

Click or Call? Auction versus Search in the Over-the-Counter Market

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Abstract

We analyze fixed income executions in an electronic auction venue and in the over-the-counter dealer search market to toward understand the value of an electronic auction process, endogenous venue selection, and the determinants of bond trading costs. Analysis of an extensive sample of corporate bond execution data from January 2010 through April 2011 provides evidence that: (1) Traders select between dealer and auction markets based on a tradeoff between leakage about trading intentions and search costs; (2) Costs of trading are significant relative to a last trade benchmark. (3) Costs are directly related to measures of dealer competition and decline with size; (4) Dealer competition can be predicted as a function of bond attributes, trade size, past activity, and seasonalities; and (5) Competition is a strong determinant of trading cost and can explain our results in terms of trade size. The results demonstrate the value of intelligent sourcing of liquidity and suggest that electronic auctions will play an increasingly important role in the future evolution of over-the-counter markets.

1. Introduction

Trading in over-the-counter (OTC) markets typically involves a bilateral transaction with a dealer over the phone with limited pre- or post-trade transparency. Price negotiation with a single dealer enables a trader to control information leakage regarding their positions and intentions, but concedes some temporary bargaining power to the dealer. The advent of new trading technologies, however, allows even relatively illiquid assets to be traded in an electronic auction mechanism where a trader can simultaneously contact multiple potential counterparties. As electronic trading volumes increase across all asset classes, a market structure transition sometimes referred to as "voice to electronic," many questions remain open. How do new, auction-type mechanisms coexist with existing OTC markets, and are there natural limits to their growth? Are they preferred for certain kinds of transactions? What is the impact of the competition between voice and electronic trading on liquidity and trading costs? This paper examines these questions using unique data for all 1.8 million transactions in US investment grade corporate bonds from January 2010-April 2011.

Fixed income markets are a natural candidate for an analysis of the potential and limits for electronic auction trading. Despite being the largest asset class, most fixed income securities are typically not traded on an open exchange.¹ Further, the proliferation and complexity of fixed income instruments further complicates execution and limits the opportunity for standardized exchange trading. Indeed, relative to other asset classes such as equities, price discovery and liquidity sourcing are far more challenging. Hence, the limits of electronic trading are in the sharpest relief in these markets.

We examine traders' choice of electronic auctions versus traditional dealer trading mechanisms using data for all trades in investment grade US corporate bonds which also identify and detail the transactions executed in an electronic auction market. This feature of the data permits an analysis of mechanism choice and costs under the two structures. We show that traders are most likely to use electronic auctions when their search costs are likely high and leakage is less important. We find strong evidence that fixed income costs decrease in size and vary with proxies for risk and inventory carrying costs. We highlight the value of competition among dealers,

¹ Exceptions include fixed-income futures contracts, interdealer electronic brokerage systems, and transactions on certain electronic markets such as MarketAxess and TradeWeb, typically in liquid government issues.

showing that increased auction participation sharply reduces costs. To the extent that technology will continue to reduce search costs, these results support the view that even traditional bastions of over-the-counter trading will face strong competition from auction type markets.

The paper contributes to the growing literature on the evolution of market structure and fixed income markets in particular. Our results are consistent with Biais and Green (2007) who note that there was an active market in corporate and municipal bonds on the NYSE prior to the 1940s. They argue that the decline of exchange trading was driven by the growing importance of institutional investors, who prefer to trade in over the counter markets. That dynamic is shifting again with the advent of new, electronic trading technologies that allow traders to easily engage in multilateral trading. More practically, the results confirm the value to traders and investors from sourcing liquidity widely and using tools to optimally select venue. We show that these gains are significant and can materially influence realized investment returns.

Recent regulatory requirements have improved trade reporting, leading to a growing literature providing valuable insight into the magnitude and determinants of fixed income trading costs in OTC markets dominated by dealers. Edwards, Harris and Piwowar (2007) and Goldstein, Hotchkiss and Sirri (2007) document large transactions costs in corporate bonds, and contrary to most microstructure theories based on asymmetric information or inventory control, the costs of trade are higher for small trades and subsequently decline. Harris and Piwowar (2006) find, for example, that municipal bond trades are significantly more expensive than equivalent sized equity trades, which is surprising given that bonds are lower risk securities. One explanation may be the lack of pre-trade transparency that confers rents to dealers who possess bargaining power in bilateral trading situations. Green, Hollifield, and Schürhoff (2007) develop and estimate a structural model of bargaining between dealers and customers, and conclude that dealers exercise substantial market power.

Bessembinder, Maxwell, and Venkataraman (2007) argue that improvements in post-trade transparency associated with the implementation of the TRACE system provides market participants with better indications of true market value, allowing for a reduction in costs for those bonds included in the TRACE system. While these papers all suggest that the relatively large transactions costs facing bondholders are due to the OTC structure of the bond market, they do not provide insights into the costs in an alternative, electronic market with lower search costs. Nor do they help us understand whether the OTC market in bonds and other asset classes will evolve over time towards a more standardized, exchange traded form.

A number of empirical papers examine trading mechanism choice in financial markets both in terms of electronic versus non-electronic and searching for liquidity. Bessembinder and Kaufman (1997) examine trading costs across different stocks exchanges. Conrad, Johnson, and Wahal (2003) and Barclay, Hendershott, and McCormick (2003) analyze stock trading on electronics markets and traditional exchanges. Much of the equity market research focuses on both information flow across markets and trading costs. Barclay, Hendershott, and Kotz (2006) study the venue choice for U.S. Treasury securities between fully electronic limit order book and human voice broker intermediation. Consistent with our results that more liquid bonds trade more electronically, they find that trading moves from the electronic systems to the voice mechanisms when securities go off the run and liquidity falls. Bessembinder and Venkataraman (2004) examine large equity trades upstairs in a dealer search market versus immediate execution in the electronic limit order book. They along with others find that the electronic venue is used for easier trades.

By contrast, the auction “request for quote” mechanism analyzed here is quite distinct from the more familiar electronic communications networks (ECNs) that characterize many stock and derivative exchanges. In less liquid instruments, mechanisms that require liquidity providers to post continuous and firm quotations face challenges from adverse selection and possible tacit collusion. The auction mechanism described here mitigates these challenges and offers traders an alternative method of sourcing liquidity over the traditional dealer model. For institutional traders with many securities in their trading list, it is difficult to simultaneously call many counterparties in a short interval of time. By contrast, the request for quote auction mechanism allows traders to reach multiple counterparties simultaneously and avoid prolonged negotiations by setting a time limit for the auction. Since the trader can reveal how many other dealers are being queried, this can be a credible way induce dealers to improve pricing. Indeed, the results show that electronic auction markets based on a competitive sealed bid process are a viable and important source of liquidity even in inactively traded instruments.

Our results augment our knowledge of trading costs in fixed income markets and our understanding of the value of the competition inherent in an auction setting. The evolution of bilateral, sequential trading into an auction type framework offers a path from an over-the-counter market to centralized, continuous trading.

