The Electronic Evolution of Corporate Bond Dealers*

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Abstract

Technology has transformed the trading of financial assets, but it has been slower to come to corporate bond trading. Combining a proprietary data from MarketAxess with a regulatory version of the TRACE data, we investigate how electronic request for quote (RFQ) trading affects corporate bond dealers and bond trading more generally. We demonstrate that while electronic trading remains fairly small and segmented, it has had wide-ranging effects on transactions costs and execution quality in both electronic and voice trading, and on the inter-dealer market. We identify features particular to bond markets that have and may continue to limit the growth of electronic bond trading. Our results provide an intriguing portrait of a market in transition.

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1. Introduction

Technology has transformed the trading process for a wide range of financial assets, rendering obsolete the roles of exchange floors, traditional stock exchange specialists, two-dollar brokers, and other remnants of trading times past. Whether it be in equities, options, futures, or foreign exchange, electronic trading has become the norm, bringing with it measurable improvements in transactions costs and various market quality metrics, as well as a host of new market participants and venues. One notable exception to this trend, however, has been corporate bond trading. Corporate bonds trade in dealer markets, and despite the in-roads made elsewhere, electronic trading has failed to dislodge the dominance of dealers. Yet change, too, is slowly coming to corporate bond trading in the guise of electronic platforms offering execution capabilities. How electronic trading is affecting corporate bond dealers, and what this portends for the future of corporate bond trading, is the focus of this paper.

Unlike in other asset classes, where electronic trading has often supplanted market intermediaries, electronic bond trading platforms have generally worked with dealers via a request for quote (RFQ) process.[1] In a RFQ, a customer sends a buy/ sell request over the platform to a number of dealers, and dealers in turn can respond with bids or offers. Alternatively, a customer can contact a dealer (or sequentially, many dealers) via traditional voice trading. Dealers generally operate in both voice and RFQ milieus. Hendershott and Madhavan (2015) examined theoretically the decision facing traders regarding whether to "click" or "call", focusing on the role of electronic

[1] An alternative electronic trading approach, termed All-to-All trading, is tiny over our sample period. Since the launch of All-to-All trading in 2012, the daily share of dealer to customer trades that are executed through All-to-All as a fraction of overall trade volume has been growing steadily, but still remains below 2% by 2017. Therefore, we focus here only on RFQ trading.
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venues in reducing search costs. Using data from January 2010 through April 2011, they show that electronic trading costs were generally lower, and particularly so for more liquid and larger bond issues, but the embryonic state of electronic trading at that time precluded analysis of more general issues.

Using an extensive data set provided to us by MarketAxess, the largest and dominant bond trading platform, as well as a regulatory version of corporate bond transaction data from the Trade Reporting and Compliance Engine (TRACE) provided by the Financial Industry Regulatory Authority (FINRA), we seek a more complete view of the electronic evolution of corporate bond trading. Our focus here is on three main issues: First, what has happened to electronic trading in corporate bonds over time and is it showing the dominance that characterizes trading in other asset classes? Second, how has electronic bond trading affected the markets and, particularly, the behavior and structure of the dealer market? And, third, what are the limitations, if any, to the growth of electronic bond trading?

Our results provide an intriguing portrait of a market in transition. We show that electronic trading has continued to grow, albeit slowly: over our sample period it never exceeds 14% of market trading volume. But despite this small stature, electronic trading has had a wide-ranging impact. Transactions costs have fallen across the board, both for electronic trades and even more so for voice trading. We find the intriguing result that bond dealers who do more electronic trading offer better prices for their voice trades. Retail trades are particular winners - at the beginning of our sample, transactions costs for retail-sized trades were much higher than for block trades, but by the end of our sample in electronic trading they are approximately the same. Dealers also appear to benefit in that they are able to find customers better, and so rely less on the inter-dealer market to offload positions – for investment grade bonds, inter-dealer trading fell from 42% to

28% over our sample period. We argue that these positive impacts are largely due to reduced search costs for both customers and dealers.

Yet, given these benefits, the puzzle remains why electronic trading has not taken on a larger role. Here our research identifies some important limits to electronic bond trading. We show that bond illiquidity plays a large role. Using bond downgrades as periods where customers need to trade specific bonds, we show how trading shifts from electronic to voice trading, reflecting that electronic trading is not robust across stress periods. Information effects are also important. We find that electronic trading is almost entirely constrained to small trade sizes. Larger trades rarely trade electronically, and unlike in equities, bond trades are not being broken up into smaller trade sizes. So, electronic trading has only made in-roads in small, less information-based trades. Moreover, most electronic trading involves investment-grade bonds, consistent with dealer unwillingness to trade more information-sensitive high-yield bonds in electronic settings. A third limit to greater growth is market structure. In other settings, electronic trading elicited a variety of new entrants. Dealer market structure in bonds, however, is little changed; the top ten dealers remain dominant and new entrants are few, resulting in a decrease in bond dealers over our sample period.

Overall, our results show that bond markets are evolving, and for the better. The impact of electronic trading to date, however, has been more evolutionary than revolutionary. While the introduction of new technologies (such as the nascent all-to-all trading) may hasten this evolution, our work points to the particular nature of bond trading as imposing limitations on any eventual domination of electronic trading in bonds. For the foreseeable future, corporate bond dealers will be central to corporate bond trading.

Our research joins a growing body of work examining bond market microstructure. A variety of research has investigated execution quality differences in corporate bond trading, see, for example, Schultz (2001), Bessembinder, Maxwell, and Venkateramen (2006), Edwards, Harris, and Piwowar (2007), Goldstein and Hotchkiss (2007), Feldhutter (2012), Bias and DeClerck (2013), Hendershott et. al. (2017), and O'Hara, Wang, and Zhou (2018). More recent work has looked at changes in bond markets post-financial crisis, with research here by Dick-Nielsen, Feldhunter and Lando (2012), DiMaggio, Kern and Song (2016), Bao, O'Hara, and Zhou (2018), Bessembinder et al (2018), and Flanagan, Kedia, and Zhou (2019). Other relevant research has looked at the impact of technology on trading, with research here by Hendershott and Madhavan (2015), Easley, Hendershott, and Ramadorai (2014), Brogaard, Hendershott, Hunt, and Ysusi (2014), and Brogaard, Hagstromer, Norden, and Riordan (2015). Our work also contributes to the broader literature on search in OTC markets, with notable papers here being Duffie, Garleneau and Petersen (2005; 2007) and Uslu (2019).

This paper is organized as follows. The next section set out the data and sample construction. Section 3 investigates the growth of electronic trading in corporate bonds. Section 4 examines the benefits of electronic trading with a focus on execution quality, the impact on dealer voice trading, and its effects on the inter-dealer market. Section 5 then examines the limitations of electronic trading in corporate bonds. Section 6 is a conclusion.

2. Data and Sample Construction

Our analyses rely on combining the regulatory version of TRACE corporate bond transaction data with data on all trades executed on MarketAxess, a leading electronic trading platform, over the period from January 2010 to December 2017. TRACE data provide detailed information for each corporate bond trade, including bond CUSIP, trade execution date and time, trade price and quantity, and an indicator for whether the dealer buys or sells the bond. In addition, our regulatory version of the data also provide information on dealer identity for each trade. For inter-dealer trades, identities of both counterparties are included in the data. Information on dealer identity is essential to our analysis on the effects of electronic trading on dealer behavior.

To identify electronic trades, we obtain data on all trades executed on MarketAxess. Since the MarketAxess data do not include the same trade identifier as in the TRACE data, we match the MarketAxess data with TRACE data using bond CUSIP, execution time, price, quantity, the buy or sell indicator and an indicator for inter-dealer trade. Based on these criteria, 98.9% of trades on MarketAxess find a unique match in the TRACE data. These trades are identified as electronic trades with the rest being classified into voice trades.[2]

We then obtain from Mergent FISD characteristic information about corporate bonds, such as credit rating, date of issuance and maturity date, and the total par amount issued. To construct our sample, we start with all corporate bonds that are issued in US dollars by US firms in the following three broad FISD industry group: industrial, financial and utility. To be included in our sample, we require each bond to have valid rating information from Moody's or S&P. We assign a numeric value to each notch of S&P (Moody's) credit rating, with 1, 2, 3, 4 … denoting AAA (Aaa), AA+ (Aa1), AA (Aa2), AA- (Aa3), …, respectively, and we take the lower of S&P and Moody's rating as a bond's credit rating. After removing private placements, we end up with a sample of over 105 million trades in 29,787 bonds.

It is important to note at the outset that our measure of electronic trading is based solely on trades executed on MarketAxess. During our sample period, there are some other electronic

[2] Trades executed through All-to-All are excluded from our sample.

corporate bond trading venues, but these are generally small in size and data on trading there is not generally available.[3] We believe our data provide the most accurate depiction of electronic bond trading, but we caution that they should be interpreted as giving a lower bound on electronic trading activity in corporate bonds.

3. The Growth of Electronic Corporate Bond Trading

We begin by examining the growth of electronic bond trading. Figure 1 shows the share of electronic trading over the period 2010 -2017. We define electronic trading as the average daily share of dealer to customer trades that are executed on MarketAxess as a fraction of overall dealer to customer trading. Panel A breaks these numbers down into the share of total par volume traded and into the number of trades. As is apparent, the volume of trade executed electronically has been increasing steadily, rising from a market share of approximately 6% in 2010 to a little over 13% in 2017. A more dramatic increase can be seen in the number of trades, where electronic trading has gone from 9% of trading to now executing approximately 25% of trades.

Panel B shows that most of this electronic trading volume is in investment-grade bonds. Electronic high-yield bond trading was almost non-existent at the start of our sample period, but it does show steady growth, particularly in the latter years of our sample. Still, by 2017, the market share of electronic investment-grade volume has reached over 17% of total investment-grade volume, with electronic high-yield trading just over 5% of total high-yield volume.

Trade size is an important dimension in bond trading, with large trade sizes the norm in what has traditionally been an institutional investor driven market. Following market norms, we

[3] According to results from Greenwich Associates' surveys to U.S. institutional corporate bond investors, MarketAxess accounts for 85% of dealer to customer institutional electronic trading in corporate bonds. See <<Greenwich Associates 2018 Corporate Bond Trading>>.

classified all trades into four size categories: 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 then calculated the share of electronic trading across trade size categories. Figure 2 Panel A presents the annual average daily share of electronic trading in each of the four size categories for investment-grade bonds; Panel B provides the same information for high-yield bonds.

The figures clearly show that electronic trading is concentrated in the smaller trade sizes. In investment-grade trading, almost 50% of Odd-lot trades are now done electronically. Micro trades and Round lots exhibit slow but steady growth over the sample period, with approximately 20% of trading volume in those categories gravitating to electronic trading. Block trades, however, remain almost entirely in the voice trading realm. The results for high-yield bonds show an even more dramatic trade size effect, with virtually all high-yield electronic trading concentrated in the smaller trade sizes.

What is important to realize, however, is that bond market trading is heavily skewed towards larger trade sizes. Figure 3 shows the distribution of bond trades across the size categories over the sample period. Two points here are particularly salient. First, for both investment-grade and high-yield bonds, micro and odd-lot trades are a very small fraction of total volume. Block trades and round-lots together account for about 90% for either bond type, with blocks having a larger share in investment-grade than in high-yield. Second, the distribution of trade sizes in daily share volume has remained remarkably stable. The advent of electronic trading has not resulted in the trade-shredding found in equity markets nor has it changed the trading patterns of bond market participants. We turn in the next section to investigate how electronic trading has affected the market and the dealers more generally.

4. The Benefits of Electronic Trading

In most market settings, electronic trading has reduced transactions cost, so a natural starting point is to examine how the rise of electronic trading has affected transaction costs in bond trading. Fundamental to any such change is the behavior of the dealers, and an interesting wrinkle in bond markets is that voice and electronic trading occur simultaneously. We examine these interaction effects by investigating how electronic trading has affected dealer pricing and behavior in voice trading. Given the large trade sizes characteristic of bond trading, dealers have traditionally relied on extensive inter-dealer trading for managing their inventory risks. If electronic trading reduces search costs and facilitates the matching of buyers and sellers, we would also expect it to have an impact on the inter-dealer market.

4.1. Transactions Costs in Electronic and Voice Venues

Transaction cost estimation in bond markets is not straightforward. Our sample contains 29,787 bonds, many of which trade infrequently. A standard approach in the literature is to use the closest in time inter-dealer trade in that bond as a benchmark price from which to estimate the price impact of a trade. This is the approach used by Hendershott and Madhavan (2015) and for comparability with their results we use this approach as well. In Appendix 1, we consider the robustness of this approach by investigating alternative approaches for benchmarks in bond transaction cost measurement, including the most recent dealer to customer trade price, or any price in the bond. [4]

[4] As we discuss in Appendix 1, the general time trends in transaction costs persist across alternative benchmarks. We note, however, that the estimates can differ notably in terms of levels.

