All-to-All Liquidity in Corporate Bonds*

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Abstract

We examine technology enabling dispersed investors to directly trade with each other in over-the-counter markets. The largest electronic trading platform in corporate bonds started Open Trading (OT) to allow investor-to-investor trading. Over our 2014-2018 sample OT grew to win 12% of trades on the platform, with 2% being investor-to-investor trading, 3% being dealers trading with new clients, and 7% being new liquidity providers acting like dealers. This suggests that investors in corporate bonds prefer intermediation to direct trade. However, OT can enable new dealers to compete in liquidity provision. We use an auction model together with OT's steady growth to measure OT's effect on investors, dealers, and competition to provide liquidity.

JEL Classification: G12, G14, G19

Key words: Over-the-counter markets, electronic trading, request for quote, open trading, corporate bonds, dealers

1 Introduction

We examine the largest electronic corporate bond trading system allowing all-to-all trading where all subscribers, both investors and dealers, can trade with each others.[1] Studying all-to-all trading provides insight into the evolution of over-the-counter (OTC) markets which Weill (2020) characterizes as "investors trading in small groups and not in all-to-all auctions." We examine the impact of investors being able to trade with dealers who are not in their network, the ability of non-dealers to become dealers, and the impact of these changes on the prices investors receive.

In 2012 the largest electronic trading platform in corporate bonds, MarketAxess, started Open Trading (OT) to allow all-to-all trading in its request for quote (RFQ) trading mechanism. This allows investors to bid in the RFQ auctions and trade with other investors and dealers with whom they do not have a credit relationship, or *non-permissioned* dealers.[2] Non-dealers who bid in RFQss can be both investors wanting to earn rather than pay the bid-ask spread and quasi-dealers who want to specialize in making markets, but are not traditional dealers. Over our 2014-2018 sample period OT steadily grew to win 12% of trades on the platform in 2018. However, of that 12%, only 2% is due to investor-to-investor trading. Traditional dealers trading with new clients is 3% of trades. The largest component of Open Trading comes from the entry of new liquidity providers that act like dealers, 7% of trades. The majority of this new liquidity provision comes from a single firm that acts like a quasi dealer and becomes a dealer at the end of our sample.

OT's steady growth facilitates measuring its effect on investors, dealers, and competition to provide liquidity. OT can impact the prices investors receive when initiating an RFQ in several ways: i) OT directly improves prices when it wins auctions; ii) OT can indirectly affect prices by changing the competitiveness of existing dealers' bids; and iii) OT can also indirectly affect prices by impacting the number of dealers that bid, i.e., crowding out or crowding in traditional dealers. OT's direct effect is the magnitude that OT improves prices over the best non-OT price when OT wins. This price improvement is very small when OT starts and increases to over 2 basis points by the end of 2018. Comparing this to O'Hara and Zhou's (2020) estimate of average electronic

[1] MarketAxess has been studied by Hendershott and Madhavan (2015) and O'Hara and Zhou (2020).

[2] Dealers who have a credit relationship with clients are known as *permissioned* dealers. While investors can agree to trade directly with one another in OT, for settlement purposes MarketAxess acts as a counterparty to both the buyer and seller.

trading costs being between 10 and 15 basis points in 2017 implies that OT's direct impact lowers trading costs by 10-20 percent.

We use an auction model to quantify the indirect impact of OT on dealers' bidding. The auction model links direct price improvement, RFQ competitiveness (the difference between the winning bid and the second best bid, often referred to as the cover), and the number of bids.[3] The model illustrates how increasing the number of bidders directly improves prices through the new bidders winning and indirectly improves prices through existing bidders improving their prices. If OT does not impact the number or competitiveness of dealers' bids, then the direct measure of OT price improvement is OT's total price impact. For a fixed number of dealers, OT's impact on dealers' bidding can be estimated through the competitiveness of dealers' bids conditional on the expected number of OT responses. We find that the number of dealer responses is roughly equal at the beginning and ending of our sample. However, the competitiveness of dealers' bids is five basis points better in the last year of our sample relative to the first year. The model translates this into investors receiving roughly one basis point better prices. Dealers bidding more aggressively improves prices even when OT does not win and reduces the directly measurable price improvement when OT does win because OT improves on an dealers' already better price. Thus, holding the number of dealers constant, the sum of the direct and indirect OT price improvement is more than three basis points at the end of our sample.

Finally, the model quantifies how changing the number of bidders impacts the prices investors receive. However, applying this to our sample requires assumptions about how the changing number of dealer responses causally relates to the change in OT bidding. Over the first few years of our sample, the average number of dealer bids per RFQ declines from 5 to 3. This seems unrelated to OT as the expected number of OT bids is only around 0.1 per RFQ during this time period. In early 2016 the number of dealer bids begins to rise. This is a few months after the large quasi dealer enters and OT bidding increases noticeably. Over the next 3 years OT bids increase to almost 2 per RFQ while the number of dealer bids steadily increases, returning to 5 per RFQ. Under the assumption that OT crowded in these dealer bids the model estimates OT's indirect impact through

[3] Estimating OT's impact using trading costs over our 6 year sample period is challenging due to potential changes in market conditions from factors other than OT. Price improvement and competitiveness are measured relative to other bids which removes market-wide factors affecting all bids.

increasing the number of dealer bids to be 5-10 basis points.

While both industry groups (Managed Fund Association (2015)) and academics (Biais and Green (2019)) have expressed concern that the OTC market structure persists because dealers prefer it,[4] our results suggest that investors in corporate bonds prefer intermediation to direct trade.[5] However, all-to-all trading can facilitate the entry of new dealers that provide significant liquidity. New entrants can improve prices directly and can force the incumbents to become more competitive.

Glode and Opp (2019) provide a relevant theoretical model helpful in rationalizing why, when given a choice between intermediation and direct trade, investors prefer the former. They show OTC markets can concentrate information acquisition with dealers regarding non-information motives for trading. They also show that when the existence of gains to trade is uncertain, dealers' more precise information in OTC markets can improve allocative efficiency, making dealers and intermediation the preferred market structure.

Our paper is related to the literature on competition in market making, RFQ trading in OTC markets, and trading and costs in OTC markets in general. For fixed income securities Bessembinder, Spatt, and Venkataraman (2020) provide an extensive survey of the OTC literature. For corporate bonds Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018) and O'Hara and Zhou (2020) examine changes in liquidity provision and trading over time.

Glode and Opp (2019) and Dugast, Uslu, and Weill (2021) theoretically examine OTC versus centralize trading. Allen and Wittwer (2021) examine this question using data on OTC and RFQ trading in Canadian government bonds. We focus on trading within a centralized RFQ platform to examine the impact of investors' ability to compete with dealers in liquidity provision. Competition in liquidity provision has been studied theoretically going back to at least Kyle (1989). In equity markets Wahal (1997) empirically analyzes how competition among Nasdaq market makers affects

[4]Investors may have heterogeneous preferences for OTC versus centralized trading. This together with liquidity externalities could result in OTC trading even though some investors prefer centralized trading. Biais and Green (2017) discuss institutions versus retails investors. Lee and Wang (2021) and Dufresne, Hoffmann, and Vogel (2019) discuss informed versus uninformed investors. Dugast, Uslu, and Weill (2021) discuss dealer heterogeneity.

[5]By this we mean that investors rarely choose to provide liquidity at competitive prices. Over 90% of RFQs enable other investors to respond. This also is a statement about preferences and decision making within the existing corporate bond market structure rather than a statement about whether the current structure is optimal.

the cost of trading.[6] Barclay, Christie, Harris, Kandel, and Schultz (1999) study the impact of regulatory changes on Nasdaq that better integrated all-to-all trading on electronic communications networks with traditional trading directly with market makers.

Several papers study RFQs for corporate bonds. Hendershott and Madhavan (2015) examine RFQs on the same platform we study, MarketAxess, prior to the introduction of open trading. O'Hara and Zhou (2020) examine the effect that electronic trading on MarketAxess had on trading costs from 2010-2017. O'Hara and Zhou (2020) focus on dealer behavior in RFQs and OTC trading and do not examine the details of bidding within RFQs. Our results help explain some of O'Hara and Zhou's (2020) findings. For example, the entry of a new dealer via open trading that bids disproportionately in small trades explains O'Hara and Zhou's (2020) result that trading costs for smaller electronic corporate bond trades fell more over time than costs for larger trade sizes.

RFQs have been studied in other markets as well. Riggs, Onur, Reiffen, and Zhu (2020) examine RFQ, limit order book, and bilateral trading in the index credit default swaps market. Consistent with our finding that investors prefer dealer intermediation to direct trade, they find that few investor choose potential direct trading as limit order markets represent a very small fraction of trading. Hendershott, Livdan, Li, and Schürhoff (2021) examine the costs of failed attempts to trade in RFQs for collateralized loan obligations (CLOs).

The remainder of the paper is organized as follows. Section 3 studies the direct impact of open trading on price improvement. Section 2 describes the data. Section 4 analyzes RFQ competitiveness. Section 5 examines the number of responses in RFQs and uses an auction model to quantify the impact of OT on prices. Section 6 concludes.

2 Data

2.1 Descriptive statistics

Our data consists of all requests for quotes (RFQs) between January 2014 and December 2018 on an electronic auction venue, MarketAxess. MarketAxess, established in 2000, is an electronic trading

[6]See Menkveld (2013) and Eisfeldt, Herskovic, Rajan and Siriwardane (2021) for evidence on the importance of individual dealers in the stock and credit default swap markets, respectively.

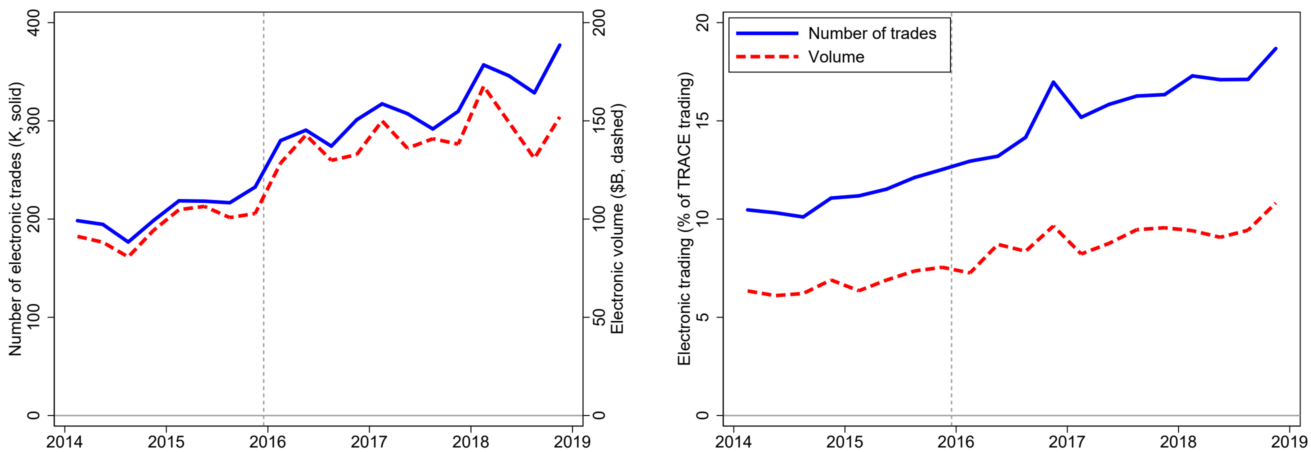


Figure 1: Electronic trading in the corporate bond markets on MarketAxess

The left plot presents the quarterly trades that are executed on MarketAxess, both in terms of number of trades (solid line) and total par amount traded (dashed line). The right plot presents the monthly average electronic trades that are executed on MarketAxess as a share of TRACE trading, both in terms of number of trades (solid line) and total par amount traded (dashed line). The vertical dotted line marks the increase in OT at the end of 2015.

platform where investors can access dealers in U.S. investment-grade and high-yield corporate bonds, Eurobonds, emerging markets, credit default swaps, and U.S. agency securities. Investors use electronic RFQs to simultaneously query multiple dealers rather than contact dealers individually. Dealers participate in the auction by submitting a quote. Auctions have a fixed duration, typically 5 to 20 minutes, after which the investor reviews the dealer responses and selects the best quote. Traditional dealers are aware of the identity of the investor, who is not required to trade. From an economic perspective, the electronic request for quote system is a sealed bid first-price auction with an undisclosed reservation price. MarketAxess charges a fee for trades on its platform which are incorporated into the transaction price. During our sample period fees for trading with permissioned dealers are approximate 0.2 basis points while OT trades have fees closer to 1.2 basis points.[7] The MarketAxess data provides an anonymized identifier for market participants queried and responding, as well as their bids.

All trades in the MarketAxess system are reported in TRACE with the fees incorporated into the reported prices. We merge the MarketAxess RFQ data with the publicly available TRACE

[7] Permissioned dealers also pay a fixed fee independent of volume. After our sample period, MarketAxess began offering OT liquidity suppliers the option of paying the higher OT variable fee or using a fixed and variable fee structure similar to dealers.

trade repository. The final data contain a total of 7,434,179 RFQs, 5,434,989 of which resulted in a trade, corresponding to a 73% success rate.[8]

Figure 1 documents changes in electronic trading in the corporate bonds on the MarketAxess platform during the sample period between January 2014 and December 2018 (see O'Hara and Zhou (2020) for additional information on trading on MarketAxess from 2010-2017). The left plot shows the quarterly number of trades (solid line) and the total par amount traded (dashed line). The vertical dotted line marks the increase in OT at the end of 2015. The number of electronic trades has risen steadily since 2014 from about 200K trades a year with a par value of about \$90B to 375K trades by the end of 2018, with a par value of \$150B. The right plot presents the data from the left plot as a share of the total corporate bond trading reported in TRACE. The fraction of electronic trades reported in TRACE and attributed to MarketAxess has risen from 10% in 2014 to just under 20% by the end of 2018. MarketAxess volume as a fraction of total trading from TRACE grew from 6% in 2014 to 10% in 2018.

Table 1 reports descriptive statistics on trade (Panel A) and bond (Panel B) characteristics in successful RFQs. Panel A shows that buys and sells are about equally split on the platform. The average trade size is equal to \$450K, with median equal to \$120K. The bond characteristics documented in Panel B are representative of the U.S. corporate bond universe, with \$1.46B average issue size, 9.5 years remaining maturity, 3.2 years of bond age, 4% coupon, 92% investment-grade (IG) rating, 4% private placements labeled as Rule 144a,[9] and 25% covenant lite. The IG rating distribution is AAA 1%, AA 14%, A 46%, and BBB 31%.

2.2 Open trading

In 2012 MarketAxess introduced Open Trading (OT), which, by selecting the all-to-all option on the RFQ, allows all platform participants, including investors and dealers, to trade directly with each

[8]Hendershott and Madhavan (2015) find a similar success rate for their 2010-2011 sample. Hendershott and Madhavan (2015) find evidence that investors whose RFQ fails are able to subsequently trade. Hendershott, Livdan, Li, and Schürhoff (2021) find that failed RFQs in CLOs are unlikely to lead to subsequent trade. The differences likely stem from the CLO RFQs being longer in duration, days versus minutes, and the larger number of dealers in corporate bonds, hundreds, versus tens in CLOs.

[9]Rule 144A modifies the Securities and Exchange Commission (SEC) restrictions on trades of privately placed securities so that these investments can be traded among qualified institutional buyers, and with shorter holding periods—six months or a year, rather than the customary two-year period.

Table 1: Descriptive statistics

The table documents descriptive statistics on trade and bond characteristics in successful RFQs. The number of successful RFQs is 5,434,989.