The paper proceeds as follows: Section 2 provides an overview of the relevant institutional detail and summarizes our data sources and procedures; Section 3 examines overall trading

costs in the corporate bond market as a whole; Section 4 analyzes endogenous mechanism choice and provides a framework to analyze the data; Section 5 contains our empirical results on bidding and trading behavior including estimates in the auction mechanism; and Section 6 concludes and offers some recommendations for public policy.

2. Institutions and Data

The data comprise all investment-grade corporate bond trades in Financial Industry Regulatory Authority's (FINRA) Trade Reporting and Compliance Engine (TRACE) from the beginning of 2010 through April 2011, a total of 1.8 million transactions. We augment the TRACE data with specific details on all trades directed to an electronic auction venue, MarketAxess, in the period. MarketAxess was formed in April 2000 to provide institutional investors an electronic trading platform with access to multi-dealer competitive pricing in U.S. high-grade corporate bonds, Eurobonds, emerging markets, high yield, credit default swaps (CDS) and U.S. agency securities. Other electronic venues – most importantly TradeWeb – are also used by fixed income traders, primarily for transactions in treasury bonds where costs are typically very low.

Access to MarketAxess typically involves the fixed costs of integration into an institutions order management system. Once integration is complete traders can simply click to send their orders to a number of dealers. Institutional clients select the number of dealers queried for a request for quote in a bond for a given size trade, providing considerable efficiencies in terms of time relative to the alternative of a sequence of bilateral negotiations. Typically dealers are aware of the number of other dealers queried and the identity of the institutional client. A time period is specified for the quotes to be submitted, also encouraging competitive behavior. At the end of the “bidding” period all dealer quotes are revealed to the client. If satisfied with the responses the client selects the best quote and the trade is executed. Essentially it operates as a sealed bid auction. MarketAxess trades with client prices are reported in TRACE. MarketAxess charges dealers a fee between 0.1 and 0.5 basis points for investment grade bonds.

The TRACE data are comprehensive and indicate the size of the trade and whether each trade is between two dealers or buyer- or seller-initiated with a dealer. This latter feature is relatively new starting in late 2008. Of special interest, the MarketAxess data are unique in several respects in that they identify the number of dealers queried and those that respond. We focus

only on bond trades in standard, e.g., non-callable, U.S. investment grade assets, excluding trades in agencies, treasuries, TIPS and mortgages.

Summary statistics are contained in Table 1. While all MarketAxess trades are included in TRACE, for ease of exposition we refer to the non-MarketAxess trades simply as TRACE trades. Interdealer trades in TRACE are also excluded. MarketAxess is designed to facilitate client to dealer transactions, so interdealer trades do not occur on MarketAxess.

[Insert Table 1 Here]

The total TRACE sample (excluding MarketAxess transactions) is approximately 1.6 million transactions in 4,129 different bonds. By comparison 191,150 transactions were in MarketAxess in 1,579 bonds. The trade size categories in Table 1 are based on dollar value traded and are chosen in accordance with standard industry conventions. The majority of these trades are micro lots (77%) defined as below \$100,000 in value. Although we will examine this point in more detail later, some size differences are already apparent in Table 1 between the auction mechanism and the over the counter market. There is a much higher concentration of odd lot (\$100,000-\$1 Million) sized trades on MarketAxess and it also appears that there are fewer large transactions. Overall, the share of the auction market in overall bond trading is 6.5% in micro (1-100K), 26.1% in odd lot (100K-1M), 21.9% in round lot (1M-5M) and 3.6% of the maximum reported size (5M+) trades.² MarketAxess' small market share in micro sized trades could result from smaller retail oriented traders not having access to the platform. This could also explain why the average trade size is larger on MarketAxess for odd and round lot trades. MarketAxess' lower market share in the largest trades likely arises from differences in the trading mechanisms.

Trading occurs in MarketAxess in 1,579 distinct bonds. The average bond characteristics of trades on and off MarketAxess differ noticeably. Younger bonds and bonds with larger issuance size are likely to be more liquid; see Harris and Piwowar (2006) and Edwards, Harris and Piwowar (2007) for evidence of this for the municipal and corporate bonds markets. The average bond age is smaller and the bond issuance size is larger for MarketAxess trades suggesting that the electronic platform may be more effective for easier trades. Table 1 also includes a standard risk measure of the bond's yield spread over treasury times duration. Our proxy for duration is years to maturity. As with issue size and age MarketAxess trades are more prevalent in less risky bonds which are expected to be more liquid. It should be noted that there are likely

² Trades greater than five million bonds are reported as five million for investment grade corporate bonds. .

some differences in the clienteles across systems, although most large institutions will likely use both venues. In general, because of the set up costs and sophistication required, we would expect a narrower pool of users for MarketAxess. We address questions of endogenous venue choice later in the paper.

3. Market-wide Transactions Costs

A number of approaches have been used to calculate trading costs in sparsely traded fixed income markets. Unlike equity markets where continuous bid and ask quotations are available, corporate bond markets only report transactions. The simplest approach is to compare buy and sell prices of the same bond around the same time to create an imputed spread. As the TRACE data identify whether a transaction is buyer- or seller-initiated, it is possible to compute the imputed spreads straightforwardly. Hong and Warga (2000) follow this approach to estimate what Harris and Piwowar (2006) refer to as a benchmark methodology by subtracting the average price for all sell transactions from the average buy price for each bond each day when there is both a buy and a sell. Imputed spreads, although simple, have some deficiencies. Given the infrequency of trading for many bonds, the same bond, same day criterion limits the amount of usable data. Further, although we know transaction side, trades may be initiated based on market moves (either contrarian or momentum) confounding the estimates. Harris and Piwowar (2006) use a regression approach to utilize more data. We adapt the Harris and Piwowar approach to allow us to more closely follow the transaction cost literature in the equity markets and to more easily include cross-sectional and time series covariates in our cost estimation. In this section we use both the imputed (benchmark) and regressions methodologies.

3.1 Imputed Half-Spreads

Table 2 calculates different between the average price for all sell transactions and the average buy price for each bond each day when there is both a buy and a sell. This cost is in basis point for MarketAxess and TRACE for each of the trade size category in Table 1. We divide the different between buy and sell prices by two to measure the one way transaction cost often referred to as half-spreads.

Panel A shows the standard decline in trading costs with trade size. Panel A also reveals substantial costs differences between MarketAxess and TRACE. For odd lot trades MarketAxess averages 8.54 basis points while for TRACE trades the cost is 32.43 basis points, substantially

higher. The costs for TRACE fall to 9.12 and 6.39 in the round and maximum trade size categories, respectively. MarketAxess costs fall with trade size also, but more slowly. These TRACE costs are similar in magnitude to previous corporate bonds cost estimates.

[Insert Table 2 Here]

While MarketAxess costs are lower than TRACE, Table 1 shows that the characteristics of bonds traded via MarketAxess and TRACE differ with bonds likely to be more liquid, e.g., bonds with larger issue sizes, trading more on MarketAxess. An initial attempt to control for differences in the types of bonds is in Panel B of Table 2 where half-spreads are calculated only for bonds traded via both MarketAxess and TRACE. The MarketAxess costs in Panel B are very similar to those in Panel A because virtually all the bonds traded on MarketAxess are also traded on TRACE. The TRACE costs generally are lower in Panel B, but the declines are modest and costs remain higher than in MarketAxess.