We estimate the transaction cost for each trade by:

$$Cost_j = ln\left(Trade\ Price_j / Benchmark\ Price_j\right) \times Trade\ Sign_j, \quad (1)$$

where $Trade\ Price_j$ refers to the transaction price for trade j, $Benchmark\ Price_j$ is the transaction price of the last trade in that bond in the interdealer market, and $Trade\ Sign_j$ is an indictor variable for trade direction. $Trade\ Sign_j$ takes the value of +1 for an investor purchase and -1 for an investor sale. We multiple $Cost_j$ by 10,000 to compute transaction cost in basis points of value. We first estimate a bond-day level *Cost* measure by averaging $Cost_j$ across trades in the same bond on the same day. We then average the bond-day level *Cost* measure across bonds to get a daily measure for market. Finally, the daily measure is averaged across days to get an annual estimate.

4.1.1. Changes in Transactions Costs over Time

We estimate these transactions costs separately for electronic trading and voice trading, with the results plotted in Figure 4. Panel A shows that transactions costs for electronic trades have fallen dramatically over our sample period for both investment-grade and high-yield bonds. Transactions costs for high-yield bonds traded electronically have dropped from approximately 35 basis points in 2010 to below 20 basis points in 2017. Similarly, investment-grade transaction costs have fallen from approximately 18 basis points to approximately 10 basis points over this period.

Transactions cost in voice trading has also fallen over this period. Panel B shows a steady decline in both investment-grade and high-yield transactions costs, with the voice trading transactions costs in high-yield now almost the same as in investment-grade trading. Comparing the two panels suggests that electronic trading is substantially cheaper than voice trading. Earlier we showed that electronic trading primarily involved smaller trade sizes, suggesting that the comparisons of trading costs between voice and electronic settings may suffer from selection bias. To address this concern, we estimated trading costs across size categories, by voice and electronic trading, and by bond type.

Figure 5 reveals a variety of results. First, transaction costs are falling across our sample period for both electronic and voice trades, and for investment-grade and high-yield issues. But the patterns of change are very different between voice and electronic settings. Whereas voice trading costs decline almost monotonically, electronic trading costs are variable and at least for high-yield block trades, almost erratic. Second, in all settings, transactions cost is highest for small trades and lowest for the largest trades. This pattern, the opposite of that found in equity markets, has traditionally been the case in bond markets, but Panels A and C show that it is disappearing in electronic trading. Indeed, trading costs in electronic markets appear to be converging to 10 basis points for investment-grade trades of all sizes and to 20 basis points for high-yield trades of all sizes. Third, electronic trading is cheaper than voice trading for both investment-grade and high-yield bonds.

4.1.2. Electronic Trading and Transaction Costs – Cross Venue Effects

The declining transaction costs for electronic trading is not surprising. With more traders adapting to new electronic mechanisms, increased competition among dealers can reduce search costs and hence result in lower transaction costs. What is intriguing here is that transaction costs for voice trading have also dropped substantially. Are these changes in transaction costs for voice trades a result of electronic trading or merely the reflection of general trends affecting bond trading? On the one hand, investors endogenously select the best mechanism for their trades (Hendershott and Madhavan (2015)). If easier trades in more liquid bonds increasingly migrate to electronic trading platforms, those that remain to execute in traditional voice trading are likely to be the difficult ones in less liquid bonds and, hence, might be expected to face larger transaction costs. This would suggest that transaction costs in voice trading would increase as more trades execute electronically. On the other hand, increasing competition from electronic trading venues can force dealers to provide more competitive prices in their voice trading. The availability of prices may also help investors to learn more about market prices, and thus lower their chances of being taken advantage of by dealers with relatively higher bargain power. In both cases, greater electronic trading should lead to lower transaction costs in voice trading.

We test for these hypothesized effects of electronic trading on the transaction costs in voice trading by estimating the following empirical model:

$$Cost_{i,t,s,d} = \alpha + \beta \times E\text{–}Share_{i,t,s,d} + \gamma \times X_{i,t} + \mu_t + \mu_s + \mu_d + \varepsilon_{i,t,s,d}. \quad (2)$$

To estimate the dependent variable $Cost_{i,t,s,d}$, we average the trade level transaction cost estimate across trades to get an average transaction cost measure for trading in the same bond (*i*), on the same day (*t*), in the same size-category (*s*), and by the same dealer (*d*). The key explanatory variable, $E\text{–}Share_{i,t,s,d}$, is the share of dealer to customer trade volume that occurs on MarketAxess, calculated at the same bond-day-trade size-dealer level as $Cost_{i,t,s,d}$. This measure captures the importance of electronic trading for a particular dealer in its trades with customers in specific bond on a given day and with the same size. $X_{i,t}$ represents a set of bond-level controls for bond *i* on day *t*, including the log of the total par amount outstanding (*Log(Outstanding Amount)*), the residual time to maturity of the bond (*Time to Maturity*), three industry dummies representing three broad industry groups (industrial, financial, and utility), and a set of dummy variables for the 21 credit ratings.

To construct our sample to estimate Model (2), we match the transaction cost measure ($Cost_{i,t,s,d}$) with the e-trading measure ($E\text{–}Share_{i,t,s,d}$), and the bond-level controls. The $Cost_{i,t,s,d}$ measure has a mean of 58 basis points, with the median being lower at 29 basis points. The $E\text{–}Share_{i,t,s,d}$ measure also has a skewed distribution. At the bond-dealer-day-trade size-trade direction level, while electronic trading on average accounts for 20% of total dealer to customer trading, the majority of the sample has no electronic trading. The median bond in our sample carries a rating of A+, has a total $800 million in total par amount standing, with 6 years till maturity. Bonds issued in the industrial and the financial industry account for 55% and 40% of our sample respectively, with the rest of the sample belonging to bonds issued in the utility industry. Appendix 2 provides more detailed information about our sample.

Model (2) is estimated with a number of fixed effects. First, we control for the general time trends in both e-trading and transaction costs by including day fixed effects (μ_t). Such time fixed effects also allow us to control for potential changes in macroeconomic conditions (e.g., market volatilities, credit risk conditions, interest rate term structures). Second, given the documented differences in transaction costs for trades with different sizes, we include trade size fixed effects (μ_s) based on the four size categories (i.e., Micro, Odd-lot, Round-lot, and Block). Lastly, we include dealer fixed effects (μ_d) to control for unobservable dealer characteristics that could also affect dealers' transaction cost and electronic trading. Standard errors are two-way clustered at the bond-day and the dealer-day levels, and the results are presented in Table (1).

Our results support the view that greater e-trading is driving transaction fees for voice trading lower. The coefficient on *E-share* is negative and highly significant, suggesting that a dealer with more e-trading with certain size in a given bond on a given day tends to offer lower transaction costs in similar voice trades in the same bond and on the same day (Column (I)). The effect is also economically meaningful. The -18.938 coefficient implies that a one-standard-deviation increase in *E-share* leads to 7 basis points deduction in transaction costs, which is about 13% of the mean transaction cost in our sample. Importantly, our finding on a dealer's transaction costs in voice trading being associated with its e-trading does not seem to be driven by the general time trends in both e-trading and transaction costs. Our results are also unlikely driven by bond, dealer, or trade characteristics as they are controlled for in the regression.

One could argue that the documented relationship between electronic trading and transaction costs in voice trading suffer from selection bias. Dealers that execute more trades electronically can also be those that trade in the most liquid bonds and, hence, provide lower transaction costs. To address this concern, we replace $X_{i,t}$, μ_t, and μ_s, with bond-day-trade size fixed effects ($\mu_{i,t,s}$). The bond-day-trade size fixed effects allow us to look within the combination of bond, day and trade size, and compare the voice trade costs offered by dealers with different electronic trading. They also allow us to control for both macro-economic factors and potential time varying influence of both bond and trade specific characteristics. Column (II) shows that the coefficient on *E-share* change little and continue to be negative and highly significant. Therefore, among dealers that trade the same bond at the same time in the same size category, those with greater electronic trading tend to provide lower voice trading transaction costs.

Given that the growth in electronic trading has been much more evident in investment-grade bonds than in high-yield bonds, we also examine how the effects of electronic trading on voice trade costs vary across rating categories. We divide our sample into an investment-grade and a high-yield subsamples based on the rating of bond *i* on day *t*, and re-estimate Model (2) on each of the subsamples. While the coefficient on *E-share* is negative and highly significant for both subsamples, it is higher for high-yield bonds than for investment-grade bonds (Columns (III) and (IV)). Therefore, although electronic trading has had limited growth in high-yield bonds, when it occurs, it has had a large impact on lower transaction costs in voice trading. Together, our results show that greater electronic trading has reduced transaction costs in voice trading. Our results are consistent with electronic trading benefitting the market by increasing dealer competition and reducing search costs. We turn in the next section to studying the potential impact that electronic trading has had on dealer behavior.

4.2. Electronic Trading and Dealer Behavior

One important advantage of RFQ electronic trading over traditional bilateral voice trading is that it allows a trader to query multiple dealers at the same time. In the current RFQ protocol, the customer initiates the trade process by giving MarketAxess a list of dealers to contact about the potential trade. Dealers can then respond with a quote, and the trader can select which dealer, if any, to trade with. Such a mechanism directly increases price-based competition among dealers, and hence can potentially explain the better prices and lower transaction costs documented in the previous section.

To capture the degree of competition among dealers in their voice trading, we take advantage of information on dealer identities included in the regulatory TRACE data and compare prices from different dealers in similar trades in the same bond and at the same time. Specifically, we first calculate for each dealer, its average prices for certain type of voice trades (i.e., trades in the same trade size category (*s*) and with the same trade direction (*B/S*)) in the same bond (*i*) and on the same day (t). We then take the difference between the highest and the lowest average prices among different dealers, and name it $PriceDiff_{i,t,s,B/S}$. A lower $PriceDiff_{i,t,s,B/S}$ suggests smaller price differences among dealers in voice trading and hence higher competition.

To study how electronic trading has affected dealer competition, we re-estimate our *E-share* measure at the same bond-day-trade size-trade direction level as $PriceDiff_{i,t,s,B/S}$. In the sample created from merging $E\text{–}Share_{i,t,s,B/S}$ with $PriceDiff_{i,t,s,B/S}$, as well as bond-level characteristics, $PriceDiff_{i,t,s,B/S}$ has a mean of 49 basis points, with the median lower at 16 basis points. Both $E\text{–}Share_{i,t,s,B/S}$ and bond characteristics exhibit similar distribution as in the sample for transaction costs. Price competition for customer buys and customer sells account for 57% and 43% of the sample respectively.

We then estimate the following model:

$$PriceDiff_{i,t,s,B/S} = \alpha + \beta \times E\text{–}Share_{i,t,s,B/S} + \gamma \times X_{i,t} + \mu_t + \mu_s + \mu_{B/S} + \varepsilon_{i,t,s,B/S}. \quad (3)$$

$X_{i,t}$ includes a set of bond-level controls for bond *i* on day *t* and is defined as in Model (2). In addition to both day fixed effects (μ_t) and trade size fixed effects (μ_s), we also control for trade direction fixed effects ($\mu_{B/S}$) as the price competition measure is estimated separately for customer buys and customer sells. Standard errors are clustered at the bond-day level.

Table 2 shows that electronic trading increases price competitions and lowers price differences across dealers in voice trading. After controlling for the influence of time trends, bond characteristics, and trade types, the coefficient on $E\text{–}Share$ is negative and highly significant. The -0.634 coefficient on $E\text{–}Share$ implies that a one-standard-deviation increase in $E\text{–}Share$ leads to 16 basis points reduction in $PriceDiff$, which is about 32% of the mean

$PriceDiff$ in our sample. Columns (III) and (IV) show that electronic trading increases dealer competition in both investment-grade and high-yield bonds. Although the effect is stronger in high-yield bonds, the overall benefit that electronic trading brings in terms of fostering dealer competition in high-yield bonds is limited by its muted growth as documented in Figure 1.

O'Hara, Wang, and Zhou (2018) find that dealers provide better execution quality to more active investors in their traditional voice trading. Since voice and electronic trade occur simultaneously, prices in the electronic venue provide information to all agents in the market, giving as it were an anchoring point in the market. In addition, as e-trading provides an opportunity for traders to source liquidity at multiple dealers at potentially better prices, it can limit dealers' ability to price discriminate among customers. The potential competition from other dealers in e-trading, therefore, can also affect the execution quality that a dealer provides in his voice trading.

To test this hypothesis, we estimate an execution quality measure in the spirit of O'Hara, Wang, and Zhou (2018). Specifically, we calculate the difference between the highest and lowest trade prices using all voice trades in the same bond (*i*), on the same day (*t*), in the same trade size category (*s*), with the same direction (*B/S*), and by the same dealer (*d*), and name it $PriceDiff_{i,t,s,B/S,d}$. Given the infrequency of bond trading, the trades used to estimate $PriceDiff_{i,t,s,B/S,d}$ are likely from different investors. Therefore, although customer identity is not provided in our data, a larger $PriceDiff_{i,t,s,B/S,d}$ is likely to be indicative of greater price discrimination among clients by the same dealer.