Panel A: Trade characteristics					
	Mean	SD	5%	Median	95%
Client buy	46%				
Trade size ($M)	0.45	1.10	0.004	0.12	2.00

Panel B: Bond characteristics					
	Mean	SD	5%	Median	95%
Issue size ($B)	1.46	1.33	0.35	1.00	3.25
Maturity (years)	9.52	9.19	1.59	6.02	28.95
Bond age (years)	3.15	3.02	0.17	2.34	8.37
Coupon rate	0.04	0.02	0.02	0.04	0.07
Zero coupon	0%				
Variable rate	1%				
IG rating	92%				
AAA	1%				
AA	14%				
A	46%				
BBB	31%				
Rule 144a	4%				
Cov-lite	25%				

Panel C: Open trading						
	Total	2014	2015	2016	2017	2018
Trades (K)	5,435	768	886	1,146	1,226	1,409
OT enabled (K)	4,947	609	757	1,065	1,162	1,354
Share of trades	91.0%	79.3%	85.5%	92.9%	94.7%	96.1%
OT trades (K)	359	9	25	65	86	174
Share of trades	6.6%	1.2%	2.8%	5.7%	7.0%	12.4%
Volume ($B)	2,468	354	415	534	565	600
OT enabled (K)	2,175	271	346	484	514	560
Share of volume	88.1%	76.5%	83.3%	90.7%	90.9%	93.4%
OT volume ($B)	123	4	14	29	30	46
Share of volume	5.0%	1.2%	3.3%	5.4%	5.4%	7.7%
Share of OT trades:						
Non-permissioned dealer	24.6%	35.3%	31.7%	24.2%	21.1%	24.9%
Buy-side institution	23.7%	50.4%	40.2%	32.7%	25.8%	15.5%
Quasi-dealer	51.7%	14.3%	28.2%	43.1%	53.1%	59.6%

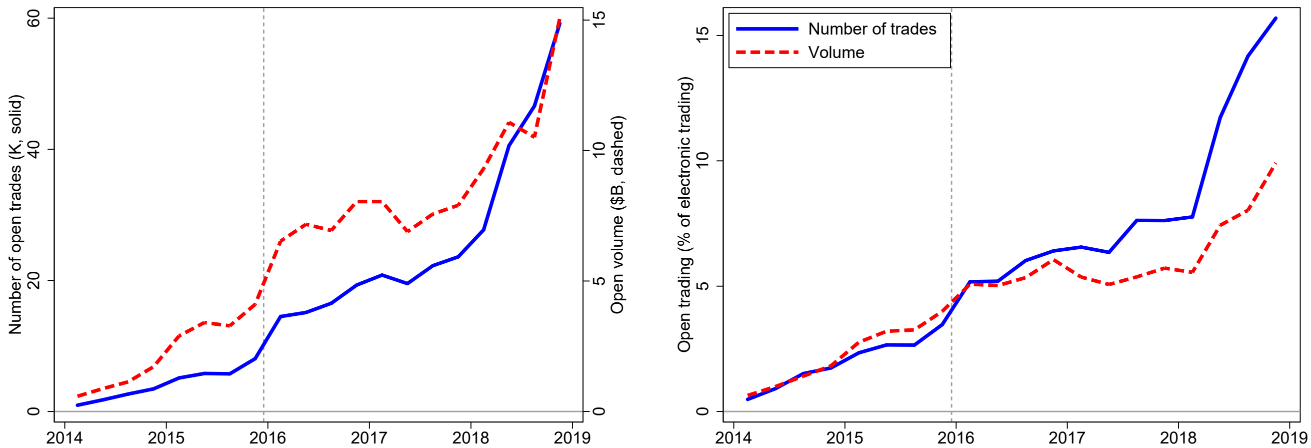


Figure 2: Open trading on MarketAxess

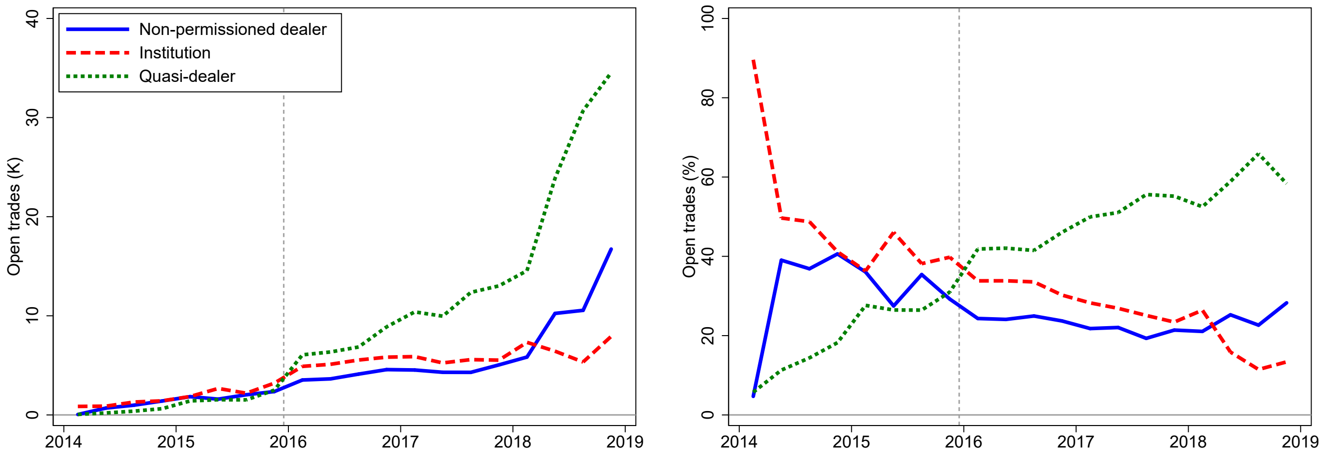
The left plot presents the quarterly open trades that are executed on MarketAxess, both in terms of number of trades (solid) and total par amount traded (dash). The right plot presents the quarterly average open trades that are executed on MarketAxess as a share of electronic trading, both in terms of number of trades (solid) and total par amount traded (dash). The vertical dotted line marks the increase in OT at the end of 2015.

other. This is done by MarketAxess acting as a counterparty to each side of the trade. A goal of OT is to improve liquidity on the platform by diversifying the pool of trading participants. Novel liquidity suppliers include asset managers, exchange-traded fund (ETF) specialists, systematic firms with strategies that arbitrage across markets, and regional or local dealers who have a different appetite or approach to risk in a particular bond compared to traditional liquidity providers. Analysing the impact of OT on liquidity and prices and identifying the role of dealers and non-dealers in influencing them is of primary interest in this paper. Using OT in a client RFQ is up the client. Panel C of Table 1 shows that almost all RFQs enable OT with the fraction being 91% of trades for the whole sample and over 96% of trades in 2018. Larger trades are slightly less likely to use OT with over 88% of all trade volume enabling OT and 93% of trade volume in 2018 enabling OT. Unlike trading with permissioned dealers, OT is anonymous. Almost all RFQs selecting OT, together with the average 25-30 permissioned dealers queried in each RFQ (Hendershott and Madhavan (2015), below we find similar numbers for our sample), suggests that limiting disclosure is not important for most trades on MarketAxess.

Univariate analysis: Figure 2 and Panel C of Table 1 document the evolution of the OT trading on MarketAxess during the sample period between January 2014 and December 2018. The left plot of Figure 2 graphs the quarterly OT trades that are executed on MarketAxess, both in terms of number of trades (solid line) and total par amount traded (dashed line). It shows that at the beginning of the sample period, which starts about one and a half years after the introduction of OT on MarketAxess, both the number of OT trades and their volume were still quite low at around 2K trades, resulting in approximately \$1B of trading volume per quarter. During the sample period, both the number of OT trades and their trading volume grow tremendously, ending up at around 60K of quarterly trades totalling \$15B in trading volume. The right plot presents the quarterly share OT trades in all electronic trading executed on MarketAxess, both in terms of number of trades (solid line) and total par amount traded (dashed line). The left plot shows both the number of OT trades and their trading volume are barely 1% of their respective totals on MarketAxess at the beginning of our sample. By the end of our sample, the share of OT represents 16% of trades and 10% of volume. Panel C of Table 1 further quantifies OT trading. It shows that OT has risen steadily from about 1% of trades (8,862 trades) and volume (\$4.32B) in 2014 to 12.4% of trades (174,044 trades) and 7.7% of volume (\$45.98B) by 2018. For the whole sample, OT is 6.6% of trades and 5% of volume.

To understand how different types of liquidity suppliers on MarketAxess platform contribute to these changes, we split them into traditional dealers, quasi-dealers, and buy-side institutions. We designate a liquidity supplier as a dealer or quasi-dealer if across all electronic trades over the sample period she provides liquidity (responds to RFQ) as opposed to demands liquidity (initiates RFQ) more than two-thirds of the time, and the number of times that she provides liquidity exceeds 400. The remaining liquidity suppliers are designated as buy-side institutions. We then separate traditional dealers and quasi-dealers. A traditional dealer is a dealer who supplies liquidity on more than 1,000 RFQs and the fraction of RFQs to total liquidity supply (that is, RFQ plus OT) exceeds 1/3. The others are *quasi-dealers*. We then further split traditional dealers into permissioned dealers and non-permissioned dealers. Permissioned dealers trade directly with customers with which they have a credit relationship. Non-permissioned dealers trade with customers they do not have a credit relationship; in these non-permissioned trades MarketAxess acts as the counterparty to both sides

Panel A. Open trades split by type of liquidity provider



Panel B. Open volume split by type of liquidity provider

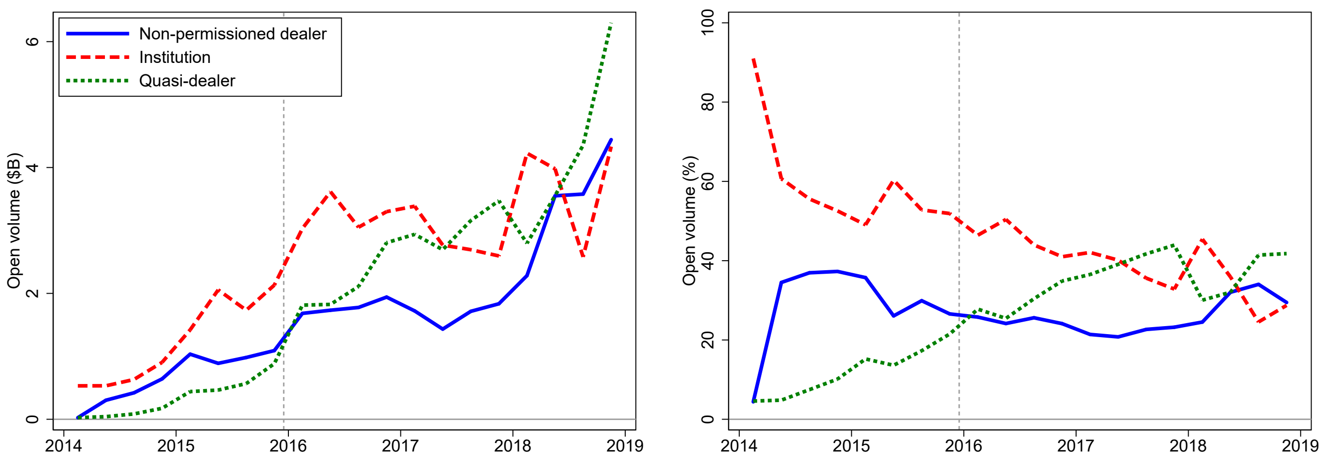


Figure 3: Non-permissioned dealers and non-dealer liquidity providers in OT

Panel A presents the number of trades and Panel B presents the total par amount traded (dash). The left plots present the quarterly open trades that are executed on MarketAxess, split by liquidity provider type into non-permissioned dealer, buy-side institution, and quasi-dealer. The right plots present the shares of OT by each liquidity provider. The vertical dotted line marks the increase in OT at the end of 2015.

of the trade.

Figure 3 documents the contribution of non-permissioned dealers, buy-side institutions, and quasi-dealers to OT. Panel A illustrates the number (left plot) and the share (right plot) of quarterly open trades executed on MarketAxess by each liquidity provider type. The left plot shows that all liquidity providers have increased their OT trading, with quasi-dealers showing the largest increase. The right plot confirms that quasi-dealers are the main force behind the growth in OT as their share of OT trades has increased from 5% in 2014 to 60% in 2018. The OT share of trades by non-permissioned dealers has experienced rapid growth from 5% to 40% between the first and second quarters of 2014, before settling to a steady-state 28% share for the rest of our sample. Buy-side institutions are the main liquidity providers in OT trading in 2014, comprising almost 90% of all open trading. Their share shows steady decline to approximately 12% by the end of 2018.

Panel B of Figure 3 graphs the par amount (left plot) and the share (right plot) of quarterly OT volume on MarketAxess by OT liquidity provider type. Consistent with the right plot in Panel A, all OT liquidity providers have increased their volume, with quasi-dealers showing the largest increase closely followed by non-permissioned dealers. Also consistent with the right plot of Panel A, the right plot of Panel B shows quasi-dealers are mainly responsible for the growth in OT volume, as their share of OT volume has increased from 5% in 2014 to 42% in 2018. The OT share of volume by non-permissioned dealers has experienced rapid growth from 5% to 37% between the first and second quarters of 2014 before settling to a steady-state 30% share for the rest of our sample. Initially buy-side institutions are responsible for more than 90% of the OT volume in 2014. As OT volume increases, their share of the OT trading volume has steadily declined to approximately 30% by the end of 2018. The fact that post 2014 buy-side institutions' volume share is larger than their share of trades indicates that their open trades are, on average, larger than open trades executed by other OT liquidity providers.

Table 2 reports results of univariate analysis of the determinants of OT. We split the sample into terciles along the sorting variable and then report the percent of open trades in the low and high terciles of the sorting variable. Reported t-statistics allow for unequal variance across the terciles. The first two rows of Table 2 show that open trades tend to be smaller sales. The rest of Table 2 indicates that bonds traded using the OT protocol tend to be older and have higher credit rating, shorter maturity, larger issue, and more covenants. These bonds are also more likely to be coupon-paying with coupon rates being lower and non-variable. Finally, privately placed bonds are slightly less likely to be open-traded.

Table 2: Determinants of OT

The table documents the determinants of OT. We split the sample into terciles along the sorting variable and report the percent of open trades in the low and high terciles of the sorting variable. t-statistics allow for unequal variance in the terciles.

	Open trades as percent of all trades			
Sorting variable	Low/No	High/Yes	ΔHigh–Low/ΔYes–No	(t-statistic)
Buy	6.83	6.36	-0.47	(-21.86)
Trade size	6.47	5.70	-0.77	(-31.38)
Size	6.05	6.57	0.53	(20.13)
Maturity	7.21	5.19	-2.02	(-78.93)
Bond age	5.08	7.63	2.55	(98.19)
Rating	6.29	7.48	1.19	(44.42)
Coupon rate	6.54	5.80	-0.74	(-28.60)
Zero coupon	6.61	11.96	5.35	(1.57)
Variable rate	6.62	5.85	-0.77	(-7.63)
Rule 144a	6.65	5.69	-0.96	(-18.72)
Cov-lite	6.66	6.44	-0.22	(-9.03)

Multivariate analysis: We use multivariate analysis to further understand the determinants of OT in the pooled sample using the following panel regression:

$$\text{Open trade}_{ibt} = \alpha + \alpha_b + \alpha_t + \boldsymbol{\beta}_1' \boldsymbol{X}_{it} + \boldsymbol{\beta}_2' \boldsymbol{X}_b + \epsilon_{ibt}, \tag{1}$$

where Open trade$_{ibt}$ is an indicator equal to one if trade i in bond b on day t is classified as open, and zero otherwise. Table 3 documents results of panel regression (1). Panel regression (1) uses trade controls, $\boldsymbol{X}_{it}$, and either both day, α_t, and bond, α_b, fixed effects (Column 1 of Table 3), or only day fixed effects (Column 2 of Table 3), or yearly dummies and only bond fixed effects (Column 3 of Table 3), or yearly dummies and bond controls, $\boldsymbol{X}_b$, (Column 4 of Table 3). Trade and bond controls include a buy-sell indicator; trade size indicators for odd (\$100K-\$1M), round (\$1M-\$5M), and large (\$5M+) sizes; issue size indicators for medium (\$250M-\$1B), large (\$1B-\$5B), giant (\$5B+); maturity indicators for intermediate (5-12yrs), long (12yrs+); bond age; an indicator for investment-grade rating; coupon rate; indicators for zero coupon, variable rate, rule 144a, and cov-lite. Standard errors are robust to clustering at day and bond levels.

Multivariate results from Table 3 support our univariate findings from Table 2. The number of open client sells is greater than the number of open client buys, 19% (column 1) and 39% (column

Table 3: Determinants of OT in the full sample

The table documents the determinants of OT. Estimates are obtained from panel regressions with day fixed effects or day and bond fixed effects. Trade and bond controls include a buy-sell indicator; trade size indicators for odd, round, large; issue size indicators for medium, large, giant; maturity indicators for intermediate, long; bond age; an indicator for investment-grade rating; coupon rate; indicators for zero coupon, variable rate, rule 144a, and cov-lite. Standard errors are robust to clustering at day and bond levels. ***1%, **5%, *10%.

	(1)	(2)	(3)	(4)
Client buy	-0.19**	-0.32***	-0.30***	-0.39***
	(0.09)	(0.09)	(0.09)	(0.09)
Odd lot ($100K-$1M)	1.02***	1.16***	0.96***	1.13***
	(0.09)	(0.09)	(0.10)	(0.10)
Round lot ($1M-$5M)	-0.96***	-0.83***	-1.05***	-0.87***
	(0.14)	(0.13)	(0.14)	(0.13)
Large lot ($5M+)	-2.56***	-2.42***	-2.78***	-2.59***
	(0.17)	(0.16)	(0.17)	(0.17)
Size medium ($250M-$1B)		-3.92***		-3.71***
		(0.59)		(0.59)
Size large ($1B-$5B)		-3.48***		-3.26***
		(0.59)		(0.59)
Size giant ($5B+)		-4.25***		-3.94***
		(0.67)		(0.67)
Maturity intermediate (5-12yrs)		-0.27***		-0.27***
		(0.09)		(0.09)
Maturity long (12yrs+)		-2.20***		-2.19***
		(0.11)		(0.12)
Bond age		0.19***		0.22***
		(0.02)		(0.02)
Investment grade		-0.12		-0.13
		(0.14)		(0.14)
Coupon rate		14.34***		10.22***
		(3.44)		(3.47)
Zero coupon		1.45		1.20
		(2.03)		(2.06)
Variable rate		-4.50***		-4.15***
		(0.37)		(0.36)
Rule 144a		-0.38**		-0.42***
		(0.15)		(0.15)
Cov-lite		-0.04		-0.03
		(0.11)		(0.12)
2015			1.83***	1.69***
			(0.07)	(0.07)
2016			4.97***	4.60***
			(0.10)	(0.10)
2017			6.63***	5.95***
			(0.13)	(0.12)
2018			12.18***	11.27***
			(0.27)	(0.26)
Day FE	Yes	Yes	No	No
Bond FE	Yes	No	Yes	No
Bond controls	No	Yes	No	Yes
R^2	0.052	0.036	0.045	0.028
N	5432393	5289627	5432394	5289628

4). All four specifications show that odd lots ($100K-$1M) are more likely to be open-traded, while round ($1M-$5M) and large ($5M+) lots are less likely to be open-traded. Columns 2 and 4 show that OT is mostly used for bonds with smaller issue sizes as the regression coefficients on medium, large, and giant size dummies are all negative and statistically significant at the 1% level. Columns 2 and 4 also reveal that OT is prevalent in bonds with short maturity as the regression coefficients on intermediate and long maturity dummies are both negative and statistically significant at the 1% level. The regression coefficient on the Coupon rate is positive and both statistically and economically significant in both specifications 2 and 4, shows that open-traded bonds pay higher coupon rates than non-open-traded bonds in the multivariate regressions, unlike in the univariate sorts. Open-traded bonds are less likely to be privately placed as the regression coefficient on the Rule 114a dummy is negative and statistically significant in both specifications 2 and 4. Finally, regression coefficients on the Investment grade, Zero coupon, and Cov-lite dummies are not statistically significant, indicating that, unlike in the univariate case, these two bond characteristics are not important determinants of OT. Investment grade bonds tend to be more liquid, which may help explain why OT is used less for them and more for less liquid bonds for whom it can more increases the probability of sale.

Overall, OT shows steady growth over our sample period with noticeable changes in the rate of growth in 2016 and 2018. While OT grows in all types of bonds and trades, there exists heterogeneity across types of trades and bonds.

3 Price Improvement from Open Trading

OT's steady growth facilitates measuring its effect on investors, dealers, and competition to provide liquidity. OT's effect on investors is measured through the prices they receive. OT's effect on dealer is through the number of RFQs they bid in and the aggressiveness those bids. Competition in liquidity provision is measured through how close together is the winning bid and second best bid, which we refer to as competitiveness.