Limiting the analysis to only bonds traded on both MarketAxess and TRACE controls for cross-sectional differences in bond characteristics. However, it is still possible that bonds are more likely to trade on MarketAxess on days where liquidity in those bonds is higher. Panel C of Table 2 controls for this by only examining on days where costs for a bond can be calculated for both MarketAxess and TRACE. The costs and cost differences are not greatly affected by further narrowing the sample, but the number of observations falls substantially, especially in the larger trade sizes. A natural approach to controlling for bond characteristics and market conditions is in a multivariate regression framework.

3.2 Regression Cost Estimates

To control for bonds characteristics, market conditions, and trade characteristics it is useful to construct a cost of transacting for each trade. Typically, trading costs are defined the difference in return between the actual investment return and the return to a notional or paper portfolio. Costs include commissions, market impact, and opportunity costs. One important unobservable opportunity cost for OTC markets is the time traders spend searching for a counterparty.

We compute percentage transaction costs in basis points relative to a variety of benchmarks but focus here on the last trade in that bond in the interdealer market as most representative. Then the cost or implementation shortfall) is defined as:

$$Cost = \ln\left(\frac{TradePrice}{BenchmarkPrice}\right) \times Trade\ Sign \quad (1)$$

Trade sign is the standard buy/sell indicator which is +1 if the client is buying and -1 if the client is selling. It is important to note that cost in (1) is a fraction of trade value, not yield. The trading convention for high-grade corporate bonds is typically for negotiations to take place in terms of yield relative to the yield on a benchmark treasury of similar duration rather than dollar value. However, from the investment perspective, cost or shortfall should be expressed relative to the value of the trade. We compute transactions costs throughout in basis points of value by multiplying equation (1) by 10,000.

Harris and Piwowar (2006), Bessembinder, Maxwell, and Venkataraman (2006), and Edwards, Harris and Piwowar (2007) calculate trading costs with regressions of the change in price between transaction on change in the trade sign. Consistent with our approach interdealer trades are given a sign of zero. Our approach uniquely assigns a cost to each transaction. This allows for more straightforward inclusion of transaction specific covariates of interest, in particular, later when analyzing MarketAxess trades the inclusion of the number of dealers queried and number responding. The disadvantage of calculating a cost for each trade is the information in trade signs and price changes is less fully exploited. In addition, the interdealer price may include costs dealers charge each other for trading. Our baseline regression transaction costs estimates are similar to the costs in Table 2 which do not use any interdealer trades. In unreported results we obtain similar trading costs estimates using the Harris and Piwowar (2006) regression approach that utilizes both prior customer and dealer trade prices as a benchmark.

For cost computations, we favor using the last interdealer price as the benchmark price as this is a good proxy for the mid-quote. Using the last price introduces a bias from bid-ask bounce. Another popular benchmark, the Volume Weighted Average Price (VWAP) suffers from problems of relevance when there are few trades in the day.

3.3 Determinants of Costs

Table 3 analyzes trading costs for TRACE and MarketAxess while controlling for market conditions, bond characteristics, and trade size. Before presenting the results we discuss our control variables in detail.

Bond characteristics:

- Credit quality – dummy variables for A and B rated bonds.
- Maturity – natural logarithm of the time until the bond matures
- Age – natural logarithm of the time since the bond was issued
- Issue size – natural logarithm of the bond's issue size bond

- Industry sector – dummy variables for whether the bond issuer is in the financial, industrial, or utility sectors.

Market conditions:

- Risk term: DTS – the yield spread over treasury times years to maturity.
- Drift term: – change in treasury yield relative to benchmark trade \times buy-sell indicator \times years to maturity; the controls changes in price due to treasury rate shifts.
- Calendar Time Controls – beginning and ending of week dummy, 1 for Friday and Monday, 0 otherwise; month end dummy, 1 for last trading day of the month, 0 otherwise.

Trade characteristics:

- Trade size: Micro, Odd, Round, and Max dummy variables for trades of less than 100,000, 100,000 to 999,999, 1M to less than 5M, and 5M and above, respectively.
- MA – dummy equal to 1 if the trade is on MarketAxess and 0 otherwise.
- MA Micro, MA Odd, MA Round, MA Max – MA dummy variable interacted with trade size dummy variables.

[Insert Table 3 Here]

Table 3 presents three transaction cost regressions. Standard errors control for contemporaneous correlation across bonds on the same day and time series correlation within bond using the clustering approach of Petersen (2009) and Thompson (2011). The first regression's independent variables are the trade size dummy variables, the MarketAxess interacted trade size dummy variables, the calendar time dummy variables, the rating and industry dummy variables, and the treasury drift variable. All independent variables are demeaned so the trade size dummy variables can be added together to calculate average trading costs.

The constant of 78.38 represents the cost of a micro-sized TRACE trade and is close to the 70.58 cost for a micro trade in Table 2. That is a substantial trade cost relative to small trades in other asset classes. The -32.05 coefficient on the odd-lot dummy variable shows the cost for a TRACE odd-lot trade is 32.05 basis points lower than for a TRACE micro trade; making the TRACE odd-lot cost 46.33 basis points, somewhat higher than the 32.43 basis points in Table 2. Round lot TRACE costs are 20.75 basis points ($= 78.38 - 57.63$). Maximum sized TRACE trades are 19.19 basis points. The cost estimates for TRACE odd, round, and maximum trade sizes being higher in Table 3 as compared to Table 2 could arise from buys and sells occurring in the same day in bonds that are more liquid or on days that are more liquid. So, costs decline with trade size but in a non-linear manner. Beyond a round lot, there appears to be little difference in cost as a function of size.

The MarketAxess interacted trade size dummy variables capture the difference in trading costs between MarketAxess and TRACE for that trade size. For odd-lot, round-lot, and maximum trade sizes costs on MarketAxess are 27.27, 4.50, and 2.80 basis points lower than TRACE, respectively. The differences are comparable to the differences in the simple trading costs measures in Table 2.

The second regression specification in Table 3 adds the bond characteristics for time to maturity, age since issuance, and issuance size as independent variables. The coefficients on these are consistent with Edwards, Harris and Piwowar's (2007) findings that older, longer maturity, small issue bonds have higher transactions costs. Adding these controls increase the cost difference between MarketAxess and TRACE for micro and round trade sizes. For the maximum trade size the relative cost difference between MarketAxess and TRACE becomes positive, 1.81 basis points, but is not statistically significant. For larger sizes client traders have an incentive to invest more time in negotiating better prices over the phone with dealers. As noted above, such costs are not observable in prices. In contrast the time required for an auction in MarketAxess is independent of trade size. Thus, the 5M+ result is consistent with a search model where for large enough sizes the unobserved search effort for TRACE trades increase to offset the gains from lower search costs on MarketAxess. Similarly, this could lead to MarketAxess having smaller trades in the 5M+ category, complicating the cost comparison for the largest trade size.