We then re-estimate the *E-share* measure at the same bond-day-trade size-trade direction-dealer level as $PriceDiff_{i,t,s,B/S,d}$, and estimate the following regression:

$$PriceDiff_{i,t,s,B/S,d} = \alpha + \beta \times E\text{–}Share_{B/S,i,t,s,d} + \gamma \times X_{i,t} + \mu_t + \mu_s + \mu_{B/S} + \mu_d + \varepsilon_{i,t,s,B/S,d} \quad (4).$$

If, as hypothesized, e-trading reduces dealers' bargaining power in their voice trading, we would expect a higher $E\text{–}Share$ to be associated with lower $PriceDiff$. Table 3 shows that this is indeed the case. The coefficient for $E\text{–}Share$ is negative and highly significant (Column (I)). The effect of e-trading on reducing a dealer's execution quality differences is also economically significant. We find that a one standard-deviation increase in $E\text{–}Share$ is associated with a reduction in $PriceDiff$ equivalent to 11% of its sample mean. This result is not driven by potential time trends in dealer execution quality as we have controlled for day fixed effects in the model.

We also control for potential selection bias and time-varying influence of bond and trade characteristics and macro-economic conditions by replacing $X_{i,t}$, μ_t, μ_s, and $\mu_{B/S}$ with bond-day-trade size-trade direction fixed effects ($\mu_{i,t,s,B/S}$). Column (II) shows that the results are qualitatively the same. Amongst dealers that execute similar trades (i.e., with similar size and same trade direction) in the same bond and at the same time, those with greater electronic trading tend to provide better execution quality to their customers in voice trading. The results also hold for both investment-grade and high-yield bonds.

4.3. Electronic Trading and the Inter-dealer Market

The large number of bond issues, combined with typically large order sizes, means that inventory issues have always been front and center for bond dealers. Dealers have traditionally turned to the inter-dealer market, using dealer-to-dealer trading to offset unwanted inventory imbalances arising from dealer-to-customer trades. As electronic trading facilitates the matching between buyers and sellers, it can shorten the intermediation chain of dealers and provide greater inventory control. This, in turn, may contribute to lower transaction costs in voice trading as documented earlier. We hypothesize that the growth of electronic trading reduces dealers' reliance on inter-dealer market for their inventory management.

To test this hypothesis, we first estimate the share of inter-dealer trade out of total trade ($InterDealerShare_{i,t,s,d}$). For trades executed in the same bond *i*, on the same trading day *t*, within the same size category *s*, and with the same dealer *d*, we calculate the aggregate volumes for those between a dealer and a customer, and those between two dealers. $InterDealerShare_{i,t,s,d}$ is defined as the ratio of inter-dealer volume and the total trade volume (the sum of inter-dealer volume and dealer-customer volume). We then match $InterDealerShare_{i,t,s,d}$ with $E\text{–}Share_{i,t,s,d}$ estimated at the same bond-day-trade size-dealer level and estimate the following model:

$$InterDealerShare_{i,t,s,d} = \alpha + \beta \times E\text{–}Share_{i,t,s,d} + \gamma \times X_{i,t} + \mu_t + \mu_s + \mu_d + \varepsilon_{i,t,s,d}. \quad (5)$$

The results in Table 4 strongly support our hypothesis: the greater the share of electronic trading in a given bond, the lower is the share of inter-dealer trading in that bond. The effect of electronic trading is also economically meaningful, with a one-standard-deviation increase in $E\text{–}Share$ being associated with a reduction in $InterDealerShare$ equivalent to about 12% of its mean value. Particularly important is that these results are robust to the inclusion of time fixed effects, which might have been expected to play a role given the decline in inter-dealer trading from 42% to 28% of total volume over our sample period (see Figure 6). Our results are also robust to controlling for bond-day-trade size-dealer fixed effects (Column (II)), and hold for both investment-grade and high-yield bonds (Columns (III) and (IV)). These findings underscore what might have been an unanticipated benefit to electronic trading – the ability to reduce dealer risk.

Our results highlight that electronic trading has brought benefits to both customers and dealers. Underlying this benefit is the multi-faceted role played by search costs. Electronic platforms allow customers to find dealers and allow dealers to find customers. The lower search costs, in turn, make the market more competitive for customers and less risky for dealers. The end result has been an improvement in market quality. Given these benefits, the muted growth in electronic trading to date is surprising. In the next section we investigate what factors may be limiting the electronic evolution of bond trading.

5. The Limits of Electronic Trading

As noted in the introduction, bond market microstructure has a variety of unique features including the prominent role of dealers and the dominance of institutional investors. In this section, we consider whether these features can explain the limited growth of electronic trading. We focus on three specific areas. First, we look at the effects of electronic trading on market structure, with a particular focus on whether electronic RFQ trading has elicited new entrants into bond trading. If this is the case, it suggests that the increased competitiveness in markets is due not just to lower search costs but to the addition of new dealers as well. Second, we investigate how electronic trading shapes liquidity provisions in large trades, which might be expected to suffer from dealers' reduced balanced sheet capacity caused by post-crisis regulations. Our focus here is on whether the benefits of electronic trading are shared equally across all trading clienteles. A third area of enquiry is whether the benefits of electronic trading observed in normal times also prevail around stress events. We concentrate here on liquidity after downgrades, events that are particularly important to institutional investors.

5.1 Market structure effects of electronic trading

One potential opportunity that electronic bond trading brings is to allow smaller dealers to acquire new clients via more aggressive pricing on the electronic platform. Based on Greenwich Associates' interviews with 13 of the top 20 largest U.S. corporate bond dealers and 112 U.S.-based corporate bond investors, Kevin McPartland (2015) concludes that execution quality is the most important factor for investors in selecting which dealer to trade with, and that "dealers understandably want recognition for great execution."[5]

We examine whether electronic trading provides an opportunity for some dealers, especially the smaller ones, to increase their market share.[6] We first identify the top 10 dealers that have the largest total trade volume with customers over the whole sample period 2010-2017, and name them Dealer A, B, …, J. These 10 dealers together account for 70% of the aggregate dealer-to-customer trade volume over our sample period. For each dealer, we determine its ranking in terms of market share in both voice trading and electronic trading for each year in our sample. In other markets where electronic trading has emerged, new entrants have captured market share from incumbents. We hypothesize that a similar effect should occur with the rise of electronic bond trading.

Our analysis shows that this is not the case. Electronic trading is dominated by the same dealers that intermediate most of the traditional voice trading. Six out of the ten dealers rank among the top ten dealers in both voice trading and electronic trading for each year in our sample. The other four dealers rank among the top ten dealers for about 90% of the times in voice trading, and for over 50% of the times in electronic trading. Since the exact ranking of a dealer can change

[5] See "U.S. Corporate Bonds: Investors Need Dealers, Dealers Need Incentives," a research report authored by Kevin McPartland, Head of Research for Market Structure and Technology at Greenwich Associates, and released on July 13, 2015.

[6] In addition to technology, post-crisis regulations may also increase the relative competitiveness of smaller dealers, as most of the large bond dealers are also bank dealers and hence they are subject to various banking regulations.

slightly over time, we lower the cutoff and consider a dealer as a top dealer (in either voice trading or electronic trading) for a given year if it is ranked among the top 15 dealers in that year. We find that nine out of the ten largest bond dealers rank in the top 15 dealers in both voice trading and electronic trading for each year in our sample. Our results suggest that the opportunity provided by electronic trading to increase the competitiveness of smaller dealers, if any, has been minimal.

Further reinforcing this effect, Figure 7 shows that corporate bond trading has increasingly concentrated in a smaller number of dealers. A total of 775 dealers intermediated voice trades in 2010, and that number drops to 569 in 2017 (Panel A). The market share of the top 10 dealers with the largest voice trade volume in both investment-grade and high-yield bonds increases over our sample period (Panel B). A similar pattern is observed when we examine the Herfindahl index in dealers' voice trading, calculated as the summation of the squared market share of each dealer.

Even within the electronic trading realm, there is little sign of improvement in market competitiveness. Although the number of dealers intermediating electronic trading in investment-grade bonds increases from 56 in 2010 to 67 in 2017, market concentration has not declined. Both the market share of the top 10 dealers with the largest trade volume and the Herfindahl index in dealer trading are relatively stable, and the metrics end our sample period slightly higher than at the beginning of the sample. In sum, smaller dealers do not seem to benefit much from the development of electronic trading.

We conjecture that this result may reflect features specific to the RFQ process. The RFQ requires the customer to specify the dealers to be contacted, and these dealers are those with whom the customer already has established trading relationships. Such a framework reflects the bi-lateral nature of OTC markets in which default (or settlement) risks are minimized by having such direct relationships. But this process also limits the ability of other dealers, or for that matter, other customers to participate in potential trades. A developing alternative electronic framework, termed All-To-All trading, allows such broader participation, so it remains to be seen if the growth of such alternative electronic bond trading mechanisms fosters new entrants into corporate bond trading.

5.2 Size effects

Given that the growth in electronic trading is predominantly evident in smaller sized trades, an interesting question is how the effects of e-trading on various market quality metrics in voice trading differ with trade sizes. To address this question, we divide our sample into four sub-samples: Retail, Odd-lot, Round-lot, and Block, and study the role of trade size in determining the benefits of electronic trading.

First, we re-estimate Model (2) without size fixed effects (μ_s) for each of the four sub-samples, and the results are presented in Panel A of Table 5. The coefficient on *E-Share* is negative and highly significant across all trade size categories, suggesting that electronic trading has had a pervasive effect on bond trading costs. The coefficients are substantially larger, however, for retail and odd-lot trades, consistent with these effects being stronger in the smaller sized trades. We also note that the R^2 of the regressions is much smaller for the larger trade sizes, consistent with electronic trading having a greater effect on voice trading costs in smaller sized transactions.

Second, we revisit the effects of electronic trading on the competitiveness across dealers and execution quality dealers provided to customers. Higher electronic trading leads to greater dealer competition and lower execution quality differences in all trade size categories (Panels B and C). Although there is some evidence that execution quality differences by the same dealer declines more with electronic trading in larger trades, the effects of e-trading on dealer competition in voice trading is more pronounced in smaller sized trades.

Lastly, we test the role of trade size in determining the effects of electronic trading on dealers' risk sharing in the inter-dealer markets. Larger trades impose greater inventory exposure on the dealer and these trades are not typically done in electronic venues, suggesting that the influence of electronic trading on the share of inter-dealer trading might be limited for large trades. We re-estimate Model (5) without size fixed effects (μ_s) separately for the four trade size categories with results reported in Panel D. Although we find statistically significant results that a greater share of electronic trading reduces the share of inter-dealer trading in all trade sizes, the coefficients on *E-Share* indicate that the effect is much stronger in smaller sized trades. This finding suggests that inter-dealer trading still plays an important role in off-loading inventories caused by large trades.

Given our findings that large trades remain the norm in corporate bond trading, almost all block trades execute in the voice market, and large trades are not shredded into small trades, it appears that the benefits of electronic trading have not, to date, been large enough for most institutional traders.

5.3 Stress periods

Our results so far rely on the full sample of trading days. It is not clear whether investors still benefit from electronic trading when they have an unusual demand for immediacy. Ambrose, Cai, and Helwege (2008), and Ellul, Jotikasthira, and Lundblad (2011) document fire sales by insurance firms in corporate bonds that are downgraded from investment-grade to high-yield due to higher capital requirements and other regulatory constraints that they face. As these regulationinduced fire sales generate high demand for liquidity, they provide an opportunity for us to study the robustness of liquidity provided through electronic trading.

For our sample period from 2010 to 2017, we obtain data on each corporate bond's rating history from the Mergent Fixed Income Securities Database (FISD). These data provide the timing of all rating actions by the three largest rating agencies: Standard & Poor's (S&P), Moody's and Fitch. Following Elluel, Jotikasthira and Lundblad (2011), we use the date when a bond is downgraded from investment-grade to speculative grade by the first acting rating agency to identify a period with potential high demand for liquidity. Out of our sample bonds, 509 experience a rating downgrade to junk during the sample period.

Bao, O'Hara and Zhou (2018) show that trade volume spikes right after downgrade by the first acting rating agency, and it remains elevated for roughly a month. We therefore focus on studying trading during the one-month window following each rating downgrade. We consider the rating downgrade date as day +1, and define the period from day +1 to day +30 as the *Downgrade* period. To understand how liquidity provided through electronic trading change following stress events, we also study the periods when demand for liquidity is likely to be at normal levels. We start by comparing the *Downgrade* period with a *pre-Downgrade* period, defined as a period that ends three months prior to the rating action ([-180, -90]). As rating actions tend to lag changes in issuers' default risk, informative trading can occur even prior to the actual downgrade (e.g., Pinches and Singleton (1978)). Because such trading can potentially increase the demand for liquidity, we exclude the three-months right before each rating downgrade to focus on a period when liquidity conditions for the bond is likely to be normal. Panel A of Table 6 shows that electronic trading declines during periods with high demand for immediacy. Compared to the *pre-Downgrade* period, trading that occurs electronically is lower during the *Downgrade* period. The share of electronic trades out of total dealer to customer trades declines by 34% in terms of total number of trades and such change is also statistically significant. The drop in terms of total trade volume is slightly smaller, but is still over 31% and is highly significant.