Similar to how price improvement is measured in equity markets, we define the price improvement from OT as the difference between the winning bid and the counterfactual winning bid in the absence of OT. The winning bid in the absence of OT is the highest bid submitted by all traditional dealers in case of an RFQ to sell, and the lowest submitted traditional bid in case of an RFQ to buy. More formally, we define OT price improvement in RFQ i on date t by a client to sell as

$$\text{Buy}_{i,t} = 0: \qquad \text{OT price improvement}_{i,t} = \frac{\text{Bid price}_{i,t} - \max_j(\text{Non-OT bid}_{ij,t})}{max_j(\text{Non-OT bid}_{ij,t})} \geq 0, \tag{2}$$

where Bid $\text{price}_{i,t}$ is the highest bid in the RFQ and Non-OT $\text{bid}_{ij,t}$ are the bids submitted by traditional dealers on the RFQ, indexed by j. We define OT price improvement in RFQ i on date t by a client to buy,

$$\text{Buy}_{i,t} = 1: \qquad \text{OT price improvement}_{i,t} = \frac{\text{Ask price}_{i,t} - \min_j(\text{Non-OT bid}_{ij,t})}{\min_j(\text{Non-OT bid}_{ij,t})} \geq 0, \tag{3}$$

where now Ask $\text{price}_{i,t}$ is the lowest bid in the RFQ and Non-OT $\text{bid}_{ij,t}$ are the bids submitted by traditional dealers on the RFQ, indexed by j. OT price improvement is undefined if there are no OT bids and when there are no non-OT bids.[10] We express OT price improvement in basis points and winsorize our measure at 0.5% and 99.5% to eliminate outliers.

Univariate analysis: Figure 4 illustrates the monthly time series of the average OT price improvement for different trade and bond characteristics for trades when OT wins. Similar to Figure 6, the trade characteristics are buy/sale, top left plot, and trade size $\gtrless$ \$100K, top right plot. Bond characteristics consist of bond ratings (IG/HY), middle left plot, issue size (small/medium-giant), middle right plot, maturity (short/medium-long), bottom left plot, and coupon value (low/high), bottom right plot. The average OT price improvement is increasing between January 2014 to April 2016 and then subsequently declines between April 2016 and October 2018, and rises again between October and December 2018. These observations hold for all graphs except for bonds with small issue size (solid line in middle-right plot) which is too volatile for depicting trends.

The top left plot of Figure 4 shows that the OT impacts client buy/sale prices quite similarly as both plots are almost on top of each other. OT price improvement for high-yield bonds is 3-5bps

[10] 9.7% of RFQs with OT bids has no non-OT bids. Definitions (2) and (3) can not measure price improvement on these trades and do not capture the benefits of OT for these trades.

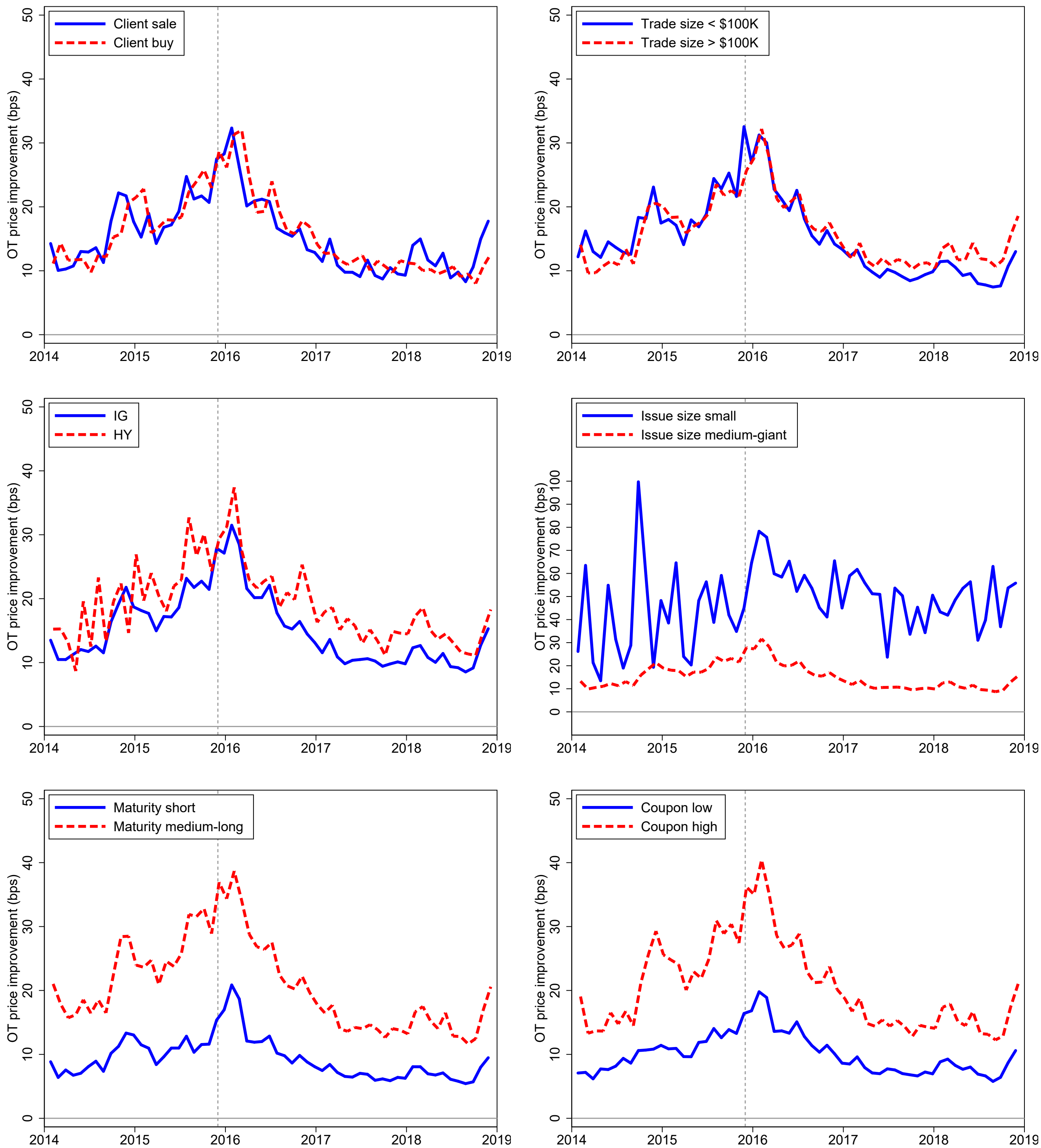


Figure 4: OT price improvement over time

The figures document OT price improvement over time. OT price improvement in RFQs is computed using expressions (2) and (3). The subplots report monthly averages for the splits indicated in the legend. The vertical dotted line marks the increase in OT at the end of 2015.

Table 4: Price improvement from OT

The table documents the determinants of price improvement from OT. We split the sample into terciles along the sorting variable and report the average price improvement from OT in the low and high terciles of the sorting variable. t-statistics allow for unequal variance in the terciles.

Panel A: Price improvement from OT (bps)

	Total	2014	2015	2016	2017	2018
All OT trades	13.64	14.75	20.64	20.54	11.14	11.33
Non-permissioned dealer	15.78	15.59	20.08	22.71	13.48	13.31
Buy-side institution	15.31	13.42	18.84	20.08	11.44	13.84
Quasi-dealer	12.05	17.49	23.71	19.83	10.21	10.05

Panel B: Trade and bond variation in price improvement from OT

	Price improvement from OT (bps)			
Sorting variable	Low/No	High/Yes	ΔHigh–Low/ΔYes–No	(t-statistic)
Buy	13.95	13.22	-0.74	(-9.89)
Trade size	11.35	15.28	3.93	(42.20)
Size	20.07	8.98	-11.09	(-111.66)
Maturity	7.69	23.46	15.77	(150.00)
Bond age	12.50	15.60	3.10	(32.37)
Rating	10.30	17.56	7.26	(77.25)
Coupon rate	7.71	21.78	14.07	(130.00)
Zero coupon	13.63	21.36	7.73	(0.74)
Variable rate	13.63	13.74	0.11	(0.27)
Rule 144a	13.47	18.72	5.26	(19.94)
Cov-lite	14.52	10.95	-3.57	(-45.69)
Buy-side institution	13.09	15.31	2.22	(23.92)
Quasi-dealer	15.53	12.05	-3.48	(-45.53)

higher than for investment grade bonds throughout the sample period. OT price improvement for high-yield bonds is also quite volatile between January 2014 and January 2016. There exists very little difference, except for the June 2017 to December 2018 period, between OT price improvements for trades less/greater than $100K. Larger trades experience larger price improvement from OT during the June 2017 to December 2018 period. Smaller issue bonds experience much higher, by at least 25-40bps, price improvement from OT than large-issue bonds, especially after January 2016. Price improvement for longer maturity bonds is at least 10bps larger than price improvement for shorter maturity bonds throughout the sample period. Finally, price improvement for high coupon-paying bonds is at least 10bps higher than price improvement for low coupon-paying bonds throughout the sample period.

Table 4 quantifies the determinants of OT price improvement. We split the sample into terciles along the sorting variable and report the average OT price improvement in the low and high terciles of the sorting variable as well as their difference. Reported t-statistics allow for unequal variance in the terciles.

Panel A of Table 4 reports the average annual OT price improvement for all trades, and trades sorted by liquidity provider. The sample average price improvement from OT is 13.64bps, with the largest price improvement observed in 2015 (20.64bps) and 2016 (20.54bps); we will see later this is when RFQs are least competitive. The smallest price improvement is in 2017 (11.14bps) and 2018 (11.33bps); we will see later this is when RFQs are most competitive. This is because the more competitive the RFQ is, the harder it is to improve the price because it is already competitive. Quasi-dealers price improvement is 12.05bps, smaller than buy-side institutions (15.31bps) and non-permissioned dealers (15.78bps). As we will see, this is mostly due to quasi-dealers providing liquidity in more competitive RFQs, relative to non-permission dealers and buy-side institutions in 2017 and 2018.

Panel B of Table 4 reports the average OT price improvement in the low and high terciles sorted on trade (buy/sell, trade size) and bond (issue size, maturity, age, rating, coupon rate, zero coupon, variable coupon rate, private placement, cov-lite) characteristics, as well as their differences, ΔHigh–Low. OT improves client sale prices by just a bit more, 0.74bps, than it improves client buy prices. OT improves prices for lager trades by 3.93bps more than it does for small trades. Average OT price improvement is larger in RFQs for bonds with a smaller issue size, longer maturity, older, higher rated, higher coupon rates, as well as coupon paying bonds, cov-lite bonds, and privately placed bonds.

Multivariate analysis: We use multivariate analysis to further understand the determinants of price improvement from OT in the pooled sample. We start by employing specification (11) with price improvement in RFQ i on day t for bond b, OT price improvement$_{ibt}$, as response variable. Table 5 documents results of several variants of such specification all using trade controls and either both day and bond fixed effects (Column 1 of Table 5), or just day fixed effects and bond controls, (Column 2 of Table 5), or yearly dummies and just bond fixed effects (Column 3 of Table 5), or yearly dummies and bond controls, $\boldsymbol{X}_b$, (Column 4 of Table 5).

Table 5: Price improvement from OT

The table documents the determinants of price improvement from OT. Estimates are obtained from panel regressions with day fixed effects or day and bond fixed effects. Trade and bond controls include a buy-sell indicator; trade size indicators for odd, round, large; issue size indicators for medium, large, giant; maturity indicators for intermediate, long; bond age; an indicator for investment-grade rating; coupon rate; indicators for zero coupon, variable rate, rule 144a, and cov-lite. Standard errors are robust to clustering at day and bond levels. ***1%, **5%, *10%.

	(1)	(2)	(3)	(4)
Client buy	1.27***	1.10***	1.10***	0.94***
	(0.16)	(0.21)	(0.17)	(0.20)
Odd lot	0.19**	0.43***	0.25**	0.48***
	(0.10)	(0.11)	(0.10)	(0.12)
Round lot	0.97***	1.04***	1.18***	1.25***
	(0.18)	(0.19)	(0.18)	(0.20)
Large lot	0.97**	1.38**	1.22***	1.69**
	(0.46)	(0.65)	(0.47)	(0.76)
Size medium		-23.55***		-23.28***
		(1.70)		(1.71)
Size large		-31.18***		-30.91***
		(1.70)		(1.72)
Size giant		-35.98***		-35.87***
		(1.94)		(1.97)
Maturity intermediate		4.99***		5.04***
		(0.19)		(0.19)
Maturity long		16.91***		17.02***
		(0.42)		(0.43)
Bond age		0.40***		0.40***
		(0.05)		(0.05)
Investment grade		-1.45***		-1.37***
		(0.39)		(0.39)
Coupon rate		91.59***		99.54***
		(10.00)		(10.41)
Zero coupon		-1.43		-0.22
		(1.38)		(1.15)
Variable rate		2.56***		2.91***
		(0.64)		(0.67)
Rule 144a		4.89***		4.74***
		(0.50)		(0.52)
Cov-lite		0.31		0.30
		(0.31)		(0.31)
2015			3.92***	5.35***
			(0.47)	(0.49)
2016			5.19***	6.36***
			(0.51)	(0.51)
2017			-2.98***	-1.78***
			(0.43)	(0.38)
2018			-2.96***	-1.42***
			(0.47)	(0.47)
Day FE	Yes	Yes	No	No
Bond FE	Yes	No	Yes	No
Bond controls	No	Yes	No	Yes
R^2	0.350	0.227	0.328	0.202
N	322,722	312,951	322,725	312,954

Results reported in Table 5 are in agreement with our univariate findings. OT improves client buy prices by 1.27bps (Column 1) more than client sale prices. Larger trades see more price improvement from OT than small trades by 0.19bps/0.97bps/0.97bps for Odd/Round/Large lot size as per Column 1. It follows from Column 4 of Table 5 that OT price improvement is larger for bonds with a smaller issue size, longer maturity, higher coupon rates, variable rates, as well as for lower rated bonds, coupon paying bonds, cov-lite bonds, and privately placed bonds. Also according to Column 4, relative to 2014, price improvement from OT is, on average, larger in 2015 by 3.92bps and in 2016 by 5.19bps, and it is smaller by 2.98bps in 2017 and by 2.96bps in 2018.

Next, we investigate the average effect of OT on prices. For the purpose of this exercise, we slightly modify definitions (2) and (3) of OT price improvement in RFQ i in month t by a client to sell/buy as

$$\text{OT price improvement}_{i,t} = [\text{Bid/Ask price}_{i,t} - \max_j / \min_j(\text{Non-OT bid}_{ij,t})]/\text{Par}_{i,t}, \tag{4}$$

where $\text{Par}_{i,t}$ is the par value of the asset traded in the RFQ_i in month t. We then calculate the average OT price improvement in month t, $\mathbb{E}_t[\text{OT price improvement}]$, as

$$\mathbb{E}_t[\text{OT price improvement}] = \Pr(\text{OT win}|t) \sum_{i=1}^{\#_{\text{OT win}}(t)} \frac{\text{OT price improvement}_{i,t}}{\#_{\text{OT win}}(t)},$$

where $\Pr(\text{OT win}|t)$ is the month-t unconditional probability of OT winning RFQ and $\#_{\text{OT win}}(t)$ is the number of RFQs won by OT in month t.

Figure 5 documents the monthly time series of the unconditional probability of OT winning RFQ, Pr(OT win) (solid line on left sub-plot), and the expected OT price improvement, $\mathbb{E}$[OT price improvement] (solid line on right sub-plot). Pr(OT win) steadily increases from a few basis points to 2.5% between January 2014 and November 2015. It further increases by approximately 1% between November 15 and February 2016, and it continues to increase at the same rate until January 2018 when it reaches 5%. Pr(OT win) jumps from 5% to close to 12.5% between January and December 2018.

$\mathbb{E}$[OT price improvement] is barely a fraction of a basis point in January 2014. However, $\mathbb{E}$[OT

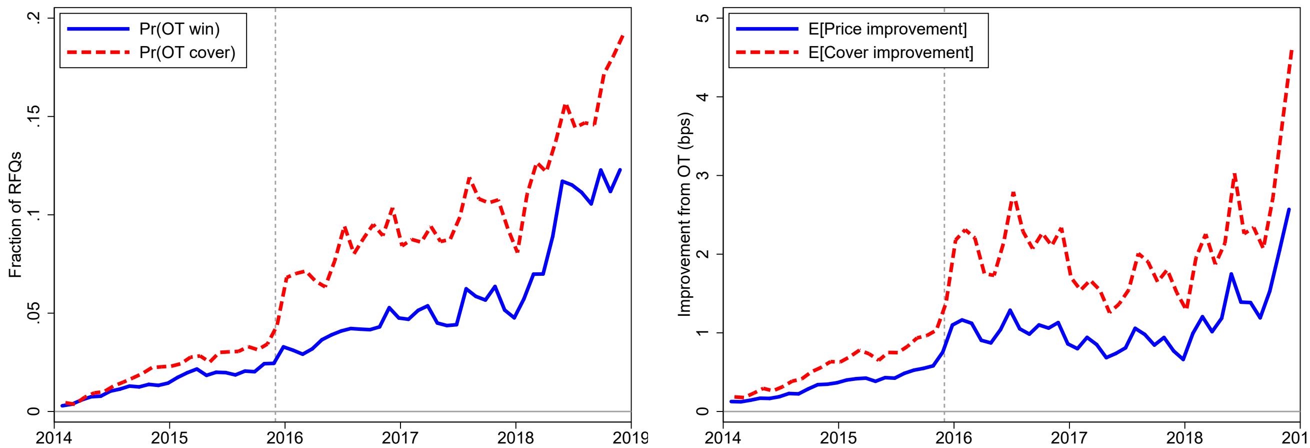


Figure 5: Probability of OT win/cover in RFQs and expected OT price/cover improvement
Right subplot documents monthly time series of expected OT price and cover improvements defined for RFQ_i as

$$\text{OT price improvement}_{i,t} = \text{Bid/Ask price}_{i,t} - \max_j / \min_j(\text{Non-OT bid}_{ij,t})/\text{Par}_{i,t},$$

$$\text{OT cover improvement}_{i,t} = \text{Cover}_{i,t} - \max_j(\text{Non-OT Cover}_{ij,t})/\text{Par}_{i,t},$$

where $\text{Par}_{i,t}$ is the par value of the asset traded in the RFQ i in month t. Left subplot documents monthly time series of probabilities of OT winning an RFQ and providing the cover. The vertical dotted line marks the increase in OT at the end of 2015.

price improvement] is equal to 0.7bps in November 2015. $\mathbb{E}$[OT price improvement] increases dramatically to 1.2bps between November 2015 and March 2016. It then hovers around 1bps until October 2018, when it increased to 2.5bps between October and December 2018, precisely the time period when Pr(OT win) increases dramatically. This evidence is consistent with findings from the top-left subplot of Figure 4 which shows that a sample average OT price improvement. For instance, Pr(OT win|Nov 2015) = 0.025 from the left subplot of Figure 5 and from the top-left subplot of Figure 4 we have that the sample average OT price improvement is equal to 29bps in November 2015. Therefore, the expected OT price improvement in November 2015 should be equal to $0.025 * 29\text{bps} = 0.73\text{bps}$, which is very close to $\mathbb{E}_{\text{Nov 2015}}[\text{OT price improvement}] = 0.70\text{bps}$ from the right subplot of Figure 5. Therefore, the expected OT price improvement remains flat around 1bps between March 2016 and January 2018 because Pr(OT win) increases and the sample average OT price improvement declines almost at the same rates during this time period.