The third regression specification in Table 3 adds the risk variable as an independent variable. Higher yield bonds with longer duration represent greater inventory risk for dealers. Surprisingly, after controlling for other bond and market characteristics, the risk variable is not statistically significant. The calendar time, industry sector, and rating dummy variables are often not statistically significant so these variables are omitted in some subsequent specifications.

4. Endogenous Venue Choice

To move beyond our largely exploratory empirical investigation thus far it is useful to build a more explicit framework to analyze endogenous venue choice. We focus on the tradeoff between the lower search costs a trader enjoys by using an electronic auction mechanism, where a trader can simultaneously request multiple quotes, and the anonymity benefits from bilateral negotiation in the over the counter market. Let C_0 denote trader's the expected cost from transacting bilaterally in the OTC market and let C_m denote the expected cost if the trader were in-

stead to select the auction mechanism. The trader selects the auction market if and only if the costs of transacting there are lower than the OTC alternative, i.e., $C_0 > C_m$.

Consider a potential buy order of size $x > 0$. We model the expected price in bilateral OTC trading as the expected value of the asset v plus a premium $C_0 = v + d(x)$, where d is the expected dealer markup which could depend on trade size x and is trader specific, depending on relative bargaining power.³ From an econometric viewpoint, the relative bargaining position of a trader is unobserved and will create selectivity bias.

Now consider the cost of trading in the auction mechanism. The trader can conduct an auction by simultaneously selecting M dealers to contact, up to a maximum of \bar{M} . The choice of M is itself endogenous and will depend also on trade size: Contacting more dealers implies a higher likelihood of responses and hence lower costs but involves additional leakage of information. We assume the number of dealers to query, conditional upon selecting the auction mechanism, is optimally selected and let $M(x)$ denote this function.⁴ Let N be the (random) number of dealers responding given that $M(x)$ dealers are queried. We model $E[N] = \lambda(z)$ where λ is the hazard rate that depends on a vector of bond and trade characteristics, z . In our later empirical analysis, we will estimate this function assuming a Poisson model for responses. We assume the auction fails (i.e., that no dealers respond) with probability $q = \Pr[N = 0] = e^{-\lambda}$. In this case, the trader is forced to go to the bilateral dealer mechanism and incurs additional costs $s(x) \geq 0$ relative to the OTC market. The additional cost has two potential components: First, given M dealers were contacted, there is potential additional leakage of information which is likely positively related to size because larger trades may be more likely to be associated with private information. Even if the trade were not information motivated, knowledge of flows may lead to front running and hence there could be a leakage cost just associated with the fact that a large buyer is in the market. So that in the event there are zero responses, the total purchase cost is $C_0 + s(x)$, where C_0 is the expected cost in the bilateral market. Implicit in this framework is the time dimension; the multilateral auction may take longer to run even though it involves a single click than a bilateral negotiation on the phone. Thus, s captures the additional

³ For simplicity we assume that if the trader engages in bilateral trading, execution will be obtained with certainty albeit at a cost, and hence there is no leakage cost. It is straightforward to extend the model to allow for a positive probability that the negotiations lead to no trade followed by subsequent searches in the future. See Duffie, Garleanu, and Pedersen (2005) for a fully developed sequential search and trading OTC model.

⁴ Levin and Smith (1994) examine entry incentives in auctions with stochastic numbers of entrants. They show that in a common value auction (in our setting the common value is the common inventory component across dealers) a seller wants to limit the number of bidders even in the absence of leakage costs.

leakage (over any in the OTC market) result. The term , s is hence trader or trade specific and is not observed by the econometrician.

If $N > 0$, with probability $1 - q$, the auction is viable. Rational dealer behavior suggests that in a sealed bid auction, each dealer will charge their reservation price which is the expected value (v) plus a dealer specific inventory based premium which depends on size. A positive premium can arise as a compensation for unwanted risk or if the dealer ascribes a positive probability to being in a monopolistic position should no other dealers respond. Alternatively, a dealer who has an opposite side inventory position may aggressively bid to reduce risk in which case the premium can be negative. We expect there to be cross-sectional dispersion in initial inventory across dealers. The expected total auction cost, C_m , for trade size x combines the cost of a failed auction with the costs of a successful auction:

$$C_m = q(C_0 + s(x)) + (1 - q)(v + p(x)) \quad (2)$$

where $p(x)$ is the expected premium. This yields the choice model; a trader chooses the OTC market ($OTC = 1$) if and only if:

$$qs(x) + (1 - q)(p(x) - d(x)) > 0 \quad (3)$$

For a given size x , the higher the costs of leakage s , the greater likelihood of searching the dealers over the auction, and vice versa with the dealer markup d . Similarly, lower dealer response rates λ (e.g., on less liquid issues) implies a higher q and hence less likelihood of selecting the auction.

The model also shows that costs can vary with size in a nonlinear way. Unlike asymmetric information models, realized cost $C(x)$ will reflect the optimal choice of venue plus the tradeoff between the cost elements:

$$C(x) = \min[C_0(x|OTC = 1), C_m(x|OTC = 0)]. \quad (4)$$

This equation forms the basis for the endogenous choice model we estimate below. For small sizes, leakage s is likely to be minimal and the auction mechanism dominates. This is also the case if dealers are competitive in bidding so that $p(x) = 0$. Beyond a point, as trade size rises, we would expect higher costs from leakage and hence more likelihood of using a dealer mechanism. If the dealer markup $d(x)$ reflects economies of scale or bargaining power, we may observe that realized cost declines with x .

4.1 Regression Cost Estimates Controlling for Selection Bias

The multivariate regressions in Table 3 control for observable differences in bond characteristics and market conditions. However, there may be unobservable characteristics of trades which affect both the costs of the trade and whether the trade is executed on MarketAxess. The standard econometric approach is an endogenous Heckman switching model.⁵ This is a two stage model. In stage 1, a trader chooses venue 1 (auction) over venue 2 (dealer phone search) if he believes that the expected cost of venue 1 are lower than those of venue 2. We model expected costs as

$$c_k = z' \delta_k + \eta_k. \quad (5)$$

Where z is a vector of explanatory terms (including possibly non-linear functions of size) and the error term η captures the unobserved costs of search and slippage, as detailed in the model. The auction venue is chosen if

$$c_1 \leq c_2 \quad \text{or} \quad z'(\delta_2 - \delta_1) + (\eta_2 - \eta_1) \geq 0 \quad \text{or} \quad z' \delta + \eta \geq 0, \quad (6)$$

which forms the basis of the Probit equation in Table 4.

In stage 2, we model the true cost equation (if there was no selection bias) as

$$y_k = x' \beta_k + \varepsilon_k. \quad (7)$$

The residual captures unobserved cost factors such as dealer inventory effects. Assuming joint normality:

$$E[y_1 | x, z, c_1 \leq c_2] = x' \beta_1 + \rho_1 \sigma_{\varepsilon_1} \frac{\varphi(z' \delta)}{\Phi(z' \delta)} = x' \beta_1 + \rho_1 \sigma_{\varepsilon_1} \overline{mr}(z' \delta) \quad (8)$$

$$E[y_2 | x, z, c_1 \geq c_2] = x' \beta_2 - \rho_2 \sigma_{\varepsilon_2} \frac{\varphi(z' \delta)}{1 - \Phi(z' \delta)} = x' \beta_2 - \rho_2 \sigma_{\varepsilon_2} \overline{mr}(z' \delta) \quad (9)$$

where ρ_k is the correlation of ε_k and η_k . Essentially to run both regressions requires two Mill's ratio variables (with appropriate dummies) where the denominators are slightly different (they sum to one).