One potential concern on using *pre-Downgrade* period as a benchmark is that the same downgraded bond carries different ratings between the *pre-Downgrade* and the *Downgrade* periods. The documented drop in electronic trading therefore can simply reflect limited electronic trading in high-yield bonds. To mitigate this concern, we develop two alternative approaches to design the benchmark. First, we compare the *Downgrade* period with a *post-Downgrade* period, which starts three months after the rating downgrade (i.e., [+90, +180]). We exclude the three months after rating downgrades as selling pressure caused by the rating action can last several months longer (Elluel, Jotikasthira and Lundblad (2011)). Panel B shows that electronic trading rebounds when we move from the *Downgrade* period to the *pre-Downgrade* period. The share of electronic trades out of total dealer to customer trades increases by 24% and 17% in terms of volume and number of trades respectively. This finding alleviates the concern that the decreased electronic trading during the *Downgrade* period is simply capturing the differential growth of electronic trading in investment-grade and high-yield bonds.

To better control for the pattern of electronic trading across different credit ratings, we compare each downgraded bond with a control group of similar bonds during the same *Downgrade* period for the downgraded bond. A bond is included into the control group if it has the same credit rating, similar time to maturity, issued in the same industry, and similar par amount outstanding as the downgrade bond.[7] For bonds with each control group, we first calculate the average share

[7] We use 5-year and 10-year as the two cutoffs to define short-term, medium-term, and long-term bonds. A bond is considered to have similar time to maturity as the downgraded bond if both of them belong to the same maturity group. To be included into the control group, a bond's total amount outstanding can not exceed that of the downgraded bond by 20%.

of electronic trading out of total dealer to customer trade, and then compare it with the downgraded bond. Using this approach, we are able to identify control bonds for a total of 498 downgraded bonds. Panel C shows that even compared to control bonds, electronic trading in downgraded bonds are substantially lower. The share of electronic trading in downgraded bonds is about 39% lower in volume, and about 22% lower in number of trades than that in control bonds. Together, our results suggest that when the demand for immediate trading in large sizes increases from some institutional investors, sourcing liquidity on electronic trading platforms can be challenging.

To understand how electronic trading affects transaction costs during stress times, we estimate the following regression for the downgrade bonds during the *Downgrade* period:

$$Cost_{i,t,s,d} = \alpha + \beta \times E\text{–}Share_{i,t,s,d} + \mu_{i,t,s} + \mu_d + \varepsilon_{i,t,s,d}, \quad (5)$$

where both $Cost_{i,t,s,d}$ and $E\text{–}Share_{i,t,s,d}$ are as defined in Model (2). The model is estimated with both bond-day-trade size fixed effects and dealer fixed effects and standard errors are double clustered at the bond-day and the dealer-deal levels.

Column (I) of Table 7 shows that the benefits of electronic trading in reducing transaction costs for customers disappear around stress times. The coefficient for *E-Share* is not significant at any conventional level. Interestingly, when we re-estimate Model (5) for the bonds in both *pre-Downgrade* and *post-Downgrade* periods, as well as bonds in the control group at the same *Downgrade* period, the coefficient for *E-Share* is negative and highly significant (see Columns (II)-(IV)). These results show that the benefits to electronic RFQ trading are not robust to stress periods of decreased liquidity. In such market conditions, orders gravitate to less transparent voice trading– a movement consistent with traders relying more on dealer relationships rather than on electronic transactional trading to source liquidity. When everyone is trying to find liquidity on the same side of the market, the optional (and transparent) nature of RFQ trading is not well-suited for the needs of large institutional orders.

These market structure, size effects, and stress period results provide some compelling reasons why electronic trading has not yet attained the dominance found in other asset classes. The empirical evidence also points to another, perhaps more fundamental limitation - the risks of informed trading. We found that electronic trading is primarily concentrated in small orders sizes in investment-grade bonds during normal market trading conditions. This pattern is consistent with a lower risk of informed trading. Because dealers take on inventory risks, their willingness to transact in electronic venues is much lower when this informed trading risk is perceived to be high. Such informed trading risk may explain why high-yield bonds (whose price behavior is often viewed as more "equity-like"), very large trades, or trades in unbalanced markets have found limited success in electronic bond trading.

6. **Conclusion**

Technology has brought greater efficiency and competition to trading, and corporate bond markets are no exception. We have shown in this paper that electronic bond trading has lowered transaction costs, reduced execution quality differences, enhanced dealers' ability to bear inventory risk, and diminished the inter-dealer trading market. What is also clear, however, is that bond markets are different from other asset classes, and these differences have impeded the dominance of electronic trading so typical of other markets. Dealers continue to play a crucial role in corporate bond trading, with electronic trading as it is currently designed so far serving to support rather than supplant this market structure.

This may change going forward with the advent of new trading platforms such as all-to-all trading which could allow new entrants to gain a foothold in customer-to-customer trading. We conjecture, however, that the impediments identified in this research will continue to play a role in these electronic venues, suggesting that bonds may prove different than other asset classes when it comes to electronic trading. We hope to investigate these issues in future research.

References

Ambrose, B. W., Cai, N. K., Helwege, J., 2008. Forced selling of fallen angels. *Journal of Fixed Income* 18, 72–85.

Bao, J., O'Hara, M., Zhou, X., 2018. The Volcker rule and corporate bond market making in times of stress, *Journal of Financial Economics* 130, 95–113.

Bias, B., DeClerck, F., 2013. Liquidity, competition, and price discovery in the European corporate bond market. Unpublished working paper, Toulouse School of Economics.

Bessembinder, H., Jacobsen, S., Maxwell, W., Venkataraman, K., 2018. Capital commitment and illiquidity in corporate bonds. *Journal of Finance* 73, 1615–1661.

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

Brogaard, J., Hagstromer, B., Norden, L., Riordan, R., 2015. Trading fast and slow: colocation and liquidity. *Review of Financial Studies* 28, 3407–3443.

Brogaard, J., Hendershott, T., Hunt, S., Ysusi, C., 2014. High-frequency trading and the execution costs of institutional investors. *Financial Review* 49, 345–369.

Dick-Nielsen, J., Feldhutter, P., Lando, D., 2012. Corporate bond liquidity before and after the onset of the subprime crisis. *Journal of Financial Economics* 103, 471–492.

DiMaggio, M., Kermani, A., Song, Z., 2017. The value of trading relationships in turbulent times. *Journal of Financial Economics* 124, 266–284.

Duffie, D., Dworczak, P., Zhu, H., 2017. Benchmarks in Search Models. *Journal of Finance* 72, 1983–2044.

Duffie, D., Garleanu, N., Pedersen, L., 2005. Over-the-counter markets. *Econometrica* 73, 1817–1845.

Duffie, D., Garleanu, N., Pedersen, L., 2007. Valuation in over-the-counter markets. *Review of Financial Studies* 20, 1865–1900.

Easley, D., Hendershott, T., Ramadorai, T., 2014. Levelling the trading field. Journal of Financial Markets 17, 65–93.

Edwards, A., Harris, L., Piwowar, M., 2007. Corporate bond market transparency and transactions costs. *Journal of Finance* 62, 1421–1452.

Ellul, A., Jotikasthira, C., Lundblad, C., 2011. Regulatory pressure and fire sales in the corporate bond market. *Journal of Financial Economics* 101, 596–620.

Feldhutter, P., 2012. The same bond at different prices: identifying search frictions and selling pressures. *Review of Financial Studies* 25, 1155–1206.

Flanagan, T., Kedia, S., Zhou, X., 2019. Secondary market liquidity and primary market allocations in corporate bonds. Unpublished working paper.

Goldstein, M., Hotchkiss, E., 2007. Dealer behavior and the pricing of newly issued corporate bonds. Unpublished working paper. Babson College and Boston College.

Hendershott, T., Li, D., Livdan, D., Schurhoff, N., 2017. Relationship trading in OTC markets. Unpublished working paper.

Hendershott, T., Madhavan, A., 2015. Click or call? Auction versus search in the Over-the-Counter market. *Journal of Finance* 70, 419–447.

O'Hara, M., Wang, Y., Zhou, X., 2018. The execution quality of corporate bonds. *Journal of Financial Economics* 130, 308 – 326.

Pinches, G., Singleton, J., 1978. The adjustment of stock prices to bond rating changes. *Journal of Finance* 33, 29–44.

Schultz, P., 2001. Corporate bond trading costs: a peek behind the curtain. *Journal of Finance* 33, 1133–1151.

Uslu, S., 2019. Pricing and liquidity in decentralized asset markets, *Econometrica, forthcoming*.

Table 1. Electronic trading and transaction cost for voice trades

This table reports results from estimating Model (2). To estimate the dependent variable $Cost_{i,t,s,d}$, we first calculate the transaction cost for each voice trade as in Hendershott and Madhavan (2015). We then average the estimate across trades executed in the same bond *i*, on the same trading day *t*, within the same size category s, and with the same dealer d. *E-share* is the share of dealer-customer trade volume that occurs on MarketAxess. It is calculated at the same bond-dealer-day-trade size level as $Cost_{i,t,s,d}$. $X_{i,t}$ represents a set of bond-level controls including the log of the total par amount outstanding (*Log(Outstanding Amount)*), the residual time to maturity of the bond (*Time to Maturity*), three industry dummies representing three broad industry groups (industrial, financial, and utility), and a set of dummy variables for the 21 credit ratings, for bond *i* on day *t*. In Column I, we include μ_t, μ_s, and μ_d, which represent day fixed effects, trade size fixed effects, and dealer fixed effects, respectively. In Columns II-IV, $X_{i,t}$, μ_t and μ_s are replaced by $\mu_{i,t,s}$, which represents bond-day-trade size fixed effects. Columns I provides results from using the full sample. Column II is based on a matched sample with transaction cost estimates from at least two dealers in the same bond, on the same day, and for the same trade size category. Columns III and IV show results for the sub-samples of investment-grade and high-yield bonds respectively. Standard errors are double clustered at the dealer-day and the bond-day levels.

	I	**II**	**III**	**IV**
	Full Sample	**Matched Sample**	**Investment-grade**	**High-yield**
E-Share	-18.938***	-17.499***	-13.347***	-29.356***
	(-3.58)	(-4.18)	(-4.12)	(-4.35)
Log(Amount out)	-2.906***			
	(-3.88)			
Time to Maturity	1.802***			
	-7.88			
Credit Rating FE	Yes	No	No	No
Industry FE	Yes	No	No	No
Size FE	Yes	No	No	No
Day FE	Yes	No	No	No
Dealer FE	Yes	Yes	Yes	Yes
Bond-Day-Size FE	Yes	Yes	Yes	Yes
Observations	14,774,258	9,726,101	6,906,160	2,819,941
R^2	0.31	0.6	0.65	0.56

Table 2. Electronic trading and dealer competition in voice trading

This table reports results from estimating Model (3). To estimate the dependent variable, $PriceDiff_{B/S,i,t,s}$. we first calculate the average trade price for each dealer *d*, using trades in the same bond *i*, on the same trading day *t*, within the same size category *s*, and with the same trade direction (i.e., whether the investor is buying (B) or selling (S) from the dealer). We then calculate the difference between the highest and the lowest average prices across dealers to get $PriceDiff_{B/S,i,t,s}$. *E-share* is the share of dealer-customer trade volume that occurs on MarketAxess. It is calculated at the same bond-day-trade size-trade direction level as $PriceDiff_{i,t,s,B/S}$. $X_{i,t}$ represents a set of bond-level controls including the log of the total par amount outstanding (*Log(Outstanding Amount)*), the residual time to maturity of the bond (*Time to Maturity*), three industry dummies representing three broad industry groups (industrial, financial, and utility), and a set of dummy variables for the 21 credit ratings, for bond *i* on day *t*. μ_t, μ_s, and $\mu_{B/S}$, day fixed effects, trade size fixed effects, dealer fixed effects, and trade direction fixed effects, respectively. Columns I provides results from using the full sample, while Columns II and III show results for the sub-samples of investment-grade and high-yield bonds respectively. Standard errors are clustered at the bond-day level.

	I Full Sample	II Investment-grade	III High-yield
E-Share	-0.634***	-0.600***	-0.809***
	(-104.53)	(-89.58)	(-83.41)
Log(Amount out)	0.081***	0.082***	0.075***
	(31.89)	(29.07)	(14.27)
Time to Maturity	0.008***	0.009***	0.004***
	(12.95)	(15.06)	(3.53)
Credit Rating FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Size FE	Yes	Yes	Yes
Direction FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Observations	4,934,180	3,514,511	1,419,669
R^2	0.18	0.19	0.17

Table 3. Electronic trading and execution quality in voice trading

This table reports results from estimating Model (4). The dependent variable, $PriceDiff_{i,t,s,B/S,d}$, is defined as the difference between the highest price and the lowest price across trades executed in the same bond *i*, on the same trading day *t*, within the same size category *s*, with the same trade direction (i.e., whether the investor is buying (B) or selling (S)), and with the same dealer *d*. *E-share* is the share of dealer-customer trade volume that occurs on MarketAxess. It is calculated at the same bond-day- trade size-trade direction-level as $PriceDiff_{i,t,s,B/S,d}$. $X_{i,t}$ represents a set of bond-level controls including the log of the total par amount outstanding (*Log(Outstanding Amount)*), the residual time to maturity of the bond (*Time to Maturity*), three industry dummies representing three broad industry groups (industrial, financial, and utility), and a set of dummy variables for the 21 credit ratings, for bond *i* on day *t*. In Column I, we include μ_t, μ_s, $\mu_{B/S}$, and μ_d, which represent day fixed effects, trade size fixed effects, trade direction fixed effects, and dealer fixed effects, respectively. In Columns II-IV, $X_{i,t}$, μ_t, μ_s, and $\mu_{B/S}$ are replaced by $\mu_{i,t,s,B/S}$, which represents bond-day-trade size-trade direction fixed effects. Columns I provides results from using the full sample. Column II is based on a matched sample with $PriceDiff$ estimates from at least two dealers trading in the same bond, on the same day, in the same trade size category, and with the same trade direction. Columns III and IV show results for the sub-samples of investment-grade and high-yield bonds respectively. Standard errors are double clustered at the dealer-day and the bond-day levels.