One possible explanation of why the sample average OT price improvement increases before and then declines after March 2016 is that pre-March 2016 OT responds to less competitive RFQs than post-March 2016. To investigate this channel, we define RFQ competitiveness and RFQ competitiveness excluding OT for an RFQ i where the customer is selling (for customer buys the below are multiplied by minus one) in month t as:

$$\text{RFQ competitiveness}_{i,t} = (\text{Bid price}_{i,t} - \text{Cover}_{i,t})/\text{Par}_{i,t}, \tag{5}$$

$$\text{RFQ competitiveness ex OT}_{i,t} = (\max_j(\text{Non-OT bid}_{ij,t}) - \max_j(\text{Non-OT Cover}_{ij,t}))/\text{Par}_{i,t}, \tag{6}$$

where $\text{Cover}_{i,t}$ is the second best bid in RFQ i in month t. RFQ competitiveness is undefined if there is only one bid. In a perfectly competitive auction, all bidders bid the asset's fair value, such that best bid and cover are the same. Thus, by construction, a large value of RFQ $\text{competitiveness}_{i,t}$ means less competitive RFQ, and RFQ competitiveness equals zero if and only if winning bid and cover are tied. Change in RFQ competitiveness due to OT can be written as

$$\begin{aligned}\Delta\text{RFQ competitiveness}_{i,t} &= \text{RFQ competitiveness ex OT}_{i,t} - \text{RFQ competitiveness}_{i,t} \\ &= \underbrace{(\text{Cover}_{i,t} - \max_j(\text{Non-OT Cover}_{ij,t}))/\text{Par}_{i,t}}_{\text{OT cover improvement}_{i,t}} - \\ &\quad - \text{OT price improvement}_{i,t},\end{aligned} \tag{7}$$

where if OT improves/reduces RFQ competitiveness, then

$$\text{RFQ competitiveness ex OT}_i \gtrless \text{RFQ competitiveness}_i \Rightarrow \Delta\text{RFQ competitiveness}_i \gtrless 0.$$

Constructing expectations in (7) readily yields

$$\mathbb{E}_t[\text{OT price improvement}] = \mathbb{E}_t[\text{OT cover improvement}] - \mathbb{E}_t[\Delta\text{RFQ competitiveness}]. \tag{8}$$

Relation (8) links the expected OT price improvement, expected OT cover improvement, and expected change in RFQ competitiveness due to OT. In a perfectly competitive RFQ all bids are equal to the true value of the asset. Because the cover is further away from the true value of the asset than the best bid, making RFQ more competitive improves the cover no less than it improves the best bid. Intuitively, it follows from (8) that the change in the RFQ competitiveness is largest when the cover improves significantly while the best bid improves very little. Therefore, OT price improvement should be larger in RFQs with smaller OT competitiveness improvement.

Figure 5 documents monthly time series of the unconditional probability of OT providing the cover, Pr(OT cover) (dashed line on left sub-plot) and the expected OT cover improvement, $\mathbb{E}$[OT cover improvement] (dashed line on right sub-plot). Pr(OT cover) behaves very similar to Pr(OT win) pre-November 2015 increasing from a few basis points to approximately 3%. However, Pr(OT cover) more than doubles to approximately 7% between November 2014 and March 2016. It continues to increase, on average, until December 2018 when it reaches its highest value of 19%.

$\mathbb{E}$[OT cover improvement] is no less than $\mathbb{E}$[OT price improvement] in our sample implying that OT improves RFQ competitiveness. $\mathbb{E}$[OT cover improvement] is, on average, 1bps higher than the expected OT price improvement post-November 2015, implying that the expected change in RFQ competitiveness due to OT post-November 2015 is more than three times its pre-November 2015 value. This noticeable difference is mostly because OT is much more likely to provide the cover than to win during this time period. Because of the important link between OT price improvement and RFQ competitiveness, we investigate the latter in-depth in the next section.

4 RFQ Competitiveness

Here, we slightly modify the definition of RFQ competitiveness from (5). First, we normalize the difference between the winning bid and the cover by the winning bid instead of the par value as in (5). Second, to improve the exposition, RFQ competitiveness is now measured as a negative number, with greater negative number implying less competitive RFQ. More formally, we define in RFQ sale i on date t,

$$\text{Buy}_{i,t} = 0: \qquad \text{RFQ competitiveness}_{i,t} = \frac{\text{Cover}_{i,t} - \text{Bid price}_{i,t}}{\text{Bid price}_{i,t}} \leq 0, \tag{9}$$

and in RFQ buy i on date t,

$$\text{Buy}_{i,t} = 1: \qquad \text{RFQ competitiveness}_{i,t} = \frac{\text{Ask price}_{i,t} - \text{Cover}_{i,t}}{\text{Ask price}_{i,t}} \leq 0. \tag{10}$$

We express RFQ competitiveness in basis points and winsorize our measure at 0.5% and 99.5% to eliminate outliers.

Univariate analysis: Figure 6 presents the monthly time series of average RFQ competitiveness for different trade and bond characteristics. The trade characteristics are buy/sale, top left plot, and trade size $\gtrless$ \$100K, top right plot. Bond characteristics consist of bond ratings (IG/HY), middle left plot, issue size (small/medium-giant), middle right plot, maturity (short/medium-long), bottom left plot, and coupon value (low/high), bottom right plot. The top left plot of Figure 6 indicates that RFQ competitiveness is similar for client buys and sells. RFQ's for investment grade bonds are slightly, about 2-5bps, more competitive that RFQs for high-yield bonds throughout the sample period. Trades less than \$100K are, on average, about 5bps more competitive than trades greater than \$100K. RFQs for larger issue bonds are much more, by at least 35-50bps, more competitive than RFQs for small-issue bonds throughout the sample period. The RFQ competitiveness for small-issue bonds is much more volatile than the RFQ competitiveness for larger issue bonds, possible due many RFQs with few bidders for such bonds. RFQs for short maturity bonds are at least 10bps more competitive than RFQs for medium-long maturity bonds throughout the sample period. Finally, RFQs for low coupon-paying bonds are at least 10bps more competitive than RFQs for high coupon-paying bonds throughout the sample period.

A striking feature shared by all subplots in Figure 6 is that average RFQ competitiveness gradually declines between January 2014 and November 2015, then drops sharply during the first quarter of 2016, and then gradually increases until October 2018, and then declines sharply again. At the same time Figures 1 and 2 both show a steady increase in the number of electronic trades and volume in general and in the OT specifically. When put together, evidence from all three figures can be potentially rationalized as follows: demand for electronic execution is increasing between January 2014 and January 2016, the number of traditional dealers remains fixed, while they are the

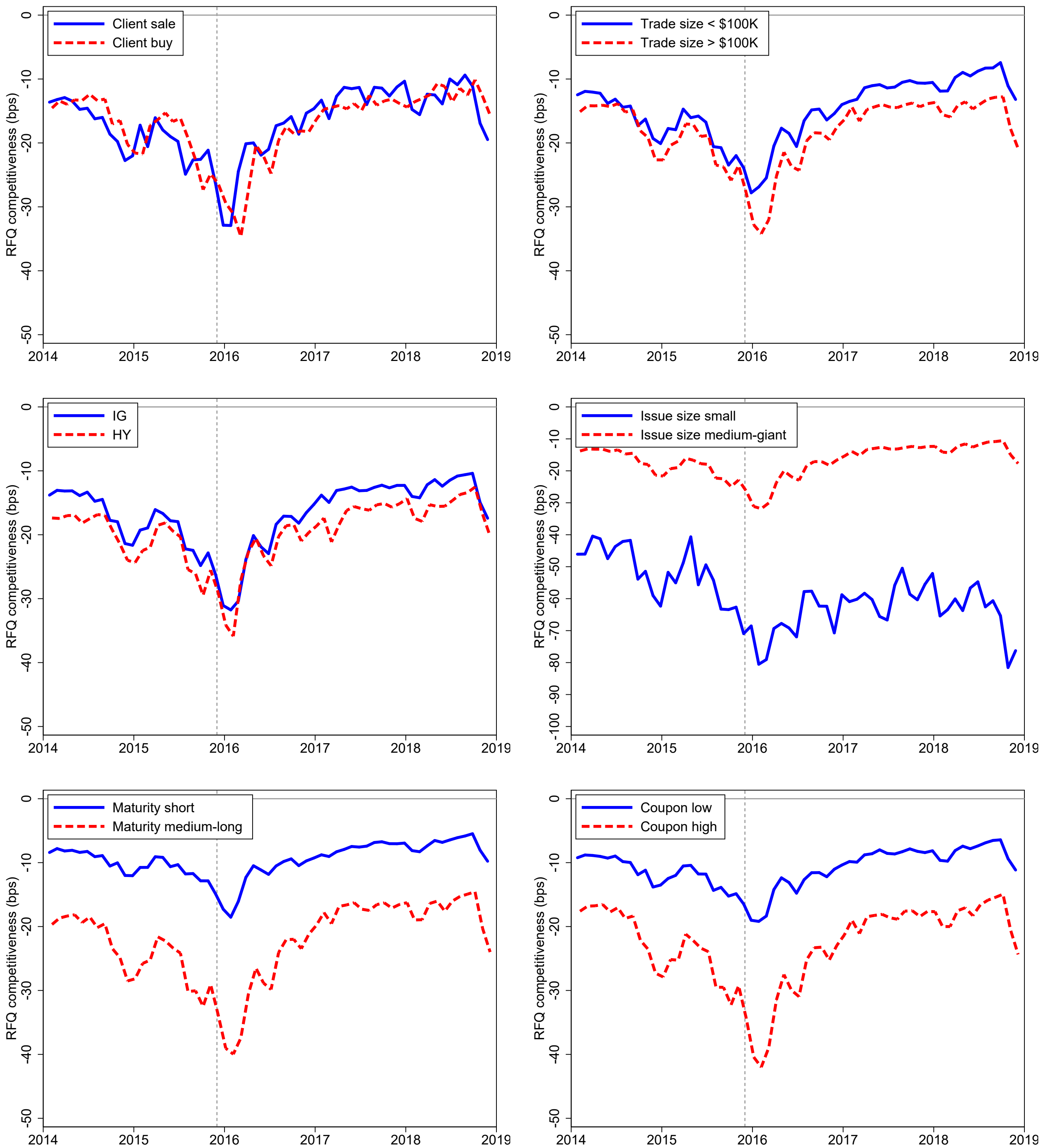


Figure 6: RFQ competitiveness over time

The figures document RFQ competitiveness. All subplots report monthly averages for the splits indicated in the legend. Sell/Buy RFQ competitiveness is defined in equation (9)/(10). The vertical dotted line marks the increase in OT at the end of 2015.

main liquidity providers and continue to respond to the same "steady-state" number of RFQs thus leading to a decline in per-RFQ participation and, consequently, its competitiveness. Quasi-dealers enter in late 2015 increasing the per-RFQ participation and forcing traditional dealers to expand their RFQ participation and improve their bids. We further investigate this hypothesis in later sections.

This evidence also provides additional support to our hypothesis that post-March 2016 OT price improvement decline is due to increased RFQ competitiveness. Top-left subplot of Figure 6 shows RFQ competitiveness improves sharply between March 2016 and October 2018, precisely when the sample average OT price improvement declines and $\mathbb{E}$[OT price improvement] stays flat. Both measures of OT price improvement go up between October and December 2018, precisely when RFQ competitiveness declines.

Table 6 quantifies the determinants of RFQ competitiveness. We split the sample into terciles along the sorting variable and report the average RFQ competitiveness in the low and high terciles of the sorting variable as well as their difference. Reported t-statistics allow for unequal variance in the terciles.

Panel A of Table 6 reports the average annual RFQ competitiveness for all trades, OT/non-OT trades, and trades sorted by liquidity provider. The sample average RFQ competitiveness is equal to -15.23bps, with RFQ being the most competitive in 2018 (-11.75bps) and least competitive in 2016 (-20.14bps). Non-OT trades are on average less competitive than OT trades (-15.36bps to -13.41bps). Non-OT trades are more competitive than OT trades in 2014-2016, and then they are less competitive in 2017-2018. Quasi-dealers (-11.85bps) are on average more competitive than non-permissioned dealers (-15.12bps) and buy-side institutions (-15.16bps). This is mostly due to the increase in OT at the end of 2015 increasing competitiveness relative to non-permission dealers and buy-side institutions in 2017 and 2018.

Panel B of Table 6 reports the average RFQ competitiveness in the low and high terciles sorted on trade (buy/sell, trade size) and bond (issue size, maturity, age, rating, coupon rate, zero coupon, variable coupon rate, private placement, cov-lite) characteristics, as well as their differences, ΔHigh–Low. In agreement with Figure 6, client buys are very slightly (-0.05bps) less competitive than client sales, and smaller trades are by -2.1bps more competitive than large trades. RFQs for bonds with a

Table 6: RFQ competitiveness

The table documents RFQ competitiveness and its determinants. In Panel B, we split the sample into terciles along the sorting variable and report the average RFQ competitiveness in the low and high terciles of the sorting variable. t-statistics allow for unequal variance in the terciles.

Panel A: RFQ competitiveness

	Total	2014	2015	2016	2017	2018
All trades	-15.23	-14.95	-19.24	-20.14	-12.24	-11.75
non-OT trades	-15.36	-14.94	-19.18	-20.11	-12.31	-11.90
OT trades	-13.41	-15.85	-21.18	-20.64	-11.28	-10.73
Non-permissioned dealer	-15.12	-16.05	-20.04	-21.78	-13.89	-12.49
Buy-side institution	-15.16	-14.86	-19.36	-20.16	-11.35	-13.01
Quasi-dealer	-11.85	-18.86	-24.96	-20.40	-10.26	-9.44

Panel B: Trade and bond variation in RFQ competitiveness

	RFQ competitiveness			
Sorting variable	Low/No	High/Yes	ΔHigh–Low/ΔYes–No	(t-statistic)
Client buy	-15.21	-15.26	-0.05	(-2.08)
Trade size	-13.68	-15.78	-2.10	(-82.11)
Size	-22.56	-9.83	12.73	(450.00)
Maturity	-7.98	-24.89	-16.91	(-607.18)
Bond age	-13.91	-17.72	-3.81	(-135.34)
Rating	-12.06	-18.84	-6.78	(-237.93)
Coupon rate	-8.36	-23.11	-14.76	(-522.22)
Zero coupon	-15.23	-32.10	-16.86	(-2.80)
Variable rate	-15.28	-11.14	4.14	(48.49)
Rule 144a	-15.02	-20.85	-5.82	(-77.95)
Cov-lite	-16.28	-12.14	4.15	(180.00)
buyside	-15.23	-15.22	0.02	(0.19)

larger issue size, shorter maturity, younger, lower rated, lower coupon rates, variable rates, as well as coupon paying bonds, bonds with covenants, and non-privately placed bonds are more competitive. Finally, RFQs by buy-side institutions are just as competitive as RFQs by other market participants.

Multivariate analysis: We use multivariate analysis to further understand the determinants of RFQ competitiveness in the pooled sample. We start with the following panel regression for RFQ i on day t for bond b:

$$\text{RFQ competitiveness}_{ibt} = \alpha + \alpha_b + \alpha_t + \boldsymbol{\beta}_1' \boldsymbol{X}_{it} + \boldsymbol{\beta}_2' \boldsymbol{X}_b + \epsilon_{ibt}, \tag{11}$$

with the same fixed effects α_b and α_t, as well as trade, $\boldsymbol{X}_{it}$, and bond, $\boldsymbol{X}_b$, controls as in panel regression (1). Table 7 documents results for several variants of specification (11) all using trade controls and either both day and bond fixed effects (Column 1 of Table 7), or just day fixed effects and bond controls, (Column 2 of Table 7), or yearly dummies and just bond fixed effects (Column 3 of Table 7), or yearly dummies and bond controls, $\boldsymbol{X}_b$, (Column 4 of Table 7).

Results reported in Table 7 are, to a large degree, in agreement with our univariate findings. Client sales are very slightly, coefficients ranging from -1.11bps (Column 1) to -0.71bps (Column 4), more competitive than client buys. It follows from Column 4 of Table 7 that RFQs for bonds with a larger issue size (24.77bps/33.60bps/39.95bps for size medium/large/giant), shorter maturity (-5.47bps/-19.47bps for maturity intermediate/long), younger (-0.44bps), higher rated (0.27bps), lower coupon rates (-83.61), variable rates (-1.23bps), as well as coupon paying bonds (-9.07bps), covenant-rich bonds (0.13bps), and non-privately placed bonds (-6.09bps), are more competitive. Also according to Column 4, relative to 2014, RFQs were, on average, less competitive in 2015 by 4.14bps and in 2016 by 5.45bps, and they were more competitive by 2.15bps in 2017 and by 2.49bps in 2018. Contrary to the univariate results, RFQs for larger trade sizes are more competitive by 1.52bps/1.87bps/1.28bps for Odd/Round/Large lot size as per Column 1, with the sign being positive across all columns.