We estimate the probit model for venue selection in Table 4 with the same three specifications in Table 3. Consistent with Table 1 odd- and round-lot trades and bonds with larger issue sizes are more likely to be on MarketAxess. Unlike in Table 3 some of the bond characteristic and calendar time dummy variables are significant. A-rated bonds are more likely to trade on

⁵ Madhavan and Cheng (1997) and Bessembinder and Venkataraman (2004) use the procedure to estimate costs for block trades while controlling for selection.

MarketAxess. Trades on Monday and at the end of the month are more likely to be on MarketAxess.

[Insert Table 4 Here]

Table 5 uses the third probit specification to estimate the second-stage cost model for MarketAxess and TRACE. As before all continuous independent variables are demeaned. The selectivity adjustment (Mill's ratio) terms are *Inv Mill MA* and *Inv Mill TRACE*, respectively. The difference in independent variable coefficients (MarketAxess minus TRACE) shows that MA's relative costs decrease in issue size and increase in age and duration times spread, consistent with easier trades being done on MA. The inverse mills ratio has a negative coefficient, is consistent with our model of selection and where the auction market is chosen for orders with less likelihood of leakage and higher search costs.

[Insert Table 5 Here]

The results in Table 5 are consistent with MarketAxess being cheaper for average trades. The differences in coefficient estimate across the columns illustrate how much the independent variable must change for the cost differential between MarketAxess and TRACE to change sign. For example, leaving aside the selectivity adjustment (Mill's ratio) terms an average maximum size trade on MarketAxess costs 12.93 basis points ($= 19.14 - 6.21$) as compared to 17.23 basis points ($= 78.87 - 61.64$) on TRACE. The difference in the issue size coefficients is $-6.117 + 2 = -4.117$. The ratio of the costs difference to coefficient difference is $1.04 = -4.3 / -4.117$. Because issue size is in natural logarithm units this translates into issue size differing by a factor of 2.83 ($= e^{1.04}$). Put another way, a maximum sized trade in an otherwise average bond would need to have an issue size less than one-third the average issue size, e.g., \$600M as compared to \$1.8B, to be cheaper on TRACE than MarketAxess.

Also noteworthy are the cost differentials for odd lot trades. Very clearly, the auction mechanism is preferred for this size over the OTC alternative. Given the relative size of the coefficients, we would need the slippage term s or the probability of non-trading q to be implausibly large to explain this selection. It is likely that this result reflects some of the differences in the client composition across the venues referred to earlier. Specifically, the results may reflect the fact smaller and less active traders who could benefit from trading their odd lots in an auction framework are unwilling to bear the associated set up costs, closing out this option.

Finally, we have not considered the 30% or so of the time that a MarketAxess auction does not result in a trade. However, we also do not observe phone searches that do not result in trades. In general, to fully capture expected trading costs across venues one needs to run an experiment where orders are randomly sent to different mechanisms. This is a shortcoming of all studies of observed transaction costs.

5. Trading and Bidding Behavior in Electronic Auctions

Theory suggests that bidder's behavior is crucial for auction performance (for example, Bulow and Klemperer (2009)). We next turn to the detailed data we have on dealer's bidding behavior in MarketAxess. Figure 1 illustrates the frequency distribution of the number of dealer responses in the auction market, conditional upon at least one response. The modal response is 3. With that number of dealers, the typical auction should approach a competitive outcome. In 7.3 percent of auctions no dealers respond.

[Insert Figure 1 Here]

Table 6 provides information by trade size on the per auction average number of dealers queried, the percentage of dealers responding, and the percentage of auctions with zero responses. The number of dealer's queried decreases with trade size with 27.70 dealers queried for micro trades and 23.98 queried for maximum trades. This is consistent with a concern by traders about leakage of their intentions increasing in trade size. Despite this the number of dealers responding increases in trade size. Queries decreasing in trade size while dealer responses increasing indicates the dealers are more likely to respond for large trades. This would arise if dealers' costs of participation is fixed, making the participation cost per bond falling in trade size. The percentage of dealers responding increases substantially from 16.8% for micro trades to 29.7% for large trades. An alternative explanation is that large trades are simply done in bonds where dealers are more likely to respond.

[Insert Table 6 Here]

To control for bond characteristics requires a more formal model of the number of dealers N responding to M queries, i.e., $E[N|M] = \lambda(z)$. We model the number of dealers who respond to a trader's queries using a count data model (as $N = 0, 1, 2, \dots$) which also naturally allows for zero outcomes or auction failure. It is important to allow for cross-sectional heterogeneity which

we expect given that dealer bargaining power and perceptions of leakage will vary across traders. We model this for trade i as the outcome of a Poisson distribution with conditional mean:

$$\ln(\lambda_i) = z_i' \beta + u_i \quad (10)$$

where the error term u_i captures individual (unobserved) variation in dealer responses. When u_i has a gamma distribution $\Gamma(1, \theta)$, this yields a negative binomial model. Unlike the Poisson model, we do not restrict the mean and variance of the sample data to be equal. Over dispersion (where the variance exceeds the mean) is quite common with count data and hence the negative binomial is preferred. The distribution of the number of dealer responses N_i in auction i conditioned on z_i is

$$P(N_i = n_i | z_i) = \frac{\Gamma(n_i + \theta)}{\Gamma(\theta)\Gamma(n_i + 1)} \left(\frac{\theta}{\theta + \lambda_i} \right)^\theta \left(\frac{\lambda_i}{\theta + \lambda_i} \right)^{n_i} \quad n_i = 0, 1, 2, \dots \quad (11)$$

Table 7 reports estimates of three versions of the dealer response model.⁶ Trade size and issue size are positive predictors.

[Insert Table 7 Here]

The model can help traders better predict auction interest to utilize this mechanism more efficiently and reduce costs. Using equation (1), the probability of the auction failing with no responses at all is $P(N_i = 0 | z_i) = \left(\frac{\theta}{\theta + \lambda_i} \right)^\theta$, which is the analog to the Poisson probability with no

heterogeneity in responses. There is a marked jump in the probability of auction failure as trade size changes from a round to an odd lot. Depending on the model, the difference in the odd and round lot coefficients is approximately 0.2 implying that, all else equal, the probability of auction failure for an odd lot transaction is 1.22 times that of a comparable round lot. Risk is a negative predictor along with age and the end of week and end of month dummy variables. There are fewer dealers in higher yield bonds, which makes sense given dealer risk aversion. It is also interesting to note that the coefficient on the log number of dealers is less than one, which corresponds to the probability of dealers responding declining in the number of dealers queried.