	I Full Sample	II Matched Sample	III Investment-grade	IV High-yield
E-Share	-0.227***	-0.192***	-0.178***	-0.269***
	(-12.21)	(-9.60)	(-9.28)	(-7.70)
Log(Amount out)	0.022***			
	(4.25)			
Time to Maturity	0.004***			
	(4.47)			
Credit Rating FE	Yes	No	No	No
Industry FE	Yes	No	No	No
Size FE	Yes	No	No	No
Direction FE	Yes	No	No	No
Day FE	Yes	No	No	No
Dealer FE	Yes	Yes	Yes	Yes
Bond-Day-Size-Direction FE	No	Yes	Yes	Yes
Observations	2,810,900	981,575	637,272	344,303
R^2	0.12	0.47	0.47	0.47

Table 4. Electronic trading and inter-dealer trading

This table reports results from estimating Model (5). The dependent variable is the share of inter-dealer trade out of total trade, calculated at the bond-dealer-day-trade size level ($InderDealerShare_{i,t,s,d}$). For trades executed in the same bond *i*, on the same trading day *t*, within the same size category *s*, and with the same dealer, we calculate the aggregate volumes for those between a dealer and a customer, and those between two dealers. $InterDealerShare_{i,t,s,d}$ is defined as the ratio of inter-dealer volume and the total trade volume (the sum of inter-dealer volume and dealer-customer volume). *E-share* is the share of dealer-customer trade volume that occurs on MarketAxess. It is calculated at the same bond-dealer-day-trade size level as $InderDealerShare_{i,t,s,d}$. $X_{i,t}$ represents a set of bond-level controls including the log of the total par amount outstanding (*Log(Outstanding Amount)*), the residual time to maturity of the bond (*Time to Maturity*), three industry dummies representing three broad industry groups (industrial, financial, and utility), and a set of dummy variables for the 21 credit ratings, for bond *i* on day *t*. In Column I, we include μ_t, μ_s, and μ_d, which represent day fixed effects, trade size fixed effects, and dealer fixed effects, respectively. In Columns II-IV, $X_{i,t}$, μ_t and μ_s are replaced by $\mu_{i,t,s}$, which represents bond-day-trade size fixed effects. Columns I provides results from using the full sample. Column II is based on a matched sample with $InterDealerShare$ estimates from at least two dealers in the same bond, on the same day, and for the same trade size category. Columns III and IV show results for the sub-samples of investment-grade and high-yield bonds respectively. Standard errors are double clustered at the dealer-day and the bond-day levels.

	I **Full Sample**	**II** **Matched Sample**	**III** **Investment-grade**	**IV** **High-yield**
E-Share	-0.061***	-0.058***	-0.061***	-0.038**
	(-3.87)	(-4.68)	(-4.98)	(-2.31)
Log(Outstanding Amount)	0.010***			
	(4.16)			
Time to Maturity	-0.000**			
	(-2.43)			
Credit Rating FE	Yes	No	No	No
Industry FE	Yes	No	No	No
Size FE	Yes	No	No	No
Day FE	Yes	No	No	No
Dealer FE	Yes	Yes	Yes	Yes
Bond-Day-Size FE	No	Yes	Yes	Yes
Observations	22,779,777	14,444,377	10,752,445	3,691,932
R^2	0.38	0.58	0.57	0.6

Table 5. The effects of electronic trading across trade size categories

This table reports how the effects of electronic trading vary across trade size groups. In Panel A, the dependent variable is the bond-day-trade size-dealer level transaction cost measure ($Cost_{i,t,s,d}$). In Panel B, the dependent variable is the measure of price difference across dealers for voice trading, estimated at bond-day-trade size-trade direction level ($PriceDiff_{i,t,s,B/S}$). In Panel C, the dependent variable is the measure of execution quality for voice trading, estimated at the bond-day-trade size-trade direction-dealer level ($PriceDiff_{i,t,s,B/S,d}$). In Panel D, the dependent variable is the share of inter-dealer trading measured at the bond-dealer-trade size-day level ($InterDealerShare_{i,t,s,d}$).

Panel A: Transaction Costs

	I **Retail**	II **Odd-lot**	III **Round-lot**	IV **Block**
E-Share	-9.767***	-8.837***	-7.022***	-6.628***
	(-2.65)	(-5.80)	(-5.42)	(-3.43)
Dealer FE	Yes	Yes	Yes	Yes
Bond-Day FE	Yes	Yes	Yes	Yes
Observations	7,779,149	942,231	866,193	138,528
R^2	0.61	0.55	0.41	0.48

Panel B: Dealer Competition

	I **Retail**	II **Odd-lot**	III **Round-lot**	IV **Block**
E-Share	-0.697***	-0.462***	-0.353***	-0.209***
	(-99.15)	(-80.86)	(-54.55)	(-32.36)
Controls	Yes	Yes	Yes	Yes
Trade Direction FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Observations	3,491,958	722,497	615,684	104,041
R^2	0.13	0.14	0.1	0.14

Panel C: Execution Quality

	I **Retail**	II **Odd-lot**	III **Round-lot**	IV **Block**
E-Share	-0.146***	-0.234***	-0.415***	-0.334***
	(-7.53)	(-15.57)	(-19.85)	(-8.19)
Dealer FE	Yes	Yes	Yes	Yes
Bond-Day-Trade Direction FE	Yes	Yes	Yes	Yes
Observations	883,410	22,599	71,575	3,991
R^2	0.46	0.57	0.61	0.64

Panel D: Inter-dealer trading

	I **Retail**	II **Odd-lot**	III **Round-lot**	IV **Block**
E-Share	-0.057***	-0.046***	-0.029***	-0.021***
	(-3.86)	(-4.99)	(-5.66)	(-7.36)
Dealer FE	Yes	Yes	Yes	Yes
Bond-Day FE	Yes	Yes	Yes	Yes
Observations	10,563,258	2,323,578	1,381,168	176,373
R^2	0.53	0.65	0.63	0.73

Table 6. Electronic trading around rating downgrades from investment-grade to high-yield

This table studies electronic trading during the one-month after a bond is downgraded from investment-grade to high-yield. Day +1 is the day when rating action happens. Panel A compares electronic trading during the one-month post downgrade period ([+1, +30]) with that in the same bond during a three-month period before rating downgrade ([-90, -1]). Panel B compares electronic trading during the one-month post downgrade period ([+1, +30]) with that in the same bond during a three-month period after rating downgrade ([+31, +120]). Panel C compares electronic trading during the one-month post downgrade period ([+1, +30]) in a downgraded bond with that in a control group of bonds during the same time period. For each downgraded bonds, we identify a control group of bonds that have the same credit rating, similar time to maturity, same industry classification, and similar par amount outstanding as the downgraded bonds. *N* refers to the number of matched bonds. *E-share in volume* (*E-share in number of trades*) refers to the percentage of dealer to customer trade volume (number of trades) that occurs on MarketAxess.

Panel A. Comparing with e-trading in the same bonds before rating downgrade

				Test on Difference	
	N	Downgraded Bonds over [+1,+30]	Downgraded Bonds over [-90,-60]	Difference	p-value
E-share in volume (%)	490	7.92	11.52	-3.60	0.00
E-share in number of trades (%)	490	8.68	13.17	-4.49	0.00

Panel B. Comparing with e-trading in the same bonds after rating downgrade

				Test on Difference	
	N	Downgraded Bonds over [+1,+30]	Downgraded Bonds over [+90,+120]	Difference	p-value
E-share in volume (%)	474	7.34	9.11	-1.77	0.03
E-share in number of trades (%)	474	8.66	10.10	-1.44	0.00

Panel C. Comparing with e-trading in similar bonds at the same time

				Test on Difference	
	N	Downgraded Bonds over [+1, +30]	Control Bonds over [+1,+30]	Difference	p-value
E-share in volume (%)	498	7.64	9.76	-2.12	0.00
E-share in number of trades (%)	498	8.61	14.11	-5.50	0.00

Table 7. Electronic trading and transaction cost for voice trades around rating downgrade

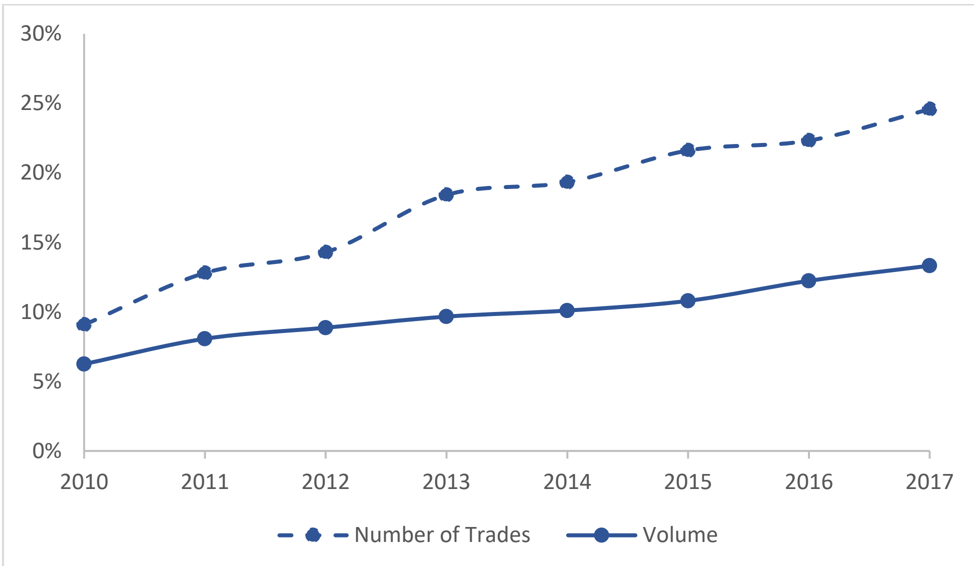
This table report results from estimating Model (5) for bonds downgraded from investment-grade to high-yield, as well as those in normal periods. To estimate the dependent variable $Cost_{i,t,s,d}$, we first calculate the transaction cost for each voice trade as in Hendershott and Madhavan (2015). We then average the estimate across trades executed in the same bond *i*, on the same trading day *t*, within the same size category *s*, and with the same dealer *d*. *E-share* is the share of dealer-customer trade volume that occurs on MarketAxess. It is calculated at the same bond-dealer-day-trade size level as $Cost_{i,t,s,d}$. All regressions are estimated with both dealer fixed effects and bond-day-trade size fixed effects. Standard errors are double clustered at the dealer-day and the bond-day levels. Column I uses all observations for downgraded bonds during the one-month after rating downgraded ([+1,+30]). Columns II and III are based on observations for the downgrade bonds during a three-month period before and after rating downgrade respectively (i.e., [-180,-90] and [+90,+180]). Column IV includes observations in bonds with similar characteristics (i.e, rating, time to maturity, amount outstanding and industry classification) as the downgrade bonds during the same one-month period.

	I	**II**	**III**	**IV**
	Downgraded Bonds over [+1,+30]	**Downgraded Bonds over [-180,-90]**	**Downgraded Bonds over [+90,+180]**	**Control Bonds over [+1,+30]**
E-Share	-15.759	-40.464***	-31.012**	-28.804**
	(-1.14)	(-3.85)	(-2.41)	(-2.26)
Dealer FE	Yes	Yes	Yes	Yes
Bond-Day-Size FE	Yes	Yes	Yes	Yes
Observations	20,063	58,869	59,484	219,523
R^2	0.44	0.65	0.58	0.71

Figure 1. Growth of electronic trading in the corporate bond markets

A presents the annual average daily share of dealer to customer trades that are executed on MarketAxess, both in terms of number of trades and total par amount traded. Panel B presents the share of electronic trading in total volume separately for investment-grade and high-yield bonds.