In the next section, we investigate a direct channel linking RFQ competitiveness and price improvement from OT.

5 Open Trading Bids

One motivation for OT was to improve liquidity by allowing both investor-to-investor trading and non-traditional liquidity provider participation in RFQs to potentially increase the number of responses. However, increased competition from new entrants can displace incumbents. In addition, the incumbents can change their bidding strategies in response to new entrants. Overall, the expected net effect of OT on RFQ participation is ambiguous.

In this section we use the evidence on the number of RFQ responses to further investigate the

Table 7: RFQ competitiveness

The table documents RFQ competitiveness and its determinants. Estimates are obtained from panel regressions with day and bond fixed effects. Trade and bond controls include a buy-sell indicator; trade size indicators for odd, round, large; issue size indicators for medium, large, giant; maturity indicators for intermediate, long; bond age; an indicator for investment-grade rating; coupon rate; indicators for zero coupon, variable rate, rule 144a, and cov-lite. Standard errors are robust to clustering at day and bond levels. ***1%, **5%, *10%.

	(1)	(2)	(3)	(4)
Client buy	-1.11***	-0.73***	-1.09***	-0.71***
	(0.11)	(0.11)	(0.12)	(0.12)
Odd lot	1.52***	1.11***	1.49***	1.09***
	(0.06)	(0.07)	(0.07)	(0.08)
Round lot	1.87***	1.62***	1.82***	1.58***
	(0.10)	(0.11)	(0.10)	(0.11)
Large lot	1.28***	1.23***	1.24***	1.22***
	(0.13)	(0.15)	(0.13)	(0.15)
Size medium		24.93***		24.77***
		(2.04)		(2.03)
Size large		33.81***		33.60***
		(2.05)		(2.04)
Size giant		40.18***		39.95***
		(2.31)		(2.30)
Maturity intermediate		-5.45***		-5.47***
		(0.18)		(0.17)
Maturity long		-19.37***		-19.47***
		(0.36)		(0.37)
Bond age		-0.45***		-0.44***
		(0.05)		(0.06)
Investment grade		0.41		0.27
		(0.38)		(0.37)
Coupon rate		-79.84***		-83.61***
		(8.78)		(8.82)
Zero coupon		-8.66***		-9.07***
		(1.51)		(1.50)
Variable rate		-1.33***		-1.23**
		(0.49)		(0.49)
Rule 144a		-6.17***		-6.09***
		(0.40)		(0.40)
Cov-lite		0.14		0.13
		(0.31)		(0.31)
2015			-4.14***	-4.14***
			(0.29)	(0.28)
2016			-5.74***	-5.45***
			(0.41)	(0.38)
2017			2.42***	2.15***
			(0.26)	(0.23)
2018			3.00***	2.49***
			(0.29)	(0.26)
Day FE	Yes	Yes	No	No
Bond FE	Yes	No	Yes	No
Bond controls	No	Yes	No	Yes
R^2	0.273	0.198	0.258	0.184
N	5153303	5031982	5153305	5031986

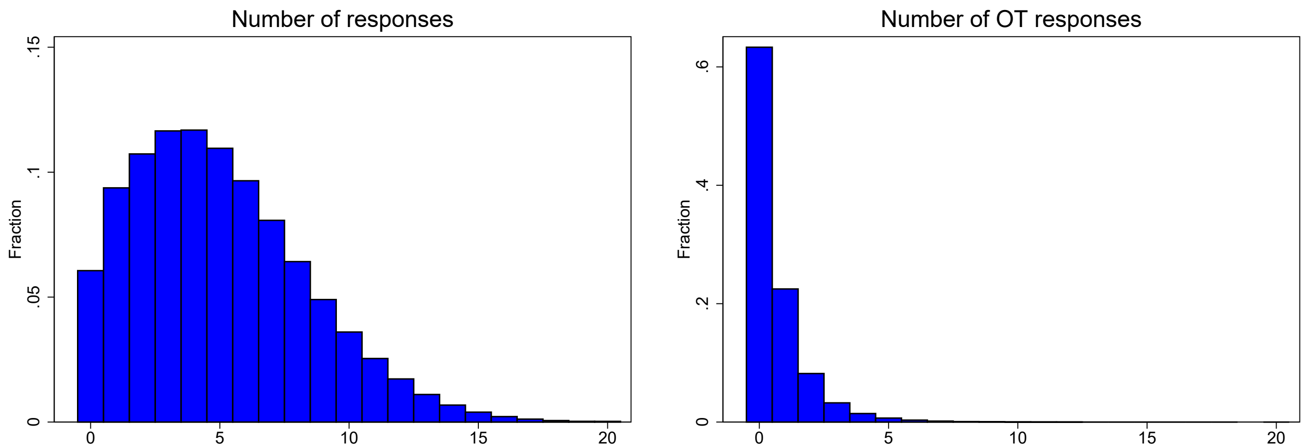


Figure 7: Responses to RFQs

The figures document the distribution of the all (left plot) and OT (right plot) number of responses to RFQs.

channels of the OT impact on trading. Figure 7 provides descriptive statistics on RFQ responses.[11] The left plot of Figure 7 displays the distribution of all responses to RFQs. It shows that while some RFQs get as many as 38 responses, the majority of RFQ responses falls in between 0 and 10 with sample average equal to 5 and standard deviation equal to 3. The right plot of Figure 7 graphs the distribution of OT responses to RFQs. It shows that the average number of OT responses hovers around 1.5 with standard deviation equal to 2.5. While some RFQs receive as many as 20 OT responses, 60% of the time they generate no response. This evidence is quite interesting as it suggests that both traditional and quasi dealers are selective in picking which RFQs to participate in. It is also consistent with our prior observation that the introduction of OT may not have resulted in much greater RFQ participation.

5.1 Bidding by time, trade, and bond characteristics

Next, we illustrate the evolution of the total number of RFQ responses over time. Figure 8 presents the monthly time series of the average number of total, both traditional and OT, RFQ responses for different trade and bond characteristics. Similar to Figure 6, the trade characteristics are buy/sale, top left plot, and trade size $\gtrless$ \$100K, top right plot. Bond characteristics consist of bond ratings (IG/HY), middle left plot, issue size (small/medium-giant), middle right plot, maturity

[11] As described in Hendershott and Madhavan (2015), the average number of dealers contacted per RFQ is between 25 and 30. Only a few percent of RFQs go to less then 10 dealers.

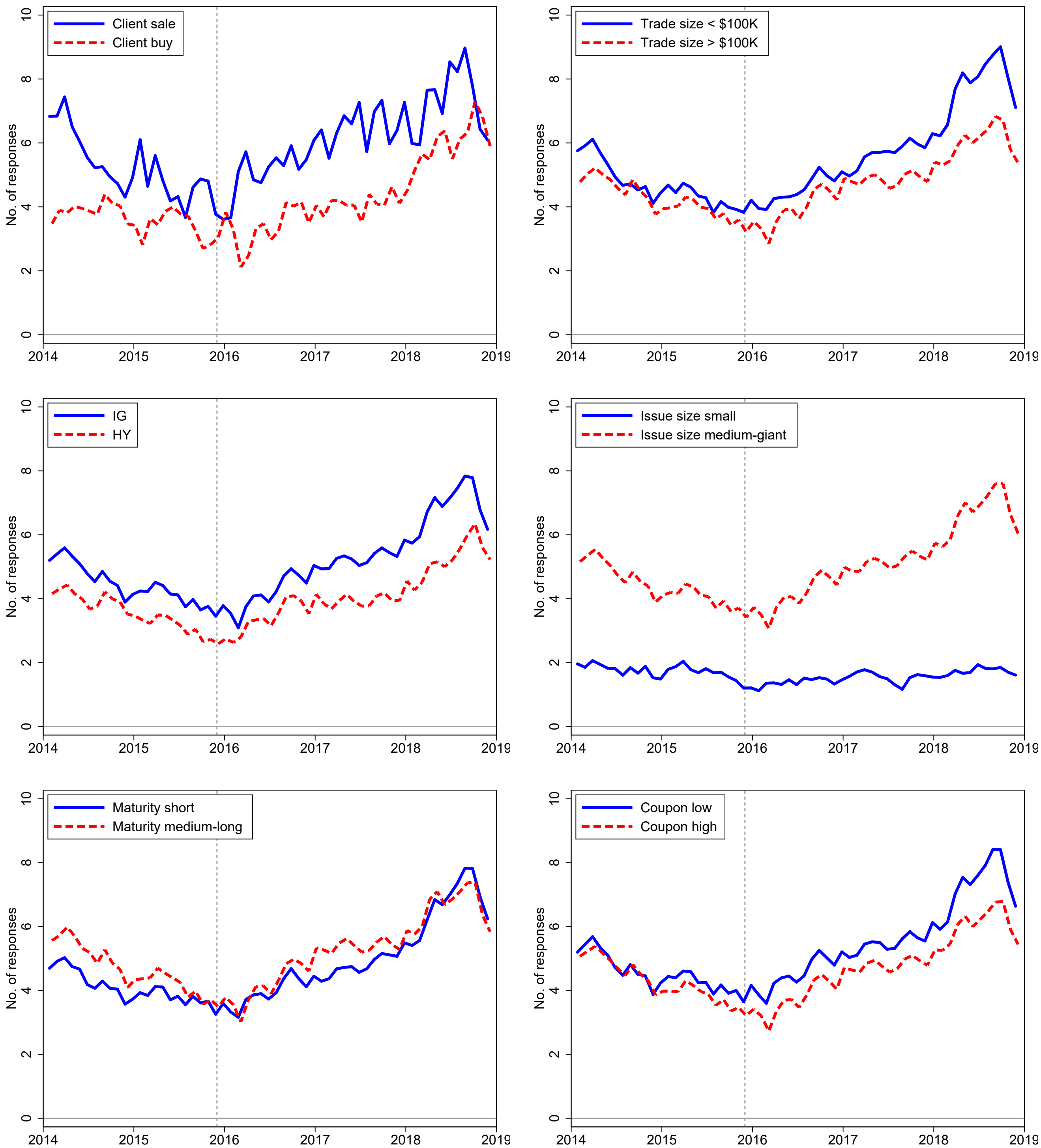


Figure 8: Number of responses to RFQ over time

The figures document the number of responses to an RFQ over time. The subplots report monthly averages for the splits indicated in the legend. The vertical dotted line marks the increase in OT at the end of 2015.

(short/medium-long), bottom left plot, and coupon value (low/high), bottom right plot.

Figure 8 shows that RFQ participation is, on average, higher for client sales, for trades less than \$100K, and for bonds that are higher rated, have larger issue size, longer maturity, and lower coupon rate. Across time, the average RFQ participation gradually declines between January 2014 and January 2016, then gradually increases until July 2018, and then falls sharply again. While this behavior is present in all subplots of Figure 8, it is more pronounced for RFQs with higher average participation. These results shed additional light on our results for RFQ competitiveness from Figure 6—the decline in RFQ competitiveness during the 2014Q1-2016Q1 period across different bonds and trades was due to decline in the RFQ participation. Once the RFQ participation began recovering after 2016Q1, the RFQ competitiveness began improving.

Figure 9 presents the monthly time series in the average number of OT responses to RFQs for the same set of trade and bond characteristics as used in Figure 8. All subplots of Figure 9 show that the average number OT responses to RFQs has been very low, around 0.2, and did not depend on trade and bond characteristics between January 2014 and November 2015. This implies that during this period the vast majority of responses to RFQs were by traditional dealers, who, on average, were reducing their RFQ participation. In November 2015, shown by a dotted vertical line, OT ramped up its RFQ participation in all types of trades and bonds. The growth in the number of OT responses is fairly steady until January 2018, when it shoots up drastically for all types of trades and bonds. The abnormal growth lasts for about a quarter and a half, then the number of OT responses briefly declines, and then continues to increase during the third quarter of 2018, and then plunges during the last quarter of 2018.

Out of six trade and bond characteristics, the most dramatic growth in the average number of OT responses took place in trades smaller than \$100K as evident from the blue solid line in the top right subplot of Figure 8. This subplot shows that the average number of OT responses more than doubles to approximately 0.3 for both smaller (<\$100K, solid blue line) and larger (≥\$100K, dashed red line) trades between November 2015 and February 2016. The growth in the number of OT responses is quite similar for both trade sizes until February 2017, when the average number of OT responses for larger trades stays flat at approximately 0.6 until January 2018, while it continues to grow for smaller trades, reaching approximately 0.75 by January 2018. In January 2018, the average number of OT responses jumps sharply for both trade sizes from 0.75/0.6 to 2.2/1.2 for smaller/larger trades. It then declines slightly, and then jumps again to 2.7/1.4 for smaller/larger

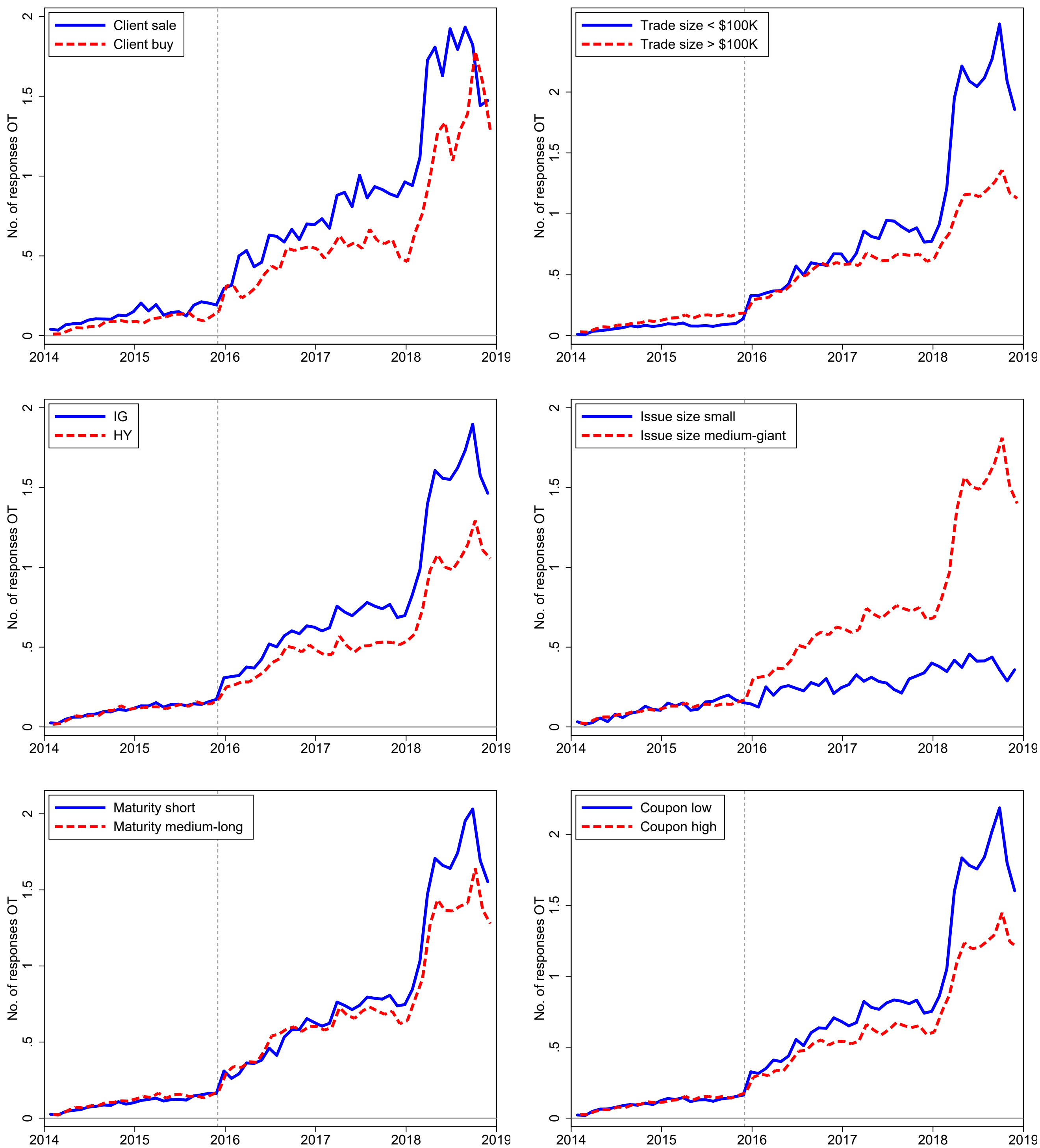


Figure 9: Number of OT responses to RFQ over time

The figures document the number of OT responses to an RFQ over time. The subplots report monthly averages for the splits indicated in the legend. The vertical dotted line marks the increase in OT at the end of 2015.

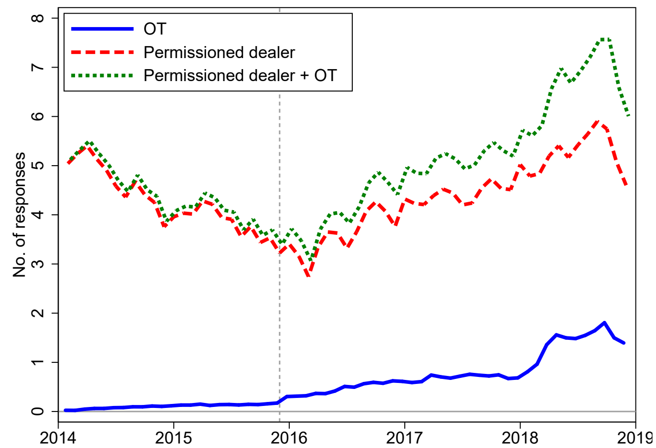


Figure 10: Number of RFQ responses and RFQ competitiveness ex-OT
The graph shows monthly average number of RFQ responses by the permissioned dealers (dashed line), OT (solid line), and by all liquidity providers (dotted line) on MarketAxess. The vertical dotted line indicates at the increase in OT at the end of 2015.

trades between July and October 2018. Between January and October 2018, the average number of OT responses increases by 2/0.8 responses for smaller/larger trades, while the average number of total RFQ responses increases by 3/2 responses, as evident from the top right subplot of Figure 8. These results hold qualitatively for other trade and bond characteristics thus indicating that non-traditional liquidity providers were responsible for much of the growth in the number of RFQ responses during 2018.

