding	-0.153	0.203	-0.043	0.411	-0.411	0.000
Age	0.191	0.003	0.237	0.004	0.151	0.002
Public Dummy	-0.191	0.279	-0.100	0.374	-0.271	0.144
% by Mutual Funds	-0.477	0.005	-0.262	0.020	-1.328	0.009
% by Pension and Insurers	0.283	0.037	0.078	0.913	0.948	0.014
Herf in Market Making	0.729	0.049	-0.109	0.591	3.757	0.003
Post-TRACE Dummy	-0.370	0.006	-0.197	0.011	-0.865	0.000
Nobs	16,191		12,024		4,167	
Adj_Rsq	0.309		0.095		0.316	

Table 11: The Dealer and Differences in Best Execution

This table examines the effect of the dealer's role on the best execution differences. The dependent variable is the absolute value of price difference between more active and less active traders when they trade the same bond *i* on day *t* in size category *s* with dealer *d* (i.e., $PriceDiff_{i,t,s,d}$). All independent variables are defined in Appendix 1. The regressions are run in the full sample and separately in buys and sells subsamples. Standard errors are clustered at the dealer level. Heteroscedasticity adjusted robust *p*-values are provided next to each estimate.

	Top Dealer						Underwriter					
	Full Sample		Buys		Sells		Full Sample		Buys		Sells	
	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value	Estimate	*p*-value
Intercept	7.836	0.000	3.679	0.004	4.908	0.011	8.112	0.000	3.438	0.011	4.972	0.010
Sell Dummy	0.583	0.000					0.577	0.000				
Price Level	-5.667	0.003	-2.429	0.037	-5.798	0.001	-5.684	0.003	-2.518	0.030	-5.813	0.001
Volatility	7.335	0.000	1.549	0.091	7.968	0.001	7.198	0.000	1.551	0.090	7.925	0.002
Credit Rating	0.083	0.001	0.003	0.763	0.551	0.000	0.079	0.006	0.004	0.647	0.549	0.000
Time to Maturity	0.682	0.003	0.653	0.000	0.733	0.038	0.684	0.001	0.663	0.000	0.738	0.036
Amount Outstanding	-0.166	0.189	-0.047	0.389	-0.398	0.000	-0.167	0.187	-0.051	0.278	-0.393	0.000
Age	0.194	0.003	0.239	0.004	0.152	0.002	0.195	0.002	0.238	0.004	0.149	0.004
Public Dummy	-0.187	0.332	-0.090	0.441	-0.269	0.173	-0.189	0.327	-0.089	0.431	-0.277	0.139
% by Mutual Funds	-0.484	0.003	-0.257	0.022	-1.334	0.007	-0.487	0.003	-0.259	0.021	-1.293	0.011
% by Pension & Insurers	0.288	0.031	0.081	0.878	0.917	0.025	0.289	0.030	0.084	0.859	0.888	0.039
Post-TRACE Dummy	-0.359	0.007	-0.201	0.010	-0.853	0.000	-0.363	0.006	-0.198	0.011	-0.863	0.000
Top Dealer Dummy	0.243	0.000	0.107	0.013	1.124	0.000	0.450	0.000	0.337	0.000	0.915	0.000
Underwriter Dummy												
Nobs	16,191		12,024		4,167		16,191		12,024		4,167	
Adj_Rsq	0.309		0.095		0.317		0.309		0.097		0.317	

Table 12: Summary Statistics of Insurance Companies' Trading Activities in Corporate Bonds

This table examines insurance companies' trading activities in corporate bonds. N Trades Per Bond /N Buys Per Bond /N Sells Per Bond refers to the number of trades/buys/sells by an insurance company in a given bond during our sample period from 2002 to 2011. N Trades Per Year Per Bond/ N Buys Per Year Per Bond /N Sells Per Year Per Bond refers to the number of trades/buys/sells by an insurance company in a given bond in a given year. Trade Gap refers to the number of days between two consecutive trades by an insurance company in a given bond. N Bonds Per Firm refers to the number of bonds held by an insurance firm per quarter. Par Amount Per Firm refers to the aggregate holding in par amount by an insurance firm per quarter. N Trades /N Buys /N Sells refers to the total number of trades/buys/sells by an insurance company in any bond during our sample period from 2002 to 2011. N Trades Per Year/ N Buys Per Year /N Sells Per Year refers to the number of trades/buys/sells by an insurance company in any bond in a given year.