Panel A. Share of electronic trading over 2010-2017



Panel B. Share of electronic trading in volume over 2010-2017: investment-grade vs. high-yield

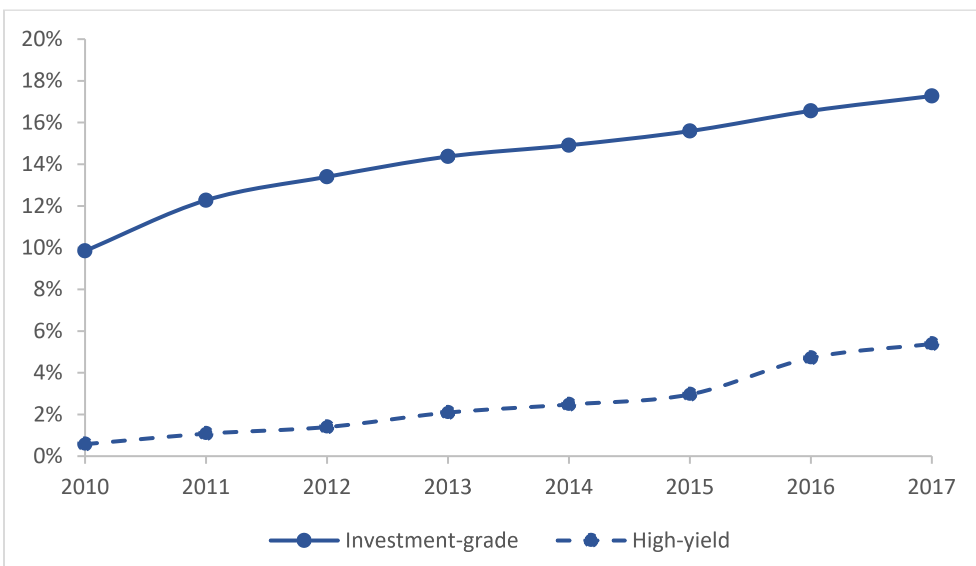
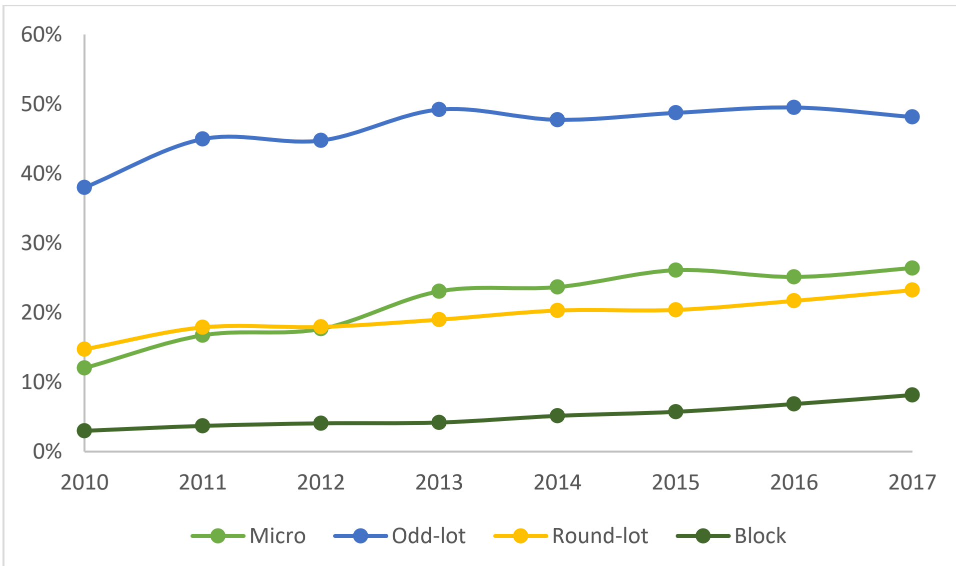


Figure 2. Share of electronic trading across trade size categories

This figure presents the share of electronic trade volume out of total trade volume for trades with different sizes. Trades are classified into four size categories based on their par amount: 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). Panels A and B present the annual average daily share of electronic trading in each of the four size categories separately for investment-grade and high-yield bonds.

Panel A. Investment-grade bonds



Panel B. High-yield bonds

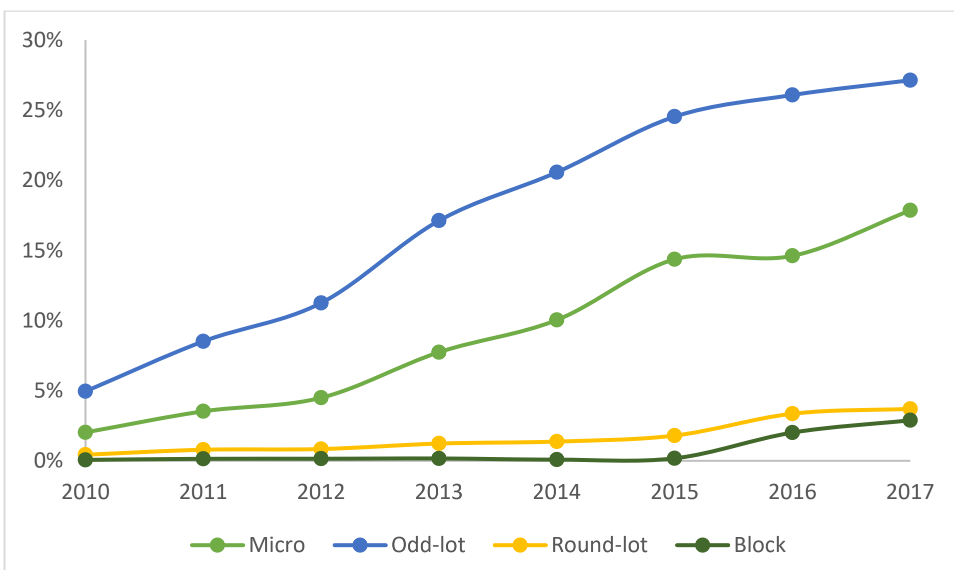
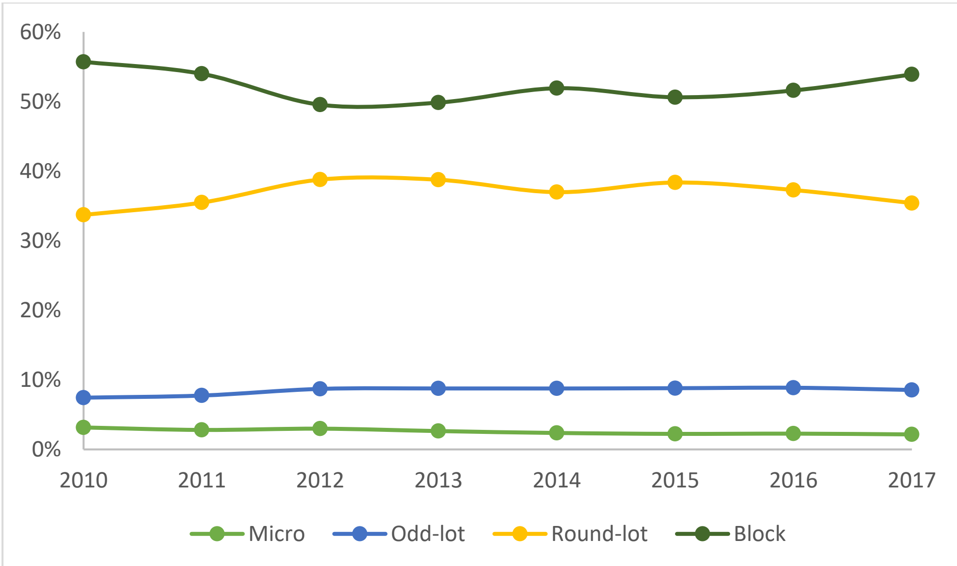


Figure 3. Distribution of bond trades across size categories

This figure shows how corporate bond trades are distributed across different size categories. Trades are classified into four size categories based on their par amount: 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). Panels A and B present the annual average daily share of volume in each of the four size categories separately for investment-grade and high-yield bonds.

Panel A. Invest-grade bonds



Panel B. High-yield bonds

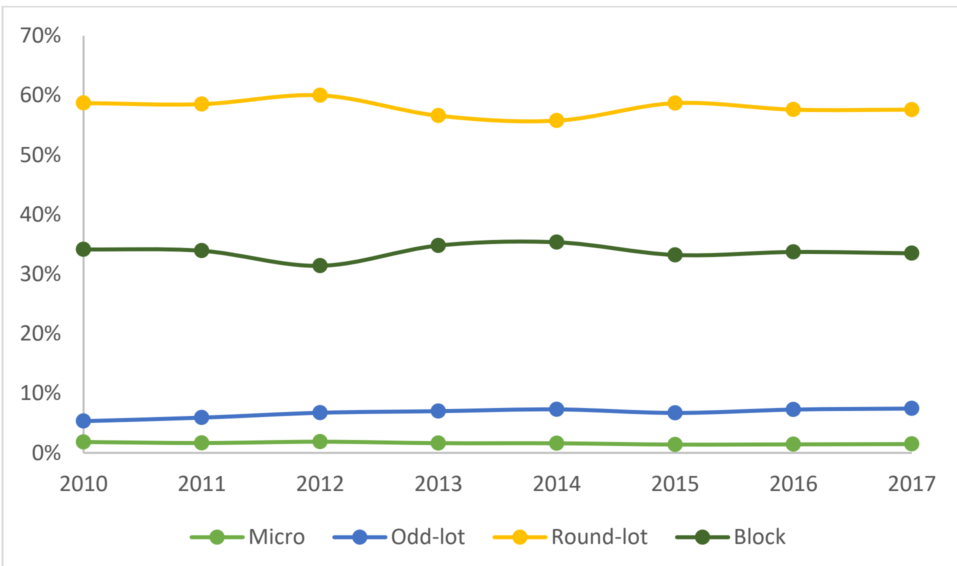


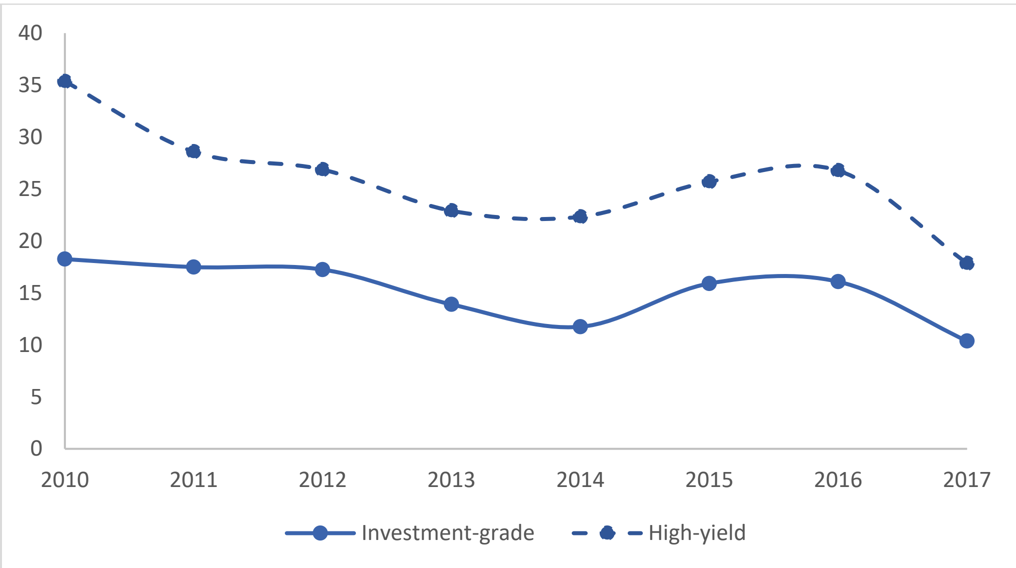
Figure 4. Transaction costs in electronic trading and voice trading

This figure presents the annual average transaction cost separately for electronic trades (Panel A) and voice trades (Panel B). Transaction cost is estimated for each trade as in Hendershott and Madhavan (2015):

$$Cost_j = ln(Trade\ Price_j / Benchmark\ Price_j) \times Trade\ Sign_j,$$

where $Trade\ Price_j$ refers to the transaction price for trade j, $Benchmark\ Price_j$ is the transaction price of the last trade in that bond in the interdealer market, and $Trade\ Sign_j$ is an indictor variable for trade direction. $Trade\ Sign_j$ takes the value of +1 for an investor purchase and -1 for an investor sale. We multiple $Cost_j$ by 10,000 to compute transaction cost in basis points of value. We first estimate a bond-day level *Cost* measure by averaging $Cost_j$ across trades in the same bond on the same day. We then average the bond-day level *Cost* measure across bonds to get a daily measure for market. Finally, the daily measure is averaged across days to get an annual estimate, which is plotted in the figure.