Next, Figure 10 graphs monthly time series of the average number of RFQ responses by OT, N_{OT}, permissioned dealers, N_{PD}, and the total number of responses, $N_{\mathrm{OT}} + N_{\mathrm{PD}}$. This plot is essential for quantifying different channels of OT price improvement using the model we introduce in the next subsection.

Figure 10, together with Figures 8 and 9, shows that permissioned dealers are responsible for almost all RFQ responses between January 2014 and November 2015. The number of OT responses, while growing, is very small during this time period. Moreover, N_{PD} is declining during this time period until March 2016, when this trend is reversed and N_{PD} starts to increase. It increases until October 2018 when, at 5.8, it is just above its highest pre-November 2015 value of 5.5. N_{PD} drops sharply to 4.5 during the last quarter of 2018. N_{OT} more than doubles between November 2015 and January 2016 to 0.4. It continues to grow between January 2016 and January 2018 reaching the value of 0.8 in January 2018. N_{PD} increases sharply to 1.8 between January and October 2018, and then drops to 1.5 during the last quarter of 2018. The highest value of $N_{\text{OT}} + N_{\text{PD}}$ equal to 7.8 takes place in October 2018. Overall, this evidence is consistent with the permissioned dealers being crowded in by OT between March 2016 and October 2018, instead of being crowded out.

5.2 A model of OT impact

OT can impact the prices investors receive when initiating an RFQ in several ways:

(i) OT directly improves prices when it bids more and wins auctions;

(ii) OT can indirectly affect prices by changing the competitiveness of existing dealers' bids; and

(iii) OT can also indirectly affect prices by impacting dealers' propensity to bid, e.g., crowding out or crowding in traditional dealers.

To help quantify the impact of OT bids on the prices investor receive, we model an RFQ as a sealed-bid first-price auction for a generic asset that is indivisible since 98.9% of trades on MarketAxess are such that the traded quantity equals the requested quantity of bonds. We start by assuming N symmetric bidders.[12] Bids B_j, $j = 1, ..., N$, are drawn from an absolutely continuous distribution $G(b; N)$ with density $g(b; N)$ and inverse function $G^{-1}(u; N)$. Here the dependence of both cdf and pdf on the total number of bidders, N, captures the fact that bidders may change their bidding strategies when the total number of bidders changes.[13] Bidders adjusting their bidding range with N and, therefore, the support of the distribution, is the most straightforward example.

We are going to report only key results here and relegate all of the model's details to the Appendix. Let $B^{1:N}$ and $B^{2:N}$ be the highest and the second highest, or the cover price, of N bids,

[12]The model encompasses both private and common value settings. We make no parametric assumptions on the distribution of bidders' private valuations beyond the regularity assumptions in the literature (Athey and Haile, 2008). We assume symmetric bidders as in Guerre, Perrigne, and Vuong (2000). The model can be extended to asymmetric bidders as in Athey and Haile (2002).

[13]The total number of bidders, N, is exogenous in our model. This assumptions is made for the simplification and clarity. Levine and Smith (1994) and Li and Zheng (2009) discuss the effects of the endogenous entry on the equilibrium bidding function. Consistent with these papers, we allow bidders to adjust their bidding strategies with the number of bidders.

respectively. Define the expected price improvement from adding a bidder to the RFQ as

$$\begin{aligned} \mathrm{PI}(N-1,N) &\equiv \mathbb{E}_N[B^{1:N}] - \mathbb{E}_{N-1}[B^{1:N-1}] = \\ &= \underbrace{\mathbb{E}_N[B^{1:N}] - \mathbb{E}_N[B^{1:N-1}]}_{\text{Holding } G(b;N) \text{ fixed}} + \underbrace{\Omega_{N-1,N}(N-1)}_{\text{Holding no. bidders fixed at } N-1}, \end{aligned} \tag{12}$$

where the the price improvement due to changed distribution of bids is equal to

$$\Omega_{N-1,N}(N-1) \equiv \mathbb{E}_N[B^{1:N-1}] - \mathbb{E}_{N-1}[B^{1:N-1}]. \tag{13}$$

Relation (12) captures two effects of changing the number of bidders on the total price improvement. First, it changes the best bid and, second, it changes the distribution of bids, that is, bidders change their bidding strategies. Price improvement is an important seller's welfare metric. In a perfectly competitive auction, i.e., when $N \to \infty$, the seller receives the asset's fair value. The difference between the asset's fair value and the expected best bid when only a single dealer participates in the auction is equal to dealers' surplus. $\mathrm{PI}(N-1,N)$ captures the reduction/improvement in dealers'/sellers' surplus from adding one extra bidder to an RFQ with $N-1$ bidders. Correspondingly, price improvement's elasticity with respect to the number of bidders captures the marginal reduction/improvement in dealers'/sellers' surplus from adding one extra bidder to an RFQ with $N-1$ bidders. If bidders' RFQ entry is costly, equating the marginal price improvement to marginal entry costs determines optimal RFQ participation.

Analogously to relation (12), define the expected cover improvement as

$$\mathrm{CI}(N-1,N) \equiv \mathbb{E}_N[B^{2:N}] - \mathbb{E}_{N-1}[B^{2:N-1}]. \tag{14}$$

Essentially, $\mathrm{CI}(N-1,N)$ captures changes in bidders' bid shading due to entry and, if normalized by a par value of 1, it is the same as its empirical counterpart from equation (7).

Similar to relation (5), the expected RFQ competitiveness is equal to the expected cover discount

$$\mathrm{CP}(N) \equiv \mathbb{E}_N[B^{1:N}] - \mathbb{E}_N[B^{2:N}] = N \times (\mathrm{PI}(N-1,N) - \Omega_{N-1,N}(N-1)). \tag{15}$$

Equation (15) can then be rewritten as

$$\mathrm{PI}(N-1,N) = \frac{\mathrm{CP}(N)}{N} + \Omega_{N-1,N}(N-1), \tag{16}$$

where the first term captures the price improvement when holding the distribution of bids fixed. This term provides a natural link between the price improvement and competitiveness - the latter can be interpreted as an average price improvement over the cover when an extra bidder supplies a winning bid greater than the cover. Because all N bidders are equally likely to win, the probability of supplying the extra bid is $1/N$. It directly follows from relation (16) that the marginal price improvement from adding $J+1$ dealers to an RFQ can be expressed in terms of cumulative average RFQ competitiveness as

$$\mathrm{PI}(N-1,N+J) = \sum_{j=0}^{J} \mathrm{PI}(N+j-1,N+j) = \sum_{j=0}^{J} \frac{\mathrm{CP}(N+j)}{N+j} + \sum_{j=0}^{J} \Omega_{N+j-1,N+j}(N+j-1). \tag{17}$$

Finally, it is straightforward to verify relation (7) holds in the model

$$\Delta\mathrm{CP}(N-1,N) = \mathrm{CP}(N-1) - \mathrm{CP}(N) = \mathrm{CI}(N-1,N) - \mathrm{PI}(N-1,N). \tag{18}$$

Overall, our very simple model of RFQ is consistent with our empirical relations (4)–(8).

5.3 Number of responses and OT impact

Total price improvement from OT: We define the *total* price improvement due to additional $\mathbb{E}[J]+1$ bidders as $\mathrm{TPI}(\mathbb{E}[N]-1, \mathbb{E}[N]+\mathbb{E}[J])$. It can be calculated from relation (17). One complication is the model relying on the integer number of bidders, while in the data the average number of bids is a non-negative real number, $\mathbb{E}[N] \in \mathbb{R}_+$. Strictly speaking, $\mathrm{PI}(\mathbb{E}[N]-1, \mathbb{E}[N])$ does not exist. Therefore, we use a *locally-linear* approximation (LLA)

$$\mathbb{E}[B^{1:N-1+\delta}] = \mathbb{E}[B^{1:N-1}] + \mathrm{PI}(N-1,N)\delta \Rightarrow \mathrm{PI}(N-1+\delta,N) = \mathrm{PI}(N-1,N)\delta, \tag{19}$$

where $\delta \ll 1$ is an infinitesimal change in the number of responses. Under LLA, the price improvement due to changing bid distribution, $\Omega_{N-1,N+\delta-1}(N-1)$, is of the order of δ,

$$\Omega_{N-1,N+\delta-1}(N-1) = \Omega_{N-1,N}(N-1)\delta. \tag{20}$$

To calculate $\text{TPI}(\mathbb{E}[N]-1, \mathbb{E}[N+J])$ under LLA rewrite relation (17) in the following form

$$\text{PI}(N-1, N+J) = \sum_{j=0}^{J} \text{PI}(\underbrace{N+j-1}_{n_j}, \underbrace{N+j}_{n_j+1})(n_{j+1}-n_j). \tag{21}$$

LLA can be implemented in (21) by setting $n_{j+1} - n_j = \delta$ with $n_0 = N-1$ to yield[14]

$$\text{TPI}(N-1, N+J) = \sum_{j=0}^{J/\delta} \text{PI}(N+j\delta-1, N+j\delta)\delta. \tag{22}$$

After switching to the expected number of RFQ responses in (22) and then taking a limit $\delta \to 0$, we obtain

$$\text{TPI}(\mathbb{E}[N]-1, \mathbb{E}[N]+\mathbb{E}[J]) = \int_0^{\mathbb{E}[J]} \text{PI}(\mathbb{E}[N]+n-1, \mathbb{E}[N]+n)dn = \int_{\mathbb{E}[N]}^{\mathbb{E}[N]+\mathbb{E}[J]} \text{PI}(n-1,n)dn. \tag{23}$$

Relation (23) implies that if we observe $\text{PI}(\mathbb{E}[N]-1, \mathbb{E}[N])$ in the data, then the total price improvement from additional $\mathbb{E}[J]+1$ bidders is equal to the integral of $\text{PI}(\mathbb{E}[N]-1, \mathbb{E}[N])$ on the interval $[\mathbb{E}[N], \mathbb{E}[N]+\mathbb{E}[J]]$. $\text{PI}(\mathbb{E}[N]-1, \mathbb{E}[N])$ can be estimated in the data with the help of relations (16) and (19).

Measuring total price improvement from OT: We start by estimating $\text{PI}(\mathbb{E}[N]-1, \mathbb{E}[N])$ over the range of $\mathbb{E}[N]$ in our data. Our first empirical proxy for $\text{PI}(\mathbb{E}[N]-1, \mathbb{E}[N])$ is defined under LLA and directly follows from relation (19),

$$\text{PI}(\mathbb{E}[N]-1, \mathbb{E}[N]) \approx \frac{\mathbb{E}\left[\text{PI}(\mathbb{E}[N]-1, \mathbb{E}[N]-1+\mathbb{E}[N_{\text{OT}}])\right]}{\mathbb{E}\left[N_{\text{OT}}\right]} = \frac{\mathbb{E}\left[\text{PI}_{\text{OT}}\right]}{\mathbb{E}\left[N_{\text{OT}}\right]}, \tag{24}$$

[14]We can solve the recursive relation as $n_1 = n_0 + \delta = N + \delta - 1$, $n_2 = n_1 + \delta = N + 2\delta - 1$, and by induction $n_j = n_{j-1} + \delta = N + j\delta - 1$.

where PI_{OT} is the price improvement from OT defined in Section 3 and N_{OT} is the number of OT bidders analyzed above. To implement (24) we compute the directly observable price improvement from OT across all RFQs $i = 1, ..., I$ in a given month

$$\widehat{\text{PI}}_{\text{OT}} = \frac{\frac{1}{I}\sum_i^I \text{OT price } \widehat{\text{improvement}}_i}{\frac{1}{I}\sum_i^I N_{\text{OT},i}}. \tag{25}$$

Under the assumption of symmetric bidders, a second proxy for $\text{PI}(\mathbb{E}[N]-1, \mathbb{E}[N])$ uses relation (16) and RFQ competitiveness defined in Section 4:[15]

$$\text{PI}(\mathbb{E}[N]-1, \mathbb{E}[N]) \approx \frac{\mathbb{E}\left[\text{CP}(N)\right]}{\mathbb{E}\left[N\right]}. \tag{26}$$

Relation (26) is constructed under the assumption that the price impact due to OT affecting dealers' competitiveness, Ω, is small. For a fixed number of dealers, OT's impact on dealers' bidding can be estimated through the competitiveness of dealers' bids conditional on the expected number of OT responses. The left subplot of Figure 10 shows that the number of RFQ responses by permissioned dealers equals 5 at the beginning and end of our sample, 2014 and 2018. However, ex-OT RFQ competitiveness from the right subplot of Figure 10 improves by 5bps in January 2018 relative to January 2014. Relation (26) translates this into investors receiving roughly 1 basis point better prices.

To implement (26) we compute competitiveness across all RFQs $i = 1, ..., I$ in a given month[16]

$$\widehat{\text{PI}} = \frac{\frac{1}{I}\sum_i^I \text{RFQ } \widehat{\text{competitiveness}}_i}{\frac{1}{I}\sum_i^I N_i}, \tag{27}$$

where $\text{CP}(N)$ is RFQ competitiveness defined in (15) with its empirical analog (5), where we reverse

[15] An alternative is the expected $\text{PI}(N-1, N)$ in a month:

$$\mathbb{E}[\text{PI}(N-1,N)] = \mathbb{E}\left[\frac{\text{CP}(N)}{N}\right] \geq (\leq) \frac{\mathbb{E}\left[\text{CP}(N)\right]}{\mathbb{E}\left[N\right]}.$$

So long as $\text{CP}(N)$ is decreasing and convex (concave), $\frac{\mathbb{E}[\text{CP}(N)]}{\mathbb{E}[N]}$ is a better (worse) proxy than $\mathbb{E}[\frac{\text{CP}(N)}{N}]$ for PI $(\mathbb{E}[N]-1, \mathbb{E}[N])$.

[16] Note that this computation averages out noise in realized RFQ competitiveness across all RFQs in the month. As a proxy for $\text{PI}(\mathbb{E}[N]-1, \mathbb{E}[N])$ it is exact if N is fixed in a month, though this assumption need not hold over longer horizons. It ignores the convexity of $\text{PI}(N-1, N)$ within a month (and across securities) and instead focuses on capturing the convexity of $\text{PI}(N-1, N)$ across months. It is straightforward to relax these assumptions.

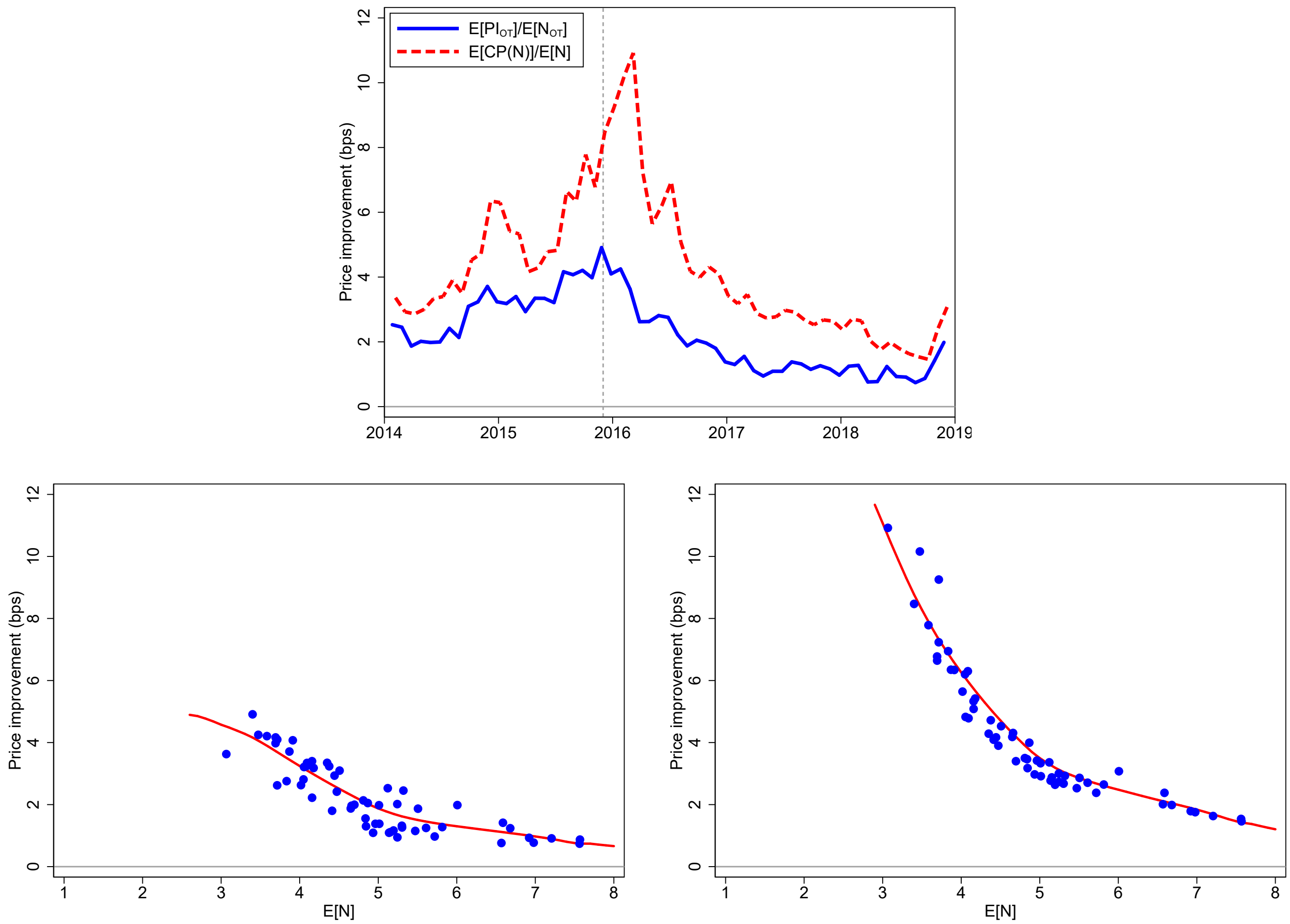


Figure 11: Estimated $\mathrm{PI}(\mathbb{E}[N]-1, \mathbb{E}[N])$

The figure documents $\mathrm{PI}(\mathbb{E}[N]-1, \mathbb{E}[N])$ estimated in the data. Top subplot of graphs monthly time series of $\widehat{\mathrm{PI}}$ given by (27) and $\widehat{\mathrm{PI}}_{\mathrm{OT}}$ given by (25). Bottom left subplot graphs $\mathrm{PI}(\mathbb{E}[N]-1, \mathbb{E}[N])$ estimated under the LLA assumption from (24) as a function of $\mathbb{E}[N]$. Bottom right subplot graphs $\mathrm{PI}(\mathbb{E}[N]-1, \mathbb{E}[N])$ estimated under the symmetric bidders' assumption from (26) as a function of $\mathbb{E}[N]$. The vertical dotted line marks the increase in OT at the end of 2015.

the sign and use the par value as scaling variable compared to (9). $\mathbb{E}[N]$ is the average monthly number of RFQ bidder responses bidders in RFQs $i = 1, ..., I$.