Auction theory predicts that the number of dealer should be closely linked to the auction outcome. Figure 2 shows the costs in basis points as a function of the number of responding

⁶ In order to utilize the results from our response model in a trading cost regression model 3 is estimated only for auctions resulting in trades. Approximately two percent of trades cannot be matched to auctions causing the number of observations in model 3 of Table 7 to be slightly less than the number of MarketAxess trades in Table 1.

dealers. Competition lowers costs as is clear from the figure. When only a few dealers respond, costs are high, 20-35 basis points. Observe that mean realized costs go to zero and actually become slightly negative (-3 to -4 basis points) when the number of responses is large, in this case above 10. While estimation error could lead to negative realized costs, recall from the model that this result is consistent with a negative premium $p(x)$, i.e., that some dealers are willing to price aggressively to liquidate unwanted inventory. It is worth noting that this does not mean that the winning dealer loses on the round trip in expectation as they may be able to charge a premium to enter into the position initially.

[Insert Figure 2 Here]

Table 8 presents cost estimates for the auction market. Model 2 shows that costs declining in the number of dealers responding in Figure 2 is robust to the inclusion of bond and trade characteristics. Essentially, this can be thought of as a regression with a log of frequency response as an explanatory variable. We use the natural logarithm of the bids because Figure 2 shows a clear nonlinearity in costs as a function of bids. Model decomposes the number of bidders into the expected and unexpected number of bidders using specification 3 of the negative binomial dealer response model in Table 7. The logarithm of expected and unexpected responses is taken after subtracting the overall minimum and adding one; this ensures that the minimum of both the logarithm of expected and unexpected responses is zero. The coefficient on the unexpected number of bidders is significantly more negative than the coefficient on the expected number showing that unexpectedly fewer bidders responding is particularly costly.

It is interesting that conditioning on the number of bids in model 2 reverses the ordering of costs for odd, round, and maximum trade sizes with the costs of trading no longer monotonically decreasing in trade size. This difference demonstrates that dealer bidding behavior drives the decline costs in trade size. This contrasts with the standard argument that costs decreasing in trade size is due to market power by intermediaries where the bargaining power the trader in increasing in trade size.⁷

[Insert Table 8 Here]

⁷ Bernhardt, Dvoracek, Hughson, and Werner (2005) provide a variant on this argument by modeling the repeated interaction between customers and dealers. They find that dealers offer better prices to more regular customers, and, in turn, these customers optimally choose to submit larger order.

Note that Model (1) and (2) in Table 7 include auctions where there was no trade. Model (3) is only for trades. The number of observations in Model 3 is slightly smaller than in Table 1 because some of the trades could not be matched to auctions, 191,150 in Tables 1 and 5 versus 187,834 in Tables 7 and 8.

It would be interesting to extend this analysis to capture the time dimension of trading (i.e., the duration between order initiation and execution), which as we noted earlier is a factor in determining the expected slippage and hence the trader's strategy. While this statistic is not in the TRACE data, in theory we could look at this for the MA data. It would, for example, also be interesting to examine to link the duration statistic to leakage and also examine dealer behavior in time, i.e., whether some dealers always wait until the end of the allotted auction period or respond right away. These more detailed questions are topics for further analysis.

6. Conclusions

As electronic trading expands more rapidly across regions and asset classes, it is natural to ask whether there are limits to the potential scope of auction markets. The fixed income markets are of particular interest given their size and the complexities of the instruments traded. Trading in this asset class still remains very much over-the-counter although electronic auctions – as in equities and derivatives markets – are gaining traction.

Using an extensive sample of corporate bond transactions from January 2010 to April 2011 we show that: (1) There is clear evidence that traders rationally select between dealer and auction markets based on a tradeoff between leakage about trading intentions and search costs; (2) Costs of trading are significant relative to a last interdealer trade benchmark. The analysis also confirms that trading costs decreases as a function of size and provides an explanation for this result; (3) Costs are directly related to measures of dealer competition and trade size; (4) Dealer competition can be predicted as a function of bond attributes, trade size, past activity, and seasonalities; and (5) Competition is a strong determinant of trading cost. There are significant gains to sourcing multiple bids for fixed income transactions. Competition is greater for larger trade sizes, providing an explanation for why costs might decline with size.

From a public policy perspective, the results here shed light on trading costs in fixed income markets and increase our understanding of the value of the competition inherent in an auction setting. It is important to understand that the evolution of bilateral, sequential trading into an auction type framework offers a path from an over-the-counter market to a centralized, con-

tinuous trading. The mechanism analyzed here is quite distinct from the more familiar electronic communications networks (ECNs) that many stock and derivative exchanges have evolved into over the past two decades. The auction “request for quote” market made possible by technological advances is a very different system altogether and may offer a way to mitigate the complexities of markets where liquidity providers post their quotes such as the original Nasdaq Automated Quotation System. In less liquid instruments, such markets pose problems of potential collusion among dealers who observe each other’s actions or adverse selection from offering free options in the form of continuous and firm quotes. Our results indicate that electronic auction markets based on “sealed bids” are a viable and important source of liquidity even in inactively traded instruments.

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Table 1
Descriptive Statistics

The table presents descriptive statistics based on a sample of all US investment-grade non-callable corporate bond trades in Financial Industry Regulatory Authority's (FINRA) Trade Reporting and Compliance Engine (TRACE) from January 2010 through April 2011, excluding all interdealer trades and trades directed to MarketAxess, an electronic auction venue. Four trade size categories by dollar size are represented based on market conventions, up to a maximum of \$5M and above. Bond characteristics such as Age and Maturity are measured in years. *DTS (duration×Spread)* is a risk measure defined the bond's duration multiplied by its yield spread over treasuries.

	MarketAxess	TRACE
Number of Trades	191,150	1,578,024
Micro (1-100K)	44.6%	77.1%
Odd (100K-1M)	42.6%	14.6%
Round (1M-5M)	11.8%	5.1%
Max (5M+)	1.0%	3.2%
Mean Trade Size (\$000)		
Micro (1-100K)	29	21
Odd (100K-1M)	320	247
Round (1M-5M)	1,794	1,896
Number of Distinct Bonds	1,579	4,129
Issue Size (\$ Billion)	1.91	1.56
Age	3.20	3.96
Maturity	7.52	7.82
DTS (<i>Duration×Spread</i>)	10.89	14.12

Table 2
Benchmark Corporate Bond Trading Costs

The table presents estimates of one-way trading costs (half the bid-offer spread) for a sample of all US investment-grade non-callable corporate bond trades in Financial Industry Regulatory Authority's (FINRA) Trade Reporting and Compliance Engine (TRACE) from January 2010 through April 2011. Half-spread is defined as the difference between the average price for all sell transactions and the average buy price for each bond-day when there is both a buy and a sell, divided by two and expressed in basis points.