Panel A. Transaction costs in electronic trading



Panel B. Transaction costs in voice trading

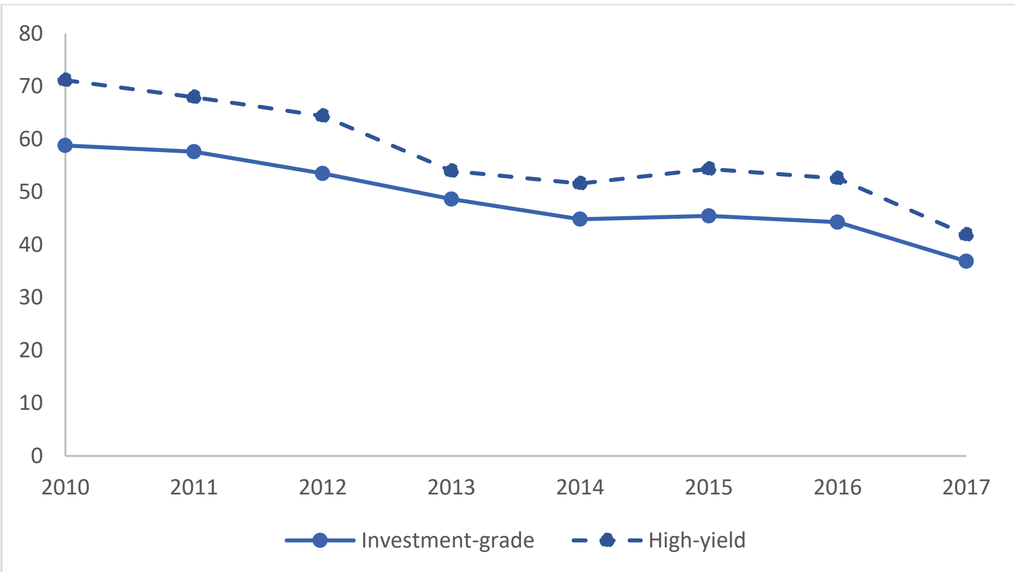


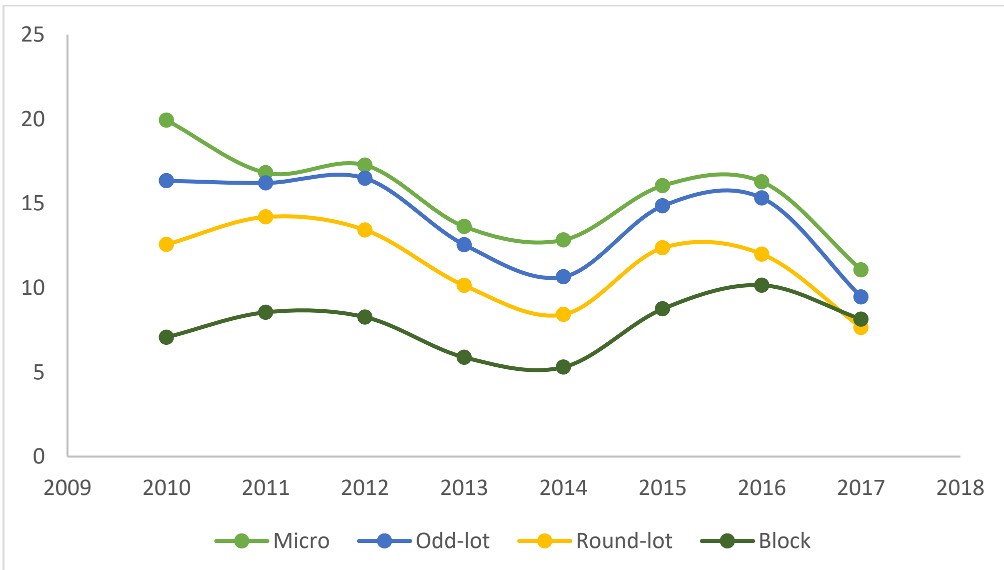
Figure 5. Transaction cost across size categories

This figure presents the annual average transaction cost for both electronic and voice trades with different sizes. Transaction cost is estimated for each trade as in Hendershott and Madhavan (2015):

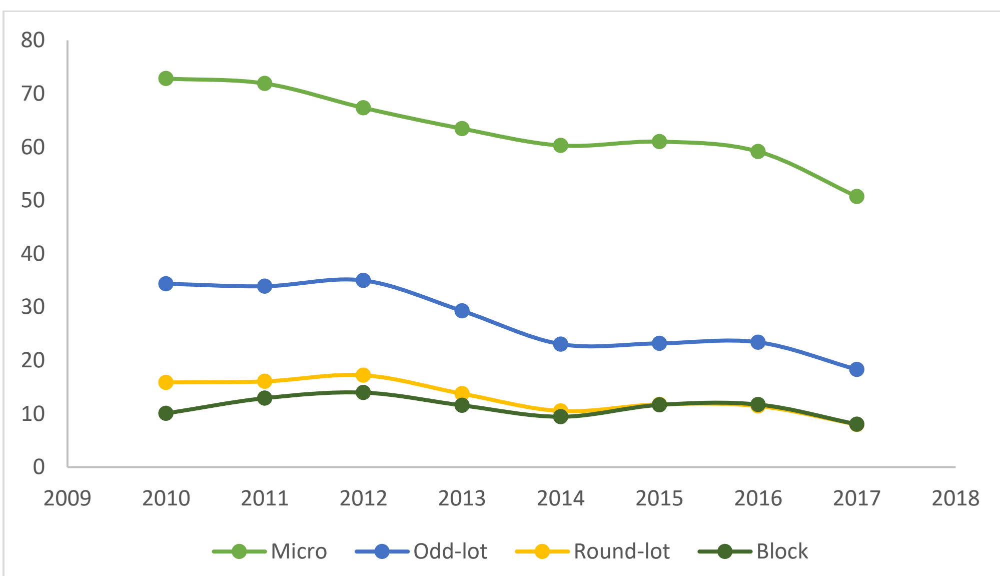
$$Cost_j = ln(Trade\ Price_j / Benchmark\ Price_j) \times Trade\ Sign_j,$$

where $Trade\ Price_j$ refers to the transaction price for trade j, $Benchmark\ Price_j$ is the transaction price of the last trade in that bond in the interdealer market, and $Trade\ Sign_j$ is an indictor variable for trade direction. $Trade\ Sign_j$ takes the value of +1 for an investor purchase and -1 for an investor sale. We multiple $Cost_j$ by 10,000 to compute transaction cost in basis points of value. We first estimate a bond-day-trade size level *Cost* measure by averaging $Cost_j$ across trades in the same bond on the same day and within the same trade size category. We then average the measure across bonds to get a daily measure for each size category. Finally, the daily measure is averaged across days to get an annual estimate for each size category, which is plotted in the figure.

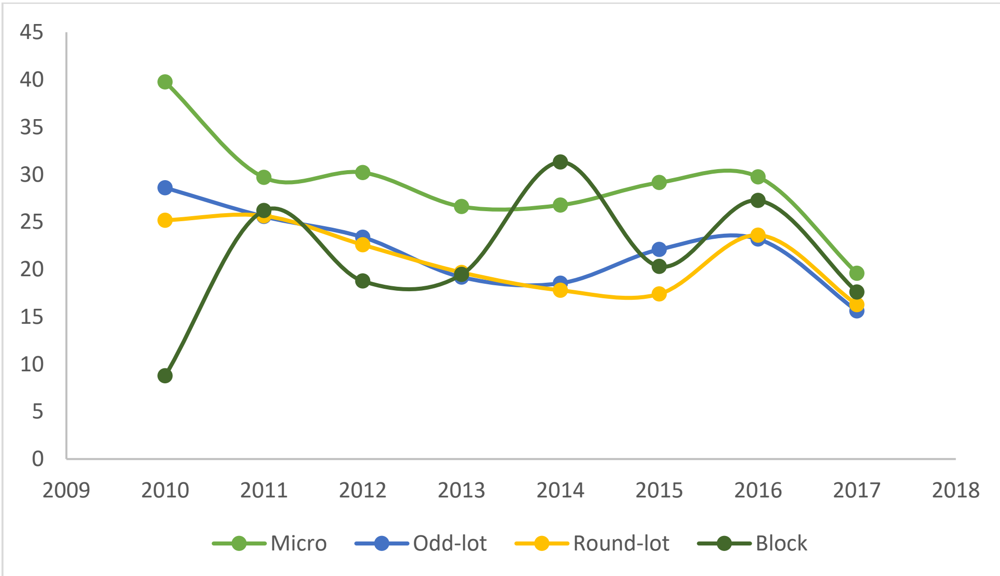
Panel A. Electronic trades in investment-grade bonds



Panel B. Voice trades in investment-grade bonds



Panel C. Electronic trades in high-yield bonds



Panel D. Voice trades in high-yield bonds

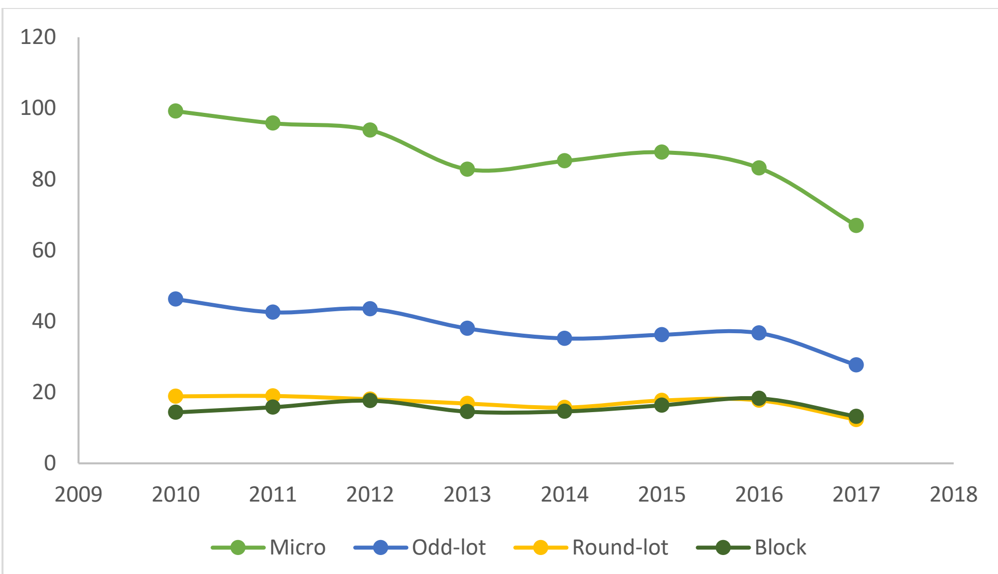


Figure 6. Inter-dealer trading in the corporate bond markets

This figure plots annual average daily share of inter-dealer trade volume out of total market volume (i.e., the summation of inter-dealer and dealer-customer trade volume) for all bonds, as well as for investment-grades and high-yield bonds separately.

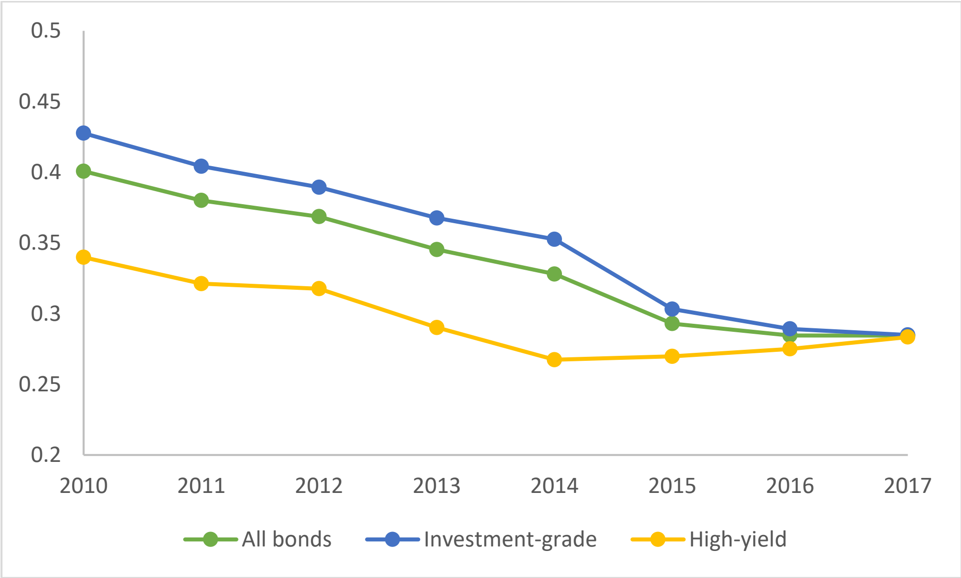
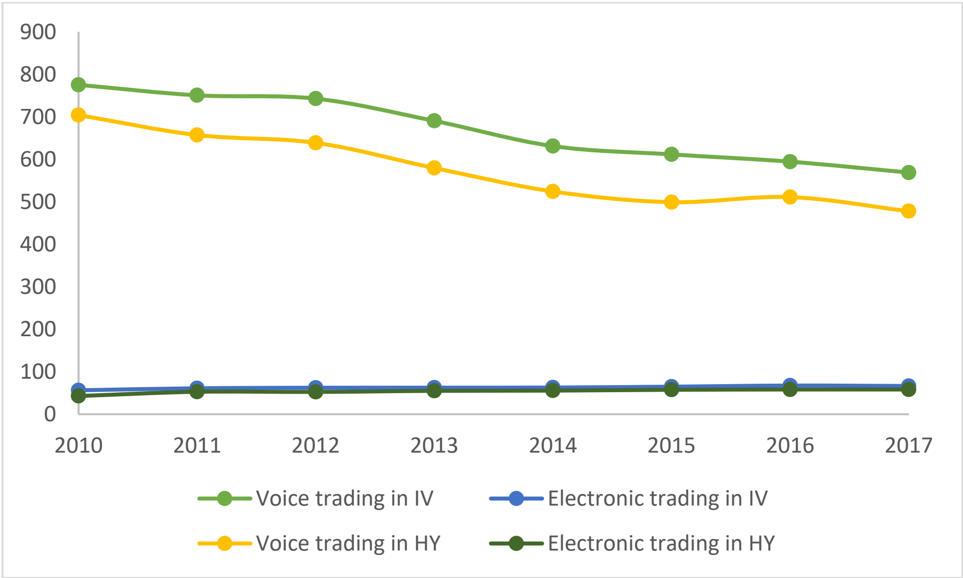