Figure 11 reports estimates from (25) and (27). The top subplot of Figure 11 graphs monthly time series of $\widehat{\mathrm{PI}}$ (solid line) and $\widehat{\mathrm{PI}}_{\mathrm{OT}}$ (dashed line). The time series of $\widehat{\mathrm{PI}}$ are constructed using the average total number of responses, $N_{\mathrm{OT}} + N_{\mathrm{PD}}$, shown in Figure 10 by a dotted line. $\widehat{\mathrm{PI}}$ increases from 3bps to 6.5bps between March and December 2014, when $N_{\mathrm{OT}} + N_{\mathrm{PD}}$ declines from 5.5 to 3.9 responses. $\widehat{\mathrm{PI}}$ declines from 6.5bps to 4.2bps between January and June 2015, when $N_{\mathrm{OT}} + N_{\mathrm{PD}}$ increases from 3.9 to 4.5 responses. $N_{\mathrm{OT}} + N_{\mathrm{PD}}$ falls from 4.5 to 3, its lowest number in our sample, between June 2015 and April 2016. Correspondingly, $\widehat{\text{PI}}$ increases from 4.2bps to 11bps, which is its highest value. As the average total number of responses rises from 3 to 7.5 between April 2016 and October 2018, $\widehat{\text{PI}}$ declines from 11bps to its lowest value 1.8bps during this time period.

The time series of $\widehat{\text{PI}}_{\text{OT}}$ are constructed using the average number of OT responses, N_{OT} shown in Figure 10 by a solid line. $\widehat{\text{PI}}_{\text{OT}}$ is lower than $\widehat{\text{PI}}$ in our sample, and its behavior is not as dramatic. $\widehat{\text{PI}}_{\text{OT}}$ increases from 1.8bps to 3.5bps between March and December 2014, when N_{OT} increases from 0.05 to 0.1 responses. $\widehat{\text{PI}}_{\text{OT}}$ stays flat between January and July 2015, when N_{OT} also stays flat. $\widehat{\text{PI}}_{\text{OT}}$ from 3bps to 4.8, its largest value, between July and November 2015. $\widehat{\text{PI}}_{\text{OT}}$ declines between November 2015 and September 2018, when N_{OT} increases from 0.4 to 2, and the goes up again during the last quarter of our sample when N_{OT} declines.

The bottom left and right subplots of Figure 11 graph $\mathbb{E}\left[\text{PI}_{\text{OT}}\right]/\mathbb{E}\left[N_{\text{OT}}\right]$ and $\mathbb{E}\left[\text{CP}(N)\right]/\mathbb{E}\left[N\right]$ as functions of $\mathbb{E}[N]$, respectively. In both subplots, we fit the relationship shown as a solid red line using a Kernel-weighted local polynomial regression.[17] $\mathbb{E}\left[\text{PI}_{\text{OT}}\right]/\mathbb{E}\left[N_{\text{OT}}\right]$ and $\mathbb{E}\left[\text{CP}(N)\right]/\mathbb{E}\left[N\right]$ are both monotonically decreasing and convex functions of N.

$\mathbb{E}\left[\text{CP}(N)\right]/\mathbb{E}\left[N\right]$ is larger and steeper than $\mathbb{E}\left[\text{PI}_{\text{OT}}\right]/\mathbb{E}\left[N_{\text{OT}}\right]$ on $\mathbb{E}[N] \in [3,5]$. For instance, the former is equal to 12pbs and 3.3bps while the latter is only 4.5bps and 1.5bps at $\mathbb{E}[N] = 3$ and $\mathbb{E}[N] = 5$, respectively. The difference likely arises from the assumption that OT bids symmetrically to dealers when using $\mathbb{E}\left[\text{CP}(N)\right]/\mathbb{E}\left[N\right]$ to estimate price improvement due to OT. If OT bidders are less aggressive than dealers, then $\mathbb{E}\left[\text{CP}(N)\right]/\mathbb{E}\left[N\right] > \mathbb{E}\left[\text{PI}_{\text{OT}}\right]/\mathbb{E}\left[N_{\text{OT}}\right]$. This is consistent with comparing the unconditional probability that OT wins in Figure 5 to N_{OT}/N from Figure 10. The unconditional probability that OT wins is less than the fraction of bids that OT represents, consistent with OT bidding less aggressively. This difference declines at the end of the sample. Correspondingly, the gap between $\mathbb{E}\left[\text{CP}(N)\right]/\mathbb{E}\left[N\right]$ and $\mathbb{E}\left[\text{PI}_{\text{OT}}\right]/\mathbb{E}\left[N_{\text{OT}}\right]$ closes at the end of the sample.

The bottom subplots of Figure 11 look similar for $\mathbb{E}[N] > 5$, and both approach 1bps for $\mathbb{E}[N] > 7$. This indicates that clients should see small value gains from additional entry once RFQ participation reaches 5 bidders.

OT's price improvement depends on the number of permissioned dealers. If we assume the

[17] In the reported results we use a locally linear model with Epanechnikov kernel and half-width equal to 0.75.

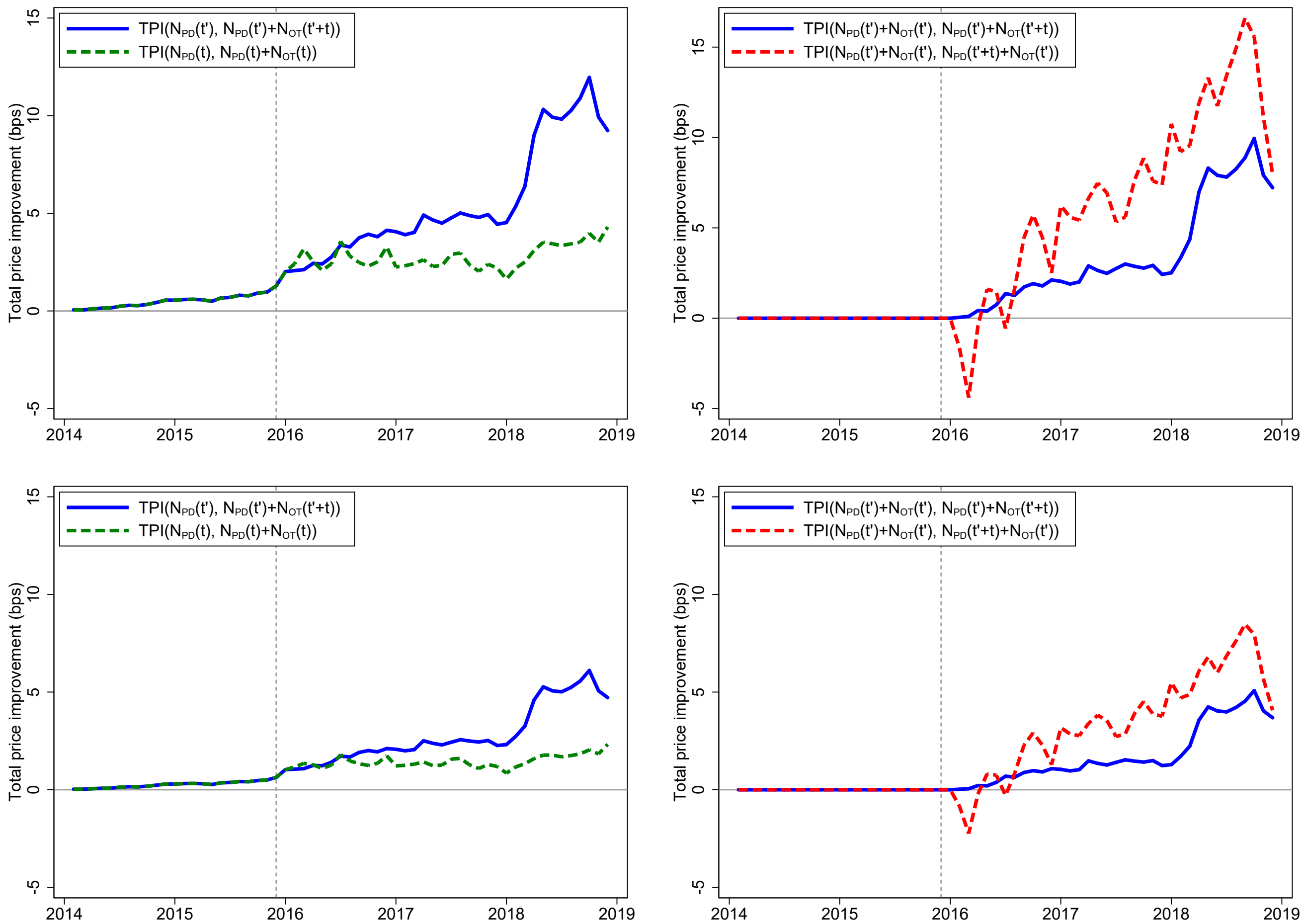


Figure 12: Total price improvement TPI(N)

The figure documents TPI(N) in the data. TPI(N) is defined in (28). All subplots use as an input monthly average number of RFQ responses by OT, $N_{\mathrm{OT}}(t)$, permissioned dealers, $N_{\mathrm{PD}}(t)$, and the total number of responses, $N_{\mathrm{OT}}(t)+N_{\mathrm{PD}}(t)$, from of Figure 10. Left subplots graph the monthly total OT price improvement, $\mathrm{TPI}(N_{\mathrm{PD}}(t), N_{\mathrm{OT}}(t)+N_{\mathrm{PD}}(t))$, and monthly OT price improvement with the number of responses by the permissioned dealers set fixed after the increase in OT at the end of 2015, $\mathrm{TPI}(N_{\mathrm{PD}}(t'), N_{\mathrm{OT}}(t'+t)+N_{\mathrm{PD}}(t'))$, where t' is the date of the increase in OT at the end of 2015. Right subplots show total price improvement with the number of RFQ responses by the permissioned dealers/OT set fixed after the increase in OT at the end of 2015, $\mathrm{TPI}(N_{\mathrm{PD}}(t')+N_{\mathrm{OT}}(t'), N_{\mathrm{OT/PD}}(t'+t)+N_{\mathrm{PD/OT}}(t'))$. Top(bottom) subplots use $\mathbb{E}\left[\mathrm{CP}(N)\right]/\mathbb{E}\left[N\right](\mathbb{E}\left[\mathrm{PI}_{\mathrm{OT}}\right]/\mathbb{E}\left[N_{\mathrm{OT}}\right])$ as a proxy for $\mathrm{PI}(n, n+1)$ in (28).

number of permissioned dealers is independent of OT, we can calculate the monthly total OT price improvement, $\mathrm{TPI}(N_{\mathrm{PD}}(t), N_{\mathrm{OT}}(t)+N_{\mathrm{PD}}(t))$, by using the month t average number of RFQ responses by OT, $N_{\mathrm{OT}}(t)$, permissioned dealers, $N_{\mathrm{PD}}(t)$, and the total number of responses, $N_{\mathrm{OT}}(t)+N_{\mathrm{PD}}(t)$, from Figure 10 in relation (23):

$$\mathrm{TPI}(N_{\mathrm{PD}}(t), N_{\mathrm{PD}}(t)+N_{\mathrm{OT}}(t)) = \int_{N_{\mathrm{PD}}(t)}^{N_{\mathrm{PD}}(t)+N_{\mathrm{OT}}(t)} \mathrm{PI}(n, n+1)dn, \tag{28}$$

by calculating the integral numerically for both estimates for $\mathrm{PI}(n, n+1)$, $\mathbb{E}\left[\mathrm{CP}(N)\right]/\mathbb{E}\left[N\right]$ and $\mathbb{E}\left[\mathrm{PI}_{\mathrm{OT}}\right]/\mathbb{E}\left[N_{\mathrm{OT}}\right]$. We refer to this as independent OT TPI. If permissioned dealers do not change their bidding strategy with the entry of OT, $\Omega_{N-1,N}(N-1) = 0$ in the model, then independent OT TPI should equal the expect OT price improvement shown in Figure 5.

We can also measure total price improvement using counter factual assumptions about the number of OT and permissioned dealer bids. First, we assume that the number of permissioned dealers does not change (remains fixed) after the increase in OT at the end of 2015, $\mathrm{TPI}(N_{\mathrm{PD}}(t'), N_{\mathrm{OT}}(t'+t) + N_{\mathrm{PD}}(t'))$, where t' is the date of the increase in OT at the end of 2015. We refer to this as fixed PD post entry OT TPI. We will sometimes refer to t' as OT entry.

We also estimate a related counter factual OT total price improvement using the same OT entry date, but measuring price improvement relative to $N(t') = N_{\mathrm{PD}}(t') + N_{\mathrm{OT}}(t')$ at the time of the increase in OT at the end of 2015 (t'), $\mathrm{TPI}(N_{\mathrm{PD}}(t') + N_{\mathrm{OT}}(t'), N_{\mathrm{OT}}(t'+t) + N_{\mathrm{PD}}(t'))$. We refer to this as OT TPI relative to N at OT entry. Finally, we estimate a related counter factual permissioned dealer total price improvement using the same OT entry date, but measuring price improvement due to PD relative to N at the time of the increase in OT at the end of 2015, $\mathrm{TPI}(N_{\mathrm{PD}}(t') + N_{\mathrm{OT}}(t'), N_{\mathrm{OT}}(t') + N_{\mathrm{PD}}(t'+t))$. We refer to this as PD TPI relative to N at OT entry.

Figure 12 presents these results where top(bottom) subplots use $\mathbb{E}\left[\mathrm{CP}(N)\right]/\mathbb{E}\left[N\right](\mathbb{E}\left[\mathrm{PI}_{\mathrm{OT}}\right]/\mathbb{E}\left[N_{\mathrm{OT}}\right])$ as a proxy for $\mathrm{PI}(n, n+1)$ in (28). We first discuss the left subplots of Figure 12, and then discuss the right subplots. Both left subplots graph the monthly independent OT TPI, $\mathrm{TPI}(N_{\mathrm{PD}}(t), N_{\mathrm{OT}}(t) + N_{\mathrm{PD}}(t))$, and fixed PD post entry OT TPI, $\mathrm{TPI}(N_{\mathrm{PD}}(t'), N_{\mathrm{OT}}(t'+t) + N_{\mathrm{PD}}(t'))$, where N_{PD} is fixed after the time of the increase in OT at the end of 2015, $t \geq t'$. The bottom/top subplot shows both the independent OT TPI and fixed PD post entry OT TPI increase from a fraction of a basis point to approximately 0.8bps/1.5bps between January 2014 and November 2015, when OT increases noticeably. The independent OT TPI increases from 0.8/1.5bps to 1.6bps/2.5bps between November 2015 and April 2016 and stays flat until the sample's end. The fixed PD post entry OT TPI increases from 0.8/1.5bps to 2.5bps/5bps between November 2015 and April 2017, and stays flat until January 2018. The fixed PD post entry OT TPI increases to approximately 7bps/12.5bps between January and October 2018.

Overall, it is clear from left subplots of Figure 12 that the increase in OT at the end of 2015 has a strong association with both independent OT TPI and fixed PD post entry OT TPI as they increase significantly after the OT enters more significantly at the end of 2015. However, the fixed PD post entry OT TPI increases by much more. To understand why this is the case, note the bottom subplots of Figure 11 show $\mathrm{PI}(n, n+1)$ is a monotonically decreasing and convex function of n, thus implying the marginal price improvement declines with n. The independent OT TPI staying flat while the fixed PD post entry OT TPI increasing after OT entry at the end of 2015 is thus consistent with permissioned dealers becoming more competitive after the entry.

The right subplots of Figure 12 compare the relative price improvement due to OT and permissioned dealers after OT entry. These provide a decomposition of price improvement changes post OT entry into those arising from OT and PD: OT TPI relative to N at OT entry, $\mathrm{TPI}(N_{\mathrm{PD}}(t') + N_{\mathrm{OT}}(t'), N_{\mathrm{OT}}(t'+t)+N_{\mathrm{PD}}(t'))$ and PD TPI relative to N at OT entry, $\mathrm{TPI}(N_{\mathrm{PD}}(t')+N_{\mathrm{OT}}(t'), N_{\mathrm{PD}}(t'+t) + N_{\mathrm{OT}}(t'))$. The base number of RFQ responses is held constant, $N_{\mathrm{PD}}(t') + N_{\mathrm{OT}}(t')$, for $t \leq t'$. The OT TPI relative to N at OT entry is qualitatively similar to independent OT TPI in the left plots, so our discussion focuses on the PD TPI relative to N at OT entry. We start by noting that the left plot of Figure 10 shows $N_{\mathrm{PD}}(t)$ starts to decline one month after the OT entry, and it continues to decline for almost three months as if permissioned dealers had a delayed response to OT entry. Consequently, the PD TPI relative to N at OT entry starts to decline sharply one month after the entry and even becomes negative by March 2016. However, PD TPI relative to N at OT entry recovers after March 2016, as $N_{\mathrm{PD}}(t)$ starts to increase. The bottom/top subplot shows the PD TPI relative to N at OT entry increases to 9bps/17bps between March 2016 and October 2018, when $N_{\mathrm{PD}}(t)$ increases from 3 to 5.5.

Overall, one interpretation of the results on OT entry and subsequent increase in permission dealer bidding and price improvement is that starting in March 2016 permissioned dealers respond to OT increasing RFQ participation by improving their own RFQ participation. Consistent with results from left subplots of Figure 12, dealers bidding more aggressively improves prices even when OT does not win and reduces the directly measurable price improvement when OT does win because OT improves on an already better price.