	MarketAxess		TRACE	
	Half-Spread	Number of Bond-Days	Half-Spread	Number of Bond-Days
Panel A: All bond-days with both a buy and sell in same size category				
Micro (1-100K)	14.35	12,029	70.58	130,529
Odd (100K-1M)	8.54	9,032	32.43	33,596
Round (1M-5M)	5.79	1,113	9.12	13,225
Max (5M+)	2.76	16	6.39	8,874
Panel B: Only bonds with both MarketAxess and TRACE trades in same trade size category				
Micro (1-100K)	14.34	12,023	58.74	73,118
Odd (100K-1M)	8.49	8,995	32.98	24,294
Round (1M-5M)	5.72	1,108	8.90	6,754
Max (5M+)	2.58	16	4.95	471
Panel C: Only bond-days with both MarketAxess and TRACE trades in same trade size category				
Micro (1-100K)	14.05	9,135	48.60	9,135
Odd (100K-1M)	6.09	2,164	30.43	2,164
Round (1M-5M)	6.22	202	7.43	202
Max (5M+)	0.36	9	5.05	9

Table 3
Regressions on Corporate Bond Trading Costs

The table presents three regression models for implementation shortfall. Standard errors are in parentheses and control for contemporaneous correlation across bonds and time series correlation within a bond. Independent variables include treasury drift and dummy variables for trade size, trade size interacted with MarketAxess (MA), calendar time, rating, and industry. DTS (*Duration* \times *Spread*) is duration multiplied by yield spread. All independent variables are demeaned.

	(1)	(2)	(3)
Odd	-32.05*** (1.523)	-27.32*** (1.494)	-27.44*** (1.487)
Round	-57.63*** (1.765)	-52.06*** (1.832)	-52.28*** (1.807)
Max	-59.19*** (1.598)	-55.04*** (1.928)	-55.23*** (1.912)
MA Micro	-55.01*** (1.582)	-45.84*** (1.394)	-45.71*** (1.404)
MA Odd	-27.27*** (1.308)	-27.75*** (1.514)	-27.61*** (1.529)
MA Round	-4.503*** (0.887)	-6.829*** (1.047)	-6.626*** (1.051)
MA Max	-2.795** (1.150)	1.812 (1.335)	1.943 (1.343)
A-Rated	-6.925** (3.293)	-3.049 (2.937)	-2.031 (2.828)
B-Rated	12.79 (11.47)	11.60 (11.02)	11.49 (11.01)
Industrial	-7.875 (8.477)	0.404 (6.183)	-0.361 (6.129)
Financial	-3.101 (7.880)	13.89** (5.678)	12.61** (5.651)
Utility	21.82** (10.34)	2.910 (7.191)	2.010 (7.208)
Monday	0.611 (0.612)	-0.111 (0.692)	-0.0881 (0.682)
Friday	-1.243** (0.627)	-1.033 (0.735)	-1.034 (0.722)
Month-End	0.566 (0.956)	-0.0693 (1.110)	-0.0864 (1.094)

Table 3 (Continued)

	(1)	(2)	(3)
Drift	0.347*** (0.0160)	0.358*** (0.0157)	0.359*** (0.0158)
ln(Maturity)		36.52*** (1.875)	34.21*** (2.629)
ln(Age)		4.867*** (1.156)	4.476*** (1.195)
ln(Issue Size)		-5.194*** (0.366)	-5.117*** (0.356)
DTS			0.117 (0.0997)
Constant	78.32*** (7.838)	58.80*** (6.109)	59.15*** (6.086)
Observations	1,769,174	1,769,174	1,769,174
R-squared	0.055	0.100	0.100

*** p<0.01, ** p<0.05, * p<0.1

Table 4
Endogenous Selection of Trading Mechanism: Stage I Choice Model

Three probit models for the binary choice between over-the-counter versus electronic trading. Trades in MarketAxess are denoted by 1; zero otherwise. Independent variables include dummy variables for trade size, calendar time, rating, and industry. DTS (Duration×Spread) is duration multiplied by yield spread. All independent variables are demeaned. Standard errors are in parentheses.

	(1)	(2)	(3)
Odd	0.897*** (0.0252)	0.863*** (0.0246)	0.876*** (0.0230)
Round	0.742*** (0.0247)	0.684*** (0.0264)	0.702*** (0.0257)
Max	-0.286*** (0.0276)	-0.373*** (0.0315)	-0.357*** (0.0310)
A-Rated	0.224*** (0.0649)	0.117* (0.0618)	0.0312 (0.0596)
B-Rated	-0.809*** (0.189)	-0.738*** (0.183)	-0.715*** (0.179)
Industrial	0.0523 (0.0839)	-0.0592 (0.0873)	-0.0208 (0.0890)
Financial	-0.153** (0.0658)	-0.264*** (0.0662)	-0.153** (0.0697)
Utility	-0.837*** (0.0951)	-0.551*** (0.0945)	-0.456*** (0.102)
Monday	0.0318** (0.0136)	0.0416*** (0.0148)	0.0404*** (0.0141)
Friday	-0.00360 (0.0138)	-0.00653 (0.0150)	-0.00588 (0.0139)
Month-End	0.194*** (0.0184)	0.201*** (0.0207)	0.202*** (0.0184)
ln(Maturity)		-0.120*** (0.0274)	0.0897* (0.0499)
ln(Age)		-0.0302 (0.0254)	-0.00289 (0.0252)
ln(Issue Size)		0.215*** (0.0194)	0.212*** (0.0186)
DTS			-0.0127*** (0.00311)
Constant	-1.581*** (0.0813)	-1.437*** (0.0807)	-1.480*** (0.0798)
Observations	1,769,174	1,769,174	1,769,174

*** p<0.01, ** p<0.05, * p<0.1

Table 5
Endogenous Selection of Trading Mechanism: Stage II Cost Model

Table 5 uses the probit specification of Table 4, model (3), to estimate the second-stage cost model for MarketAxess and TRACE. All continuous independent variables are demeaned. The selectivity adjustment (Inverse Mill's ratio) terms are *Inv Mill MA* and *Inv Mill TRACE*, respectively. Standard errors are in parentheses.

	MarketAxess	TRACE
Odd	-5.543*** (1.794)	-5.307 (4.000)
Round	-8.187*** (1.412)	-35.13*** (2.832)
Max	-6.208*** (1.622)	-61.64*** (2.294)
Drift	0.423*** (0.0169)	0.344*** (0.0177)
ln(Maturity)	6.896*** (0.838)	35.04*** (2.718)
ln(Age)	3.921*** (0.456)	3.263*** (1.101)
ln(Issue Size)	-6.117*** (0.500)	-2.000*** (0.495)
DTS	0.177*** (0.0483)	0.0469 (0.0875)
Inv Mills MA	-0.222 (2.753)	
Inv Mills TRACE		80.00*** (12.14)
Constant	19.14*** (5.088)	78.87*** (2.102)
Observations	191,150	1,578,024
R-squared	0.069	0.085

*** p<0.01, ** p<0.05, * p<0.1

Table 6
Descriptive Statistics for Number of Dealers in an Auction

The table presents descriptive statistics from January 2010 through April 2011 for the number of dealers participating in 191,150 electronic auctions. Four trade size categories by dollar size are represented, based on market conventions, up to a maximum of \$5M and above. Figures reported are sample means.