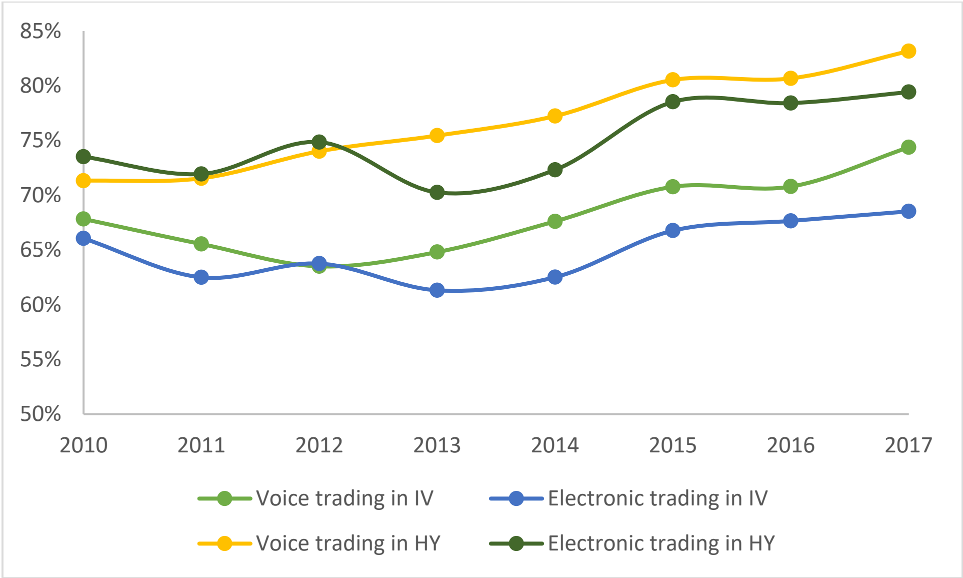
Figure 7. Market Concentration

This figure presents measures of market concentration for electronic trading and voice trading in investment-grade (IV) and high-yield (HY) bonds. Panel A shows the annual market share of the top 10 dealers. Panel B shows the annual average daily Herf index. Panel C shows the annual total number of active dealers.

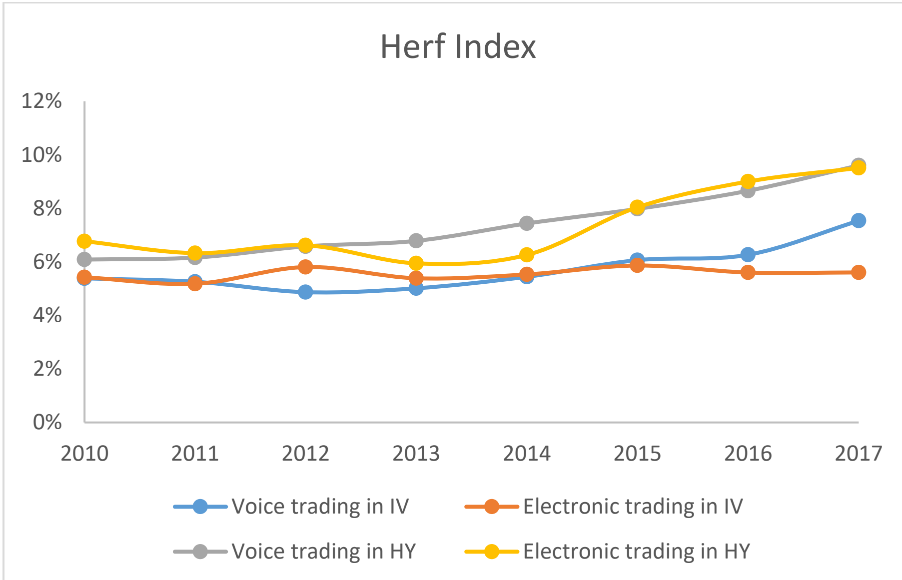
Panel A. Number of active dealers



Panel B. Market share of top 10 dealers



Panel C. Herf index

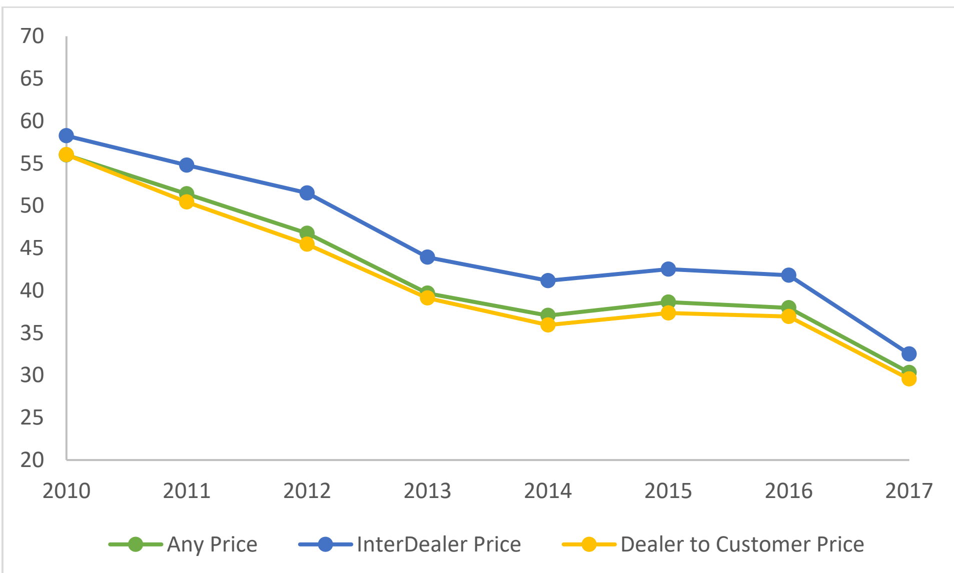


Appendix 1. Transaction cost estimated from using alternative benchmark prices

This figure compares the annual average transaction cost estimated from using alternative benchmark prices. Transaction cost is estimated for each trade following the model used in Hendershott and Madhavan (2015):

$$Cost_j = ln\left(Trade\ Price_j / Benchmark\ Price_j\right) \times Trade\ Sign_j,$$

where $Trade\ Price_j$ refers to the transaction price for trade j, and $Trade\ Sign_j$ is an indictor variable for trade direction. We use three alternative approaches to estimate $Benchmark\ Price_j$: the transaction price of the last inter-dealer trade, the last dealer-customer trade, or any trade in that bond. We multiple $Cost_j$ by 10,000 to compute transaction cost in basis points of value. We first estimate a bond-day level *Cost* measure by averaging $Cost_j$ across trades in the same bond on the same day. We then average the bond-day level *Cost* measure across bonds to get a daily measure for market. Finally, the daily measure is averaged across days to get an annual estimate, which is plotted in the figure.



Appendix 2. Summary information on samples constructed for various measures of market quality and dealer behavior

Panel A provides summary information on the sample constructed based on the availability of the bond-dealer-day-trade size level transaction cost measure ($Cost_{i,t,s,d}$). We first estimate the transaction cost for each voice trade as in Hendershott and Madhavan (2015). We then average the estimate across trades executed in the same bond *i*, on the same trading day *t*, within the same size category *s*, and with the same dealer *d* to get $Cost_{i,t,s,d}$. *E-share* is the share of dealer-customer trade volume that occurs on MarketAxess. It is calculated at the same bond-dealer-day-trade size level as $Cost_{i,t,s,d}$.

Panel B provides summary information on the sample constructed based on the availability of the measure of price difference across dealers for voice trading ($PriceDiff_{i,t,s,B/S}$), estimated at the dealer-day-trade size-trade direction level. For trades with the same trade direction (i.e., whether the investor is buying (B) or selling (S)), executed in the same bond *i*, on the same trading day *t*, within the same size category *s*, we first calculate the average price for each dealer *d*. We then calculate the difference between the highest and the lowest average prices across dealers to get $PriceDiff_{i,t,s,B/S}$. *E-share* is the share of dealer-customer trade volume that occurs onMarketAxess. It is calculated at the same bond-day-trade size-trade direction level as $PriceDiff_{i,t,s,B/S}$.

Panel C provides summary information on the sample constructed based on the availability of the measure of execution quality for voice trading ($PriceDiff_{i,t,s,B/S,d}$). $PriceDiff_{i,t,s,B/S,d}$ is defined as the difference between the highest price and the lowest price across trades with the same trade direction (i.e., whether the investor is buying (B) or selling (S)), executed in the same bond *i*, on the same trading day *t*, within the same size category *s*, and with the same dealer *d*. *E-share* is the share of dealer-customer trade volume that occurs onMarketAxess. It is calculated at the same bond-day-dealer-trade size-trade direction level as $PriceDiff_{i,t,s,B/S,d}$.

Panel D provides summary information on the sample constructed based on the availability of the share of inter-dealer trade out of total trade, calculated at the bond-dealer-day-trade size level ($InderDealerShare_{i,t,s,d}$). For trades executed in the same bond *i*, on the same trading day *t*, within the same size category *s*, and with the same dealer, we calculate the aggregate volumes for those between a dealer and a customer, and those between two dealers. $InterDealerShare_{i,t,s,d}$ is defined as the ratio of inter-dealer volume and the total trade volume (the sum of inter-dealer volume and dealer-customer volume). *E-share* is the share of dealer-customer trade volume that occurs on MarketAxess. It is calculated at the same bond-dealer-day-trade size level as $InderDealerShare_{i,t,s,d}$.

Credit Rating refers to the lower of Moody's and S&P's ratings. A numeric value is assigned to each notch of Moody’s (S&P’s) credit rating, with 1, 2, 3,… denoting Aaa (AAA), Aaa1(AA+), Aa2(AA) …, respectively. For bonds rated by both Moody’s and S&P, we keep the lower of the two credit ratings. *Time to Maturity* is the number of years between a bond’s offering date and its maturity date. *Outstanding Amount* is the total par amount outstanding for a bond, denominated in $ millions. *Industry Distribution* provides the distribution of each sample across three broad industries, industrial, financial, and utility, based on FISD’s classification. *Trade Size distribution* provides the distribution of each sample across four size categories: Micro ($1 to $100,00), Odd-lot ($100,000 to $1, 000,000), Round-lot ($1,000,000 to $5,000,000) and Block (above $5,000,000). *Trade Size distribution* provides the distribution of each sample across customer buys and customer sells.

Panel A: Transaction Cost Sample

	N	Mean	Std. Dev.	Median
Cost (bps)	14,774,258	58	92	29
E-Share (%)	14,774,258	20	39	0
Credit Rating	14,774,258	9	4	8
Time to Maturity (Year)	14,774,258	8	8	6
Outstanding Amount ($ Million)	14,774,258	1,137	1,107	800
		Industrial	**Financial**	**Utility**
Industry Distribution (%)		55.45	40.23	4.31
	Retail	**Odd-lot**	**Round-lot**	**Block**
Trade Size Distribution (%)	66.83	18.64	11.74	2.79

Panel B: Dealer Competition Sample

	N	Mean	Std. Dev.	Median
Price Dispersion (bsp)	4,934,180	49	68	16
E-Share (%)	4,934,180	14	25	0
Credit Rating	4,934,180	9	4	9
Time to Maturity (Year)	4,934,180	8	9	6
Outstanding Amount ($ Million)	4,934,180	1,100	1,080	750
		Industrial	**Financial**	**Utility**
Industry Distribution (%)		55.5	40.08	4.42
	Retail	**Odd-lot**	**Round-lot**	**Block**
Trade Size Distribution (%)	70.77	14.64	12.48	2.11
	Customer Buy		**Customer Sell**	
Trade Direction Distribution (%)	56.77		43.23	

Panel C: Execution Quality Sample

	N	Mean	Std. Dev.	Median
Price Dispersion (bsp)	2,810,900	25	39	6
E-Share (%)	2,810,900	3	12	0
Credit Rating	2,810,900	10	4	9
Time to Maturity (Year)	2,810,900	9	9	6
Outstanding Amount ($ Million)	2,810,900	1,051	1,134	700
		Industrial	**Financial**	**Utility**
Industry Share (%)		53.95	41.22	4.83
	Retail	**Odd-lot**	**Round-lot**	**Block**
Trade Size Share (%)	79.38	7.92	10.88	1.82
	Customer Buy		**Customer Sell**	
Trade Direction Share (%)	66.29		33.71	

Panel D: Inter-dealer Share Sample

	N	**Mean**	**Std. Dev.**	**Median**
Inter-dealer Share (%)	22,779,777	21	25	0
E-Share (%)	22,779,777	23	41	0
Credit Rating	22,779,777	9	4	8
Time to Maturity (Year)	22,779,777	8	9	6
Outstanding Amount ($ Million)	22,779,777	1,040	1,045	750
		Industrial	**Financial**	**Utility**
Industry Share (%)		55.38	38.99	5.63
	Retail	**Odd-lot**	**Round-lot**	**Block**
Trade Size Share (%)	63.16	20.55	13.24	3.04