The approach to measuring price improvement in Figure 12 combines together the impact of changes in the number of dealer bids together with changes in the aggressiveness/competitiveness

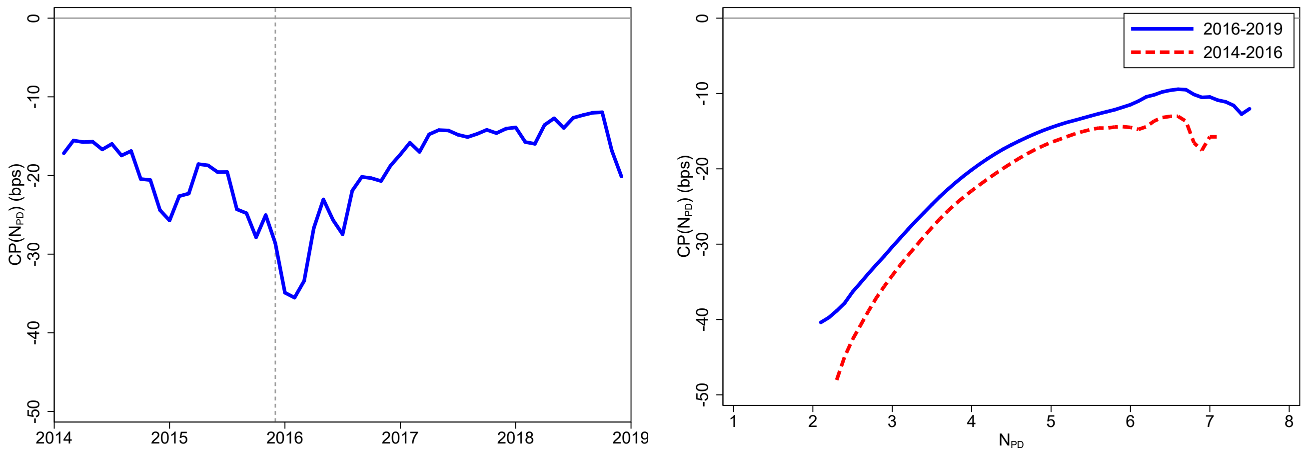


Figure 13: RFQ competitiveness ex-OT

The left subplot graphs monthly RFQ competitiveness omitting OT responses as defined in equation (6). The vertical dotted line indicates the increase in OT at the end of 2015. The right graph plots the fitted relation between the average monthly competitiveness of permission dealers (competitiveness without OT) on the y-axis and the average number of permissions dealer bids (non OT bids) on the x-axis. The relationship is graphed separately for the first and second half of the sample. We fit the relationship between CP(N_{PD}) and N_{PD} using a Kernel-weighted local linear regression with Epanechnikov kernel and half-width equal to 0.75.

of those bids. For a fixed number of dealers, OT's impact on dealers' bidding can be estimated through the competitiveness of dealers' bids conditional on the expected number of OT responses. The left subplot of Figure 13 graphs monthly RFQ competitiveness omitting OT responses, defined in equation (6). Figure 10, shows the number of dealer responses is roughly equal at the beginning and ending of our sample. However, Figure 13 shows the competitiveness of dealers' bids improves by about 5 basis points from the beginning to the end of our sample. The model translates this into investors receiving roughly 1 basis point better prices due to more aggressive dealer bidding conditional on the number of dealer bids, Ω in the model. Because OT increases steadily over the sample period, another approach to showing that OT impacts dealers' bidding is to compare the relationship between the competitiveness of dealers' bidding and the number of dealer bids in the first and second half of the sample. The right subplot of Figure 13 does this and shows that the competitiveness/number relation moves up toward zero in the second half of the sample by a magnitude consistent with the left graph. This demonstrates that when OT bidding is more prevalent dealers bid more competitively (conditional on the number of dealers).

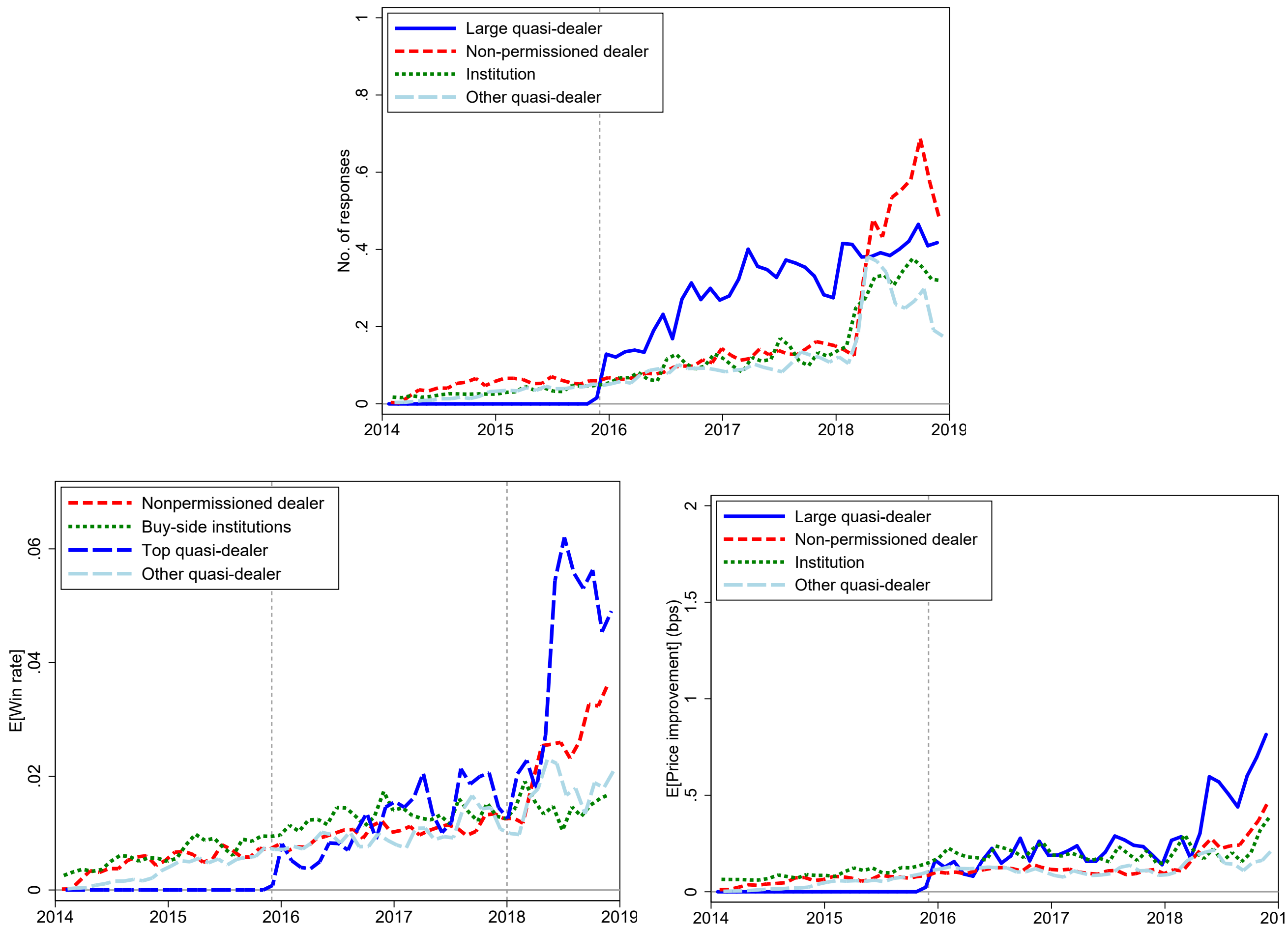


Figure 14: Number of OT responses to RFQ, expected OT win rate, and expected OT price improvement by OT type

The figure documents monthly time series of the number of OT responses (top subplot), the expected OT win rate (bottom left subplot), and the expected OT price improvement (bottom right subplot) by OT type. The OT types considered are non-permissioned dealers, buy-side institutions, large quasi-dealer, and other quasi-dealers. Vertical dotted line marks the increase in OT at the end of 2015.

5.4 Number of responses and OT impact by OT type

We next turn our attention to RFQ participation and associated price improvement by OT type. We start by further dividing the quasi-dealers, who have been treated so far as a monolith group, into sub-groups based on their trading activity. A single Large Quasi-Dealer (LQD) is responsible for the majority of quasi-dealer trades, especially later in the sample. The LQD enters OT trading during November 2015, with the precise time of entry shown by a vertical dotted line on all plots, and steadily increases its number of trades throughout the sample. At the end of 2018 the LQD's fraction of RFQs won declines. This corresponds to the LQD becoming a permissioned dealer and beginning to win trades outside of OT. Because our focus is on OT, we do not include the LQD's response and wins as a permissioned dealer as OT trades.

Figure 14 graphs monthly time series of the number of OT responses (top subplot), the expected OT win rate (bottom left subplot), and the expected OT price improvement (bottom right subplot) by OT type. The top subplot of Figure 14 shows that in two months after its entry in November 2015, LQD ramps up its RFQ participation so fast that by February 2016 its average number of RFQ responses, equal to 0.18 in February 2016, more than doubles the number of RFQ responses by any non-traditional dealer *group*. The number of responses by LQD increases sharply to 0.4 by August 2017, and then falls to 0.3 by January 2018. LQD once again increases the average number of RFQ responses from 0.3 to 0.41 between January and December 2018.

Surprisingly, LQD entry does not immediately impact the RFQ participation of other OT groups. Buy-side institutions, non-permissioned dealers, and other quasi-dealers all have a similar average number of RFQ responses, increasing from approximately 0.02 to 0.1 between January 2014 and April 2018. All OT groups increase the average number of RFQ responses between February and April 2018. Non-permissioned dealers lead other OT groups by increasing their average number of RFQ responses from 0.1 to 0.48, followed by other quasi-dealers whose average number of responses increases from 0.1 to 0.4, and then followed by buy-side institutions whose average number of responses increases from 0.1 to 0.35. Between June and December 2018, non-permissioned dealers further increase their number of responses to its highest value among all OT liquidity providers at 0.7. Other quasi-dealers reduce their average number of responses to 0.2 by December 2018. Buy-side institutions increase their average number of RFQ responses from 0.35 to 0.4 between June and December 2018, and then lower it back to 0.35 by December 2018. All non-traditional liquidity providers reduce their average number of responses between November and December 2018. Overall, it takes a year for other OT groups to significantly change their bidding after the LQD entry.

The bottom left subplot of Figure 14 shows LQD increasing its expected win rate to 0.7%, a number very close to win rates of other OT types, between November 2015 and February 2016. LQD expected win rate rises to 1% between February 2016 and January 2018, and then skyrockets to 6% by July 2018. The top subplot of Figure 14 shows that the LQD did not increase its bidding frequency during this period, so its increased win rate comes more aggressive bidding. As the LQD becomes a traditional dealer its win rate through OT falls to approximately 5% by December 2018. Just like in the case of RFQ participation, LQD entry does not immediately impact the expected win rate of other OT groups. Buy-side institutions, non-permissioned dealers, and other quasi-dealers all have similar expected win rates, increasing from approximately 0.3% to 2% between January 2014 and April 2018. However, OT groups show different bidding behavior between April and December 2018. Non-permissioned dealers increase their expected win rate from 2% to 3.5%, while buy-side institutions and other quasi-dealers both reduce their expected win rate from 2% to approximately 1.5%.

Evidence from the top and bottom-left subplots of Figure 14 is consistent with the results on the expected OT price improvement reported in the bottom right subplot of Figure 14. The expected price improvement by LQD increases to 0.2bps, once again a number very close to the expected price improvement by other OT types, between November 2015 and February 2016. It stays flat, in agreement with results from right subplots of Figure 12, between February 2016 and April 2018. The expected price improvement by LQD rises to 0.9bps by December 2018. The expected price improvements by buy-side institutions, non-permissioned dealers, and other quasi-dealers are all very similar, increasing from less than a fraction of a basis point to 0.2bps between January 2014 and April 2018. The expected price improvements by non-permissioned dealers and buy-side institutions rise from 0.2bps to 0.4bps, while the expected price improvement by other quasi-dealers stays flat, between April and December 2018.

In summary, within a year after its entry, the LQD becomes an important liquidity provider on MarketAxess. By 2018, the LQD wins more RFQs than any other OT *group* combined, and the expected price improvement by LQD is greater than by any other OT group combined. Other OT groups reacted slow by taking a whole year from the LQD entry date to adjust their bidding strategies. Finally, the LQD becomes a permissioned/traditional dealer in late 2018.

6 Conclusion

We examine the introduction of all-to-all trading (called Opening Trading or OT) in the OTC market for corporate bonds. Because OT was added in an already centralized auction/RFQ market its usage provides direct evidence on whether investors prefer to trade with dealers or prefer to provide liquidity to each other, eliminating dealer intermediation. OT also provides evidence on the impact of investors being able to trade with dealers who are not in their network and the ability of non-dealers to become dealers. Following its introduction in 2012 Open Trading steadily grew to win 12% of trades on the platform in 2018. However, only 2% is due to investor-to-investor trading. Traditional dealers trading with new clients is 3% of trades. The largest component of Open Trading comes from the entry of new liquidity providers that act like dealers, 7% of trades. The majority of this new liquidity provision comes from a single firm that becomes a dealer at the end of our sample.

OT's steady growth facilitates measuring its effect on investors, dealers, and competition to provide liquidity. OT can improve prices for investors by increasing competition in RFQs. This manifests itself directly by new bidders offering better prices than traditional dealers. The average OT price improvement is equal to 2 basis point. In addition, OT can force traditional dealers to bid more aggressively. We find that this improves prices by another basis point. Finally, an auction model quantifies how changing the number of bidders impacts the prices investors receive. We find evidence consistent with OT crowded in additional dealer bids possibly adding another 5 basis points or more to OT's indirect impact. Comparing these to O'Hara and Zhou's (2020) estimate of average electronic trading costs being between 10 and 15 basis points in 2017 implies that OT may lower trading costs by economically meaningful amounts.

While both industry groups (Managed Fund Association (2015)) and academics (Biais and Green (2019)) have expressed concern that the OTC market structure persists because dealers prefer it, our results suggest that investors in corporate bonds prefer intermediation to direct trade. This does not imply that that the current market structure is optimal. Rather our results suggest that within the current market structure investors prefer to continue using dealers.

All-to-all trading can facilitate the entry of new dealers that compete for liquidity provision. Our findings suggest that single new entrant uses OT to learn how to bid for smaller trade sizes, which historically have had higher trading costs, in higher credit quality bonds. Entry in this way could arise from the entrant using more technology to increase automation in the less risky trades. It remains to be seen if this type of automation can be used effectively for larger trades in riskier bonds, or if the technology can lead to institutions splitting their orders and trading over time as is done in equity markets.

Weill (2020) emphasizes that most theoretical analyses of OTC markets rely on tools from either search or network theory. However, in our centralized all-to-all setting, search and network frictions are small or not present. This raises the question of why does intermediation remain central in this setting? This suggests that frictions and costs observed in OTC markets may stem from the costs of bidding and the associated required expertise (Glode and Opp (2019)). More study is needed to understand this and related questions remain. For example, why, when, and where do new entrants for liquidity provision choose to compete? Why don't institution choose to bid more to eliminate intermediation? Is it due to impatience, the costs of traders' expertise in terms of monitoring, bidding, and avoiding the winner's curse, or dealers' efficiency?

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Appendix

Let $B^{1:N-k}$ be the highest of $N-k$ bids. The distribution of $B^{1:N-k}$ is the probability that all $N-k$ draws will be below b, which yields a cumulative distribution function with a corresponding probability density function:

$$\begin{aligned} &G^{1:N-k}(b;N) = G(b;N)^{N-k}, \\ &g^{1:N-k}(b;N) = (N-k)G(b;N)^{N-k-1}g(b;N). \end{aligned} \tag{A.1}$$

Then the expected transaction price in the auction with N bidders is equal to

$$\mathbb{E}_N[B^{1:N}] \equiv \mathbb{E}[B^{1:N}|\#\text{ bidders} = N] = N\int_0^1 G^{-1}(u;N)u^{N-1}du. \tag{A.2}$$

Expression (12) for the expected price improvement from adding a bidder to the RFQ follows immediately

$$\begin{aligned} &\mathrm{PI}(N-1,N) = \mathbb{E}_N[B^{1:N}] - \mathbb{E}_{N-1}[B^{1:N-1}] = \\ &= \mathbb{E}_N[B^{1:N}] - \mathbb{E}_N[B^{1:N-1}] + \mathbb{E}_N[B^{1:N-1}] - \mathbb{E}_{N-1}[B^{1:N-1}]. \end{aligned} \tag{A.3}$$

The cover price, $B^{2:N}$, is distributed according to (see David and Nagaraja 2003, p. 9)

$$\begin{aligned} &G^{2:N}(b;N) = NG(b;N)^{N-1}(1-G(b;N)) + G(b;N)^N, \\ &g^{2:N}(b;N) = N(N-1)G(b;N)^{N-2}(1-G(b;N))g(b;N). \end{aligned} \tag{A.4}$$

Analogous to expression (A.2), the expected value of the cover is equal to:

$$\begin{aligned} \mathbb{E}_N[B^{2:N}] &= N(N-1)\left[\int_0^1 G^{-1}(u;N)u^{N-2}du - \int_0^1 G^{-1}(u;N)u^{N-2}udu\right] \\ &= N\mathbb{E}_N[B^{1:N-1}] - (N-1)\mathbb{E}_N[B^{1:N}]. \end{aligned} \tag{A.5}$$

Using relation (A.5), we readily obtain expression (16) for the expected RFQ competitiveness, $\mathrm{CP}(N)$,

$$\begin{aligned} &\mathrm{CP}(N) = \mathbb{E}_N[B^{1:N}] - \mathbb{E}_N[B^{2:N}] = \mathbb{E}_N[B^{1:N}] - N\mathbb{E}_N[B^{1:N-1}] + (N-1)\mathbb{E}_N[B^{1:N}] \\ &= N \times (\mathbb{E}_N[B^{1:N}] - \mathbb{E}_N[B^{1:N-1}]) = N \times (\mathrm{PI}(N-1,N) - \Omega_{N-1,N}(N-1)), \end{aligned} \tag{A.6}$$

where the price improvement due to changed distribution of bids, $\Omega_{N-1,N}(N-1)$, is given by expression (13).