Trade Size	Number of Dealers Queried	Percentage Responding	Percentage with No Response
Micro (1-100K)	27.70	16.8%	5.9%
Odd (100K-1M)	26.60	22.3%	7.7%
Round (1M-5M)	25.66	26.6%	9.8%
Max (5M+)	23.98	29.7%	15.1%

Table 7
Negative Binomial Model for Number of Dealers Responding in Auction

The table presents three regression models for the number of dealers responding for a sample of electronic auctions from January 2010-April 2011. Independent variables include treasury drift and dummy variables for trade size, trade size interacted with MarketAxess (MA), calendar time, rating, and industry. DTS (*Duration*×*Spread*) is duration multiplied by yield spread. All independent variables are demeaned. Robust standard errors in parentheses

	(1)	(2)	(3)
Ln(Queries)	0.643*** (0.00684)	0.591*** (0.00543)	0.534*** (0.00568)
Odd	0.255*** (0.0117)	0.263*** (0.0103)	0.291*** (0.00958)
Round	0.456*** (0.0164)	0.462*** (0.0127)	0.511*** (0.0110)
Max	0.490*** (0.0215)	0.527*** (0.0176)	0.674*** (0.0138)
Monday	0.0617*** (0.00311)	0.0599*** (0.00275)	0.0589*** (0.00260)
Friday	-0.0588*** (0.00362)	-0.0555*** (0.00310)	-0.0496*** (0.00289)
Month-End	0.00716 (0.00721)	-0.0186*** (0.00523)	-0.0185*** (0.00494)
ln(Maturity)		-0.0203*** (0.00226)	0.117*** (0.0183)
ln(Age)		-0.0817*** (0.00326)	-0.0482*** (0.00509)
ln(Issue Size)		0.318*** (0.0106)	0.255*** (0.0104)
DTS			-0.00435*** (0.000869)
Constant	-0.683*** (0.0251)	-0.595*** (0.0190)	-0.130*** (0.0308)
Observations	261,306	261,306	187,834

*** p<0.01, ** p<0.05, * p<0.1

Table 8
Corporate Bond Trading Costs in an Auction Mechanism

The table presents three regression models for trading cost (implementation shortfall) for a sample of electronic auctions from January 2010-April 2011. Independent variables include treasury drift and dummy variables for trade size, bond characteristics, and dealer responses (total, expected, and unexpected) to queries based on the estimates in Table 7. *DTS* (*Duration*×*Spread*) is duration multiplied by yield spread. All independent variables are demeaned. Robust standard errors in parentheses

	(1)	(2)	(3)
Odd	-5.373*** (0.478)	-1.309*** (0.420)	-2.631*** (0.458)
Round	-7.792*** (0.594)	-0.454 (0.537)	-3.157*** (0.604)
Max	-6.277*** (1.199)	2.933*** (1.137)	-1.222 (1.196)
Drift	0.422*** (0.0169)	0.424*** (0.0165)	0.424*** (0.0165)
ln(Maturity)	6.843*** (0.827)	9.075*** (0.754)	8.395*** (0.776)
ln(Age)	2.192*** (0.205)	1.451*** (0.208)	1.677*** (0.202)
ln(Issue Size)	-6.263*** (0.420)	-1.225*** (0.390)	-3.288*** (0.420)
DTS	0.186*** (0.0449)	0.120*** (0.0382)	0.144*** (0.0396)
ln(Resp)		-17.07*** (0.640)	
ln(Exp_Resp)			-14.09*** (0.803)
ln(Unexp Resp)			-36.14*** (1.529)
Constant	27.46*** (1.365)	29.16*** (1.223)	140.3*** (4.709)
Observations	187,834	187,834	187,834
R-squared	0.069	0.101	0.097

*** p<0.01, ** p<0.05, * p<0.

Figure 1: Frequency Distribution of Number of Dealer Responses

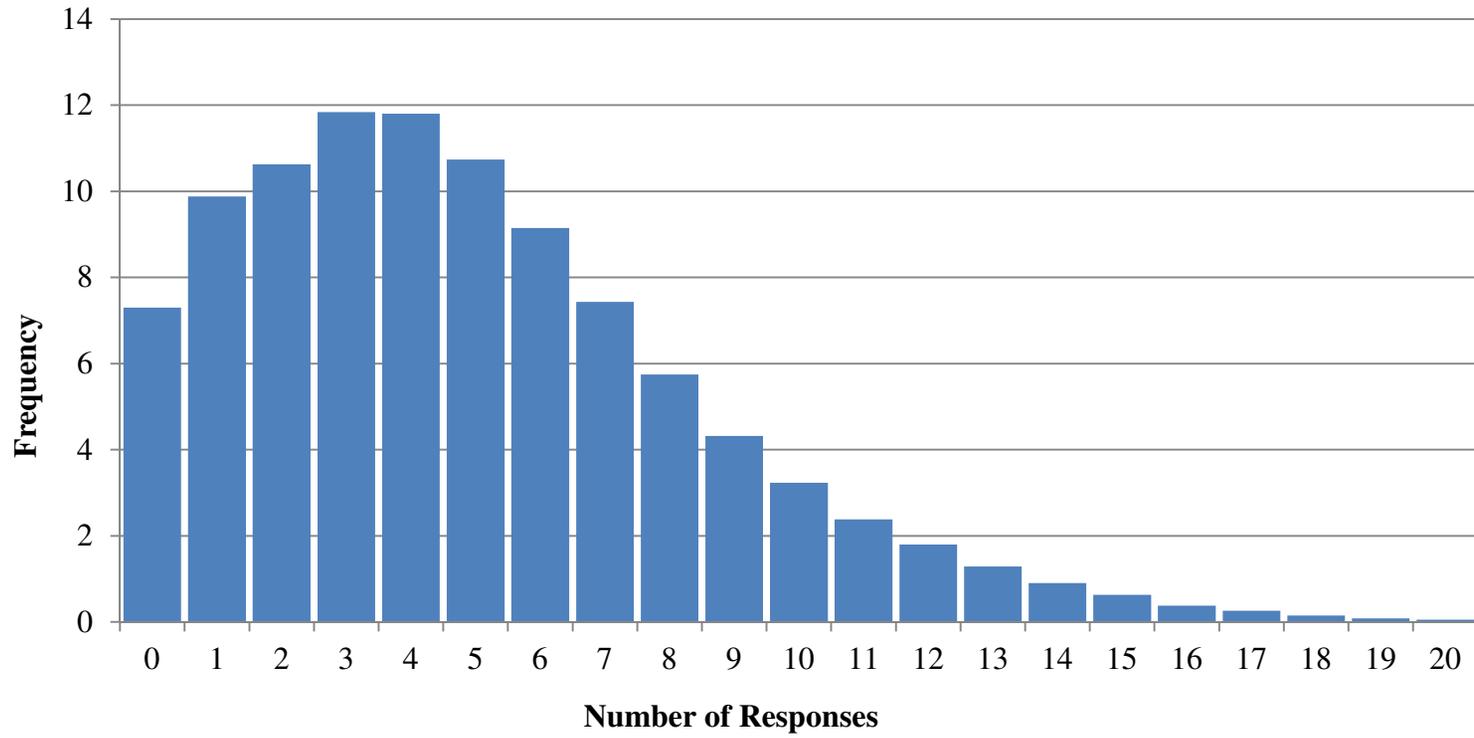


Figure 2: Transaction Costs in Basis Points by Number of Dealer Responses