Variable	Min	Q1	Median	Q3	Max	Mean	Std Dev
N Trades Per Bond	1	1	2	3	282	3	3
N Buys Per Bond	0	1	1	2	169	2	2
N Sells Per Bond	0	0	1	1	121	1	2
N Trades Per Year Per Bond	0	0	0	1	94	1	1
N Buys Per Year Per Bond	0	0	0	0	66	0	1
N Sells Per Year Per Bond	0	0	0	0	43	0	0
Trade Gap	0	94	266	595	3,627	436	494
N Bonds Per Firm	1	7	31	93	2,305	79	139
Par Amount per Firm ($million)	0	3	17	92	75,244	320	2,022
N Trades	0	17	67	255	63,251	698	3,110
N Buys	0	11	45	166	35,145	413	1,769
N Sells	0	2	17	92	28,106	285	1,352
N Trades Per Year	0	2	7	26	6,325	70	311
N Buys Per Year	0	1	5	17	3,515	41	177
N Sells Per Year	0	0	2	9	2,811	28	135

Table 13: Summary Statistics of Trading Network of Insurance Companies

This table provides summary statistics on the number of distinct dealers with whom an insurance firm trade bonds. Number of Relation Dealers per Bond refers to the number of distinct dealers with whom an insurance firm trade in a given bond in a given year. Number of Relation Dealers in All Bond refers to the number of distinct dealers with whom an insurance firm trade any bond in a given year.

	Min	Q1	Median	Q3	Max	Mean	Std Dev
Full Sample:							
Number of Relation Dealers per Bond	1	1	1	1	19	1	1
Number of Relation Dealers in All Bond	1	2	5	16	161	11	14
Buys:							
Number of Relation Dealers per Bond	1	1	1	1	16	1	1
Number of Relation Dealers in All Bond	1	1	5	14	146	10	12
Sells:							
Number of Relation Dealers per Bond	1	1	1	1	17	1	0
Number of Relation Dealers in All Bond	0	1	4	12	124	9	12

Table 14: The Impact of Trading Network on Trade Execution Quality

This table examines how a trader's trading network affects its trade execution quality. A bond trader is classified as more active (less active) if its average quarterly holdings of all corporate bonds in the previous year is above (below) the median corporate bond holding of all insurance companies at the same year. Insurance companies' quarterly holdings of corporate bonds are from Lipper eMAXX database and cover the period of 2001-2011. In Panels A-C, we use three alternative cutoffs to delineate traders with large networks and traders with small networks. We then create trade buckets that group trades by trade type, day, size, dealer, and by whether the trader has a large network or a small network, as illustrated by Figure 3. In Panel D, we create trade buckets that group trades by trade type, day, size, dealer, and network size, as illustrated by Figure 4. Then, for each trade bucket, we calculate the average price (as a percentage of the par) for more active traders ($P^{MA}_{i,t,s,d}$), that for less active traders ($P^{LA}_{i,t,s,d}$), and the difference of the two average prices ($PriceDiff_{i,t,s,d}$). We report separately for buys and sales, the mean of $P^{MA}_{i,t,s,d}$, $P^{LA}_{i,t,s.,d}$, and $PriceDiff_{i,t,s,d}$, and the *t*-statistics from testing whether the mean price difference is significantly different from zero.

	Buys					Sells				
	$P^{MA}_{i,t,s.d}$	$P^{LA}_{i,t,s,d}$	$PriceDiff_{i,t,s,d}$	*t*-test	Nobs	$P^{MA}_{i,t,s.d}$	$P^{LA}_{i,t,s,d}$	$PriceDiff_{i,t,s,d}$	*t*-test	Nobs
Panel A. Using median number of relation dealers (5) as the cutoff to divide the data into large and small network subsamples										
Small Network	101.42%	101.51%	-0.09%	-1.044	669	98.13%	97.73%	0.40%	2.873	455
Large Network	101.59%	101.82%	-0.23%	-4.136	9,650	98.67%	98.13%	0.54%	5.386	3,268
Panel B. Using mean number of relation dealers (11) as the cutoff to divide the data into large and small network subsamples										
Small Network	101.22%	101.31%	-0.09%	-1.362	997	98.32%	98.03%	0.29%	2.010	701
Large Network	101.60%	101.79%	-0.19%	-3.894	7,442	98.88%	98.33%	0.55%	5.187	2,406
Panel C. Using top quartile number of relation dealers (16) as the cutoff to divide the data into large and small network subsamples										
Small Network	101.00%	101.06%	-0.06%	-0.871	1,987	96.70%	96.35%	0.35%	3.210	876
Large Network	101.61%	101.77%	-0.16%	-2.570	5,316	97.39%	97.01%	0.38%	3.891	1,506
Panel D. Controlling for the network effect										
	101.08%	101.13%	-0.05%	-1.134	1,882	97.05%	96.73%	0.32%	3.020	735