All-to-All Liquidity in Corporate Bonds*

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Abstract

Open Trading (OT) on the largest electronic corporate-bond request-for-quote (RFQ) platform allows investor-to-investor trading. Despite only 2% of trades occurring directly between investors, OT succeeds in attracting new liquidity providers (7%) and creating new client-dealer links (3%). These result in OT improving prices by 3bps, 1bp from OT winning, and 2bps from dealers improving bids, which reduces trading costs by 15-30%. However, OT worsens prices in RFQs with few dealers, which have the largest winner's curse. A model and counterfactual experiments suggest how market redesign could mitigate adverse selection and improve liquidity in corporate bond markets.

JEL Classification: G12, G14, G19

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

All-to-all trading is a decentralized mechanism where all market participants—investors and dealers—can trade directly with each other, eliminating the need for financial intermediaries. We examine the largest electronic corporate bond trading platform introducing all-to-all trading. Studying all-to-all trading offers insights 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 document the adoption of all-to-all trading and analyze the volume of trades from allowing investors to trade with each other and dealers outside their networks. Additionally, we explore the entry of new liquidity providers who act as quasi-dealers. We then decompose observed price (dis)improvements from investors being able to trade with alternative liquidity providers into three economic forces: entry, competition, and information.

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.[1] In addition to dealers with whom investors have a credit relationship, so-called *permissioned* dealers, OT allows RFQ bidding by other investors and dealers with whom investors do not have a credit relationship, or *non-permissioned* dealers.[2] Non-dealers who bid in RFQs can be both investors wanting to earn rather than pay the bid-ask spread and *quasi-dealers* who wish to specialize in making markets but are not traditional dealers. Even with all-to-all available, investors may prefer to pay the spread when the spread is small compared to the costs of waiting to trade and adverse selection due to the winner's curse. Quasi-dealers also face adverse selection, but by bidding in many RFQs they can amortize the cost of learning to bid accurately over a larger number of RFQs.

During our 2014-2018 sample period, OT steadily grew to bid in 70% of all RFQs and win 12% of trades on the platform. However, of that 12%, only 2% is due to investor-to-investor trading. Traditional dealers trading with new clients are 3% of trades. The largest component of OT comes from the entry by a small group of new liquidity providers acting like dealers in 7% of trades. Hence, OT entry is dominated by quasi-dealers who bid frequently.

OT's steady growth facilitates measuring its effect on prices, dealers' bidding behavior, and competition to provide liquidity. Figure 1 helps illustrate these effects with two examples from the data. The left subplot of Figure 1 shows all four RFQs in a bond over a week, each with a single dealer bid; the right subplot of Figure 1 is similar, but each RFQ has 10 dealer bids. In both plots, OT enters and bids in the third RFQ. In RFQs with OT entry, the best bids by permissioned dealers and OT bids are shown in green and red squares, respectively. In RFQs without OT entry, the best bids by permissioned dealers are shown in solid blue circles. In all RFQs, the black circles denote other permissioned dealer bids.

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

[1] MarketAxess has been studied by Hendershott and Madhavan (2015), O'Hara and Zhou (2020), and Kargar et al. (2023).

[2] 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 the seller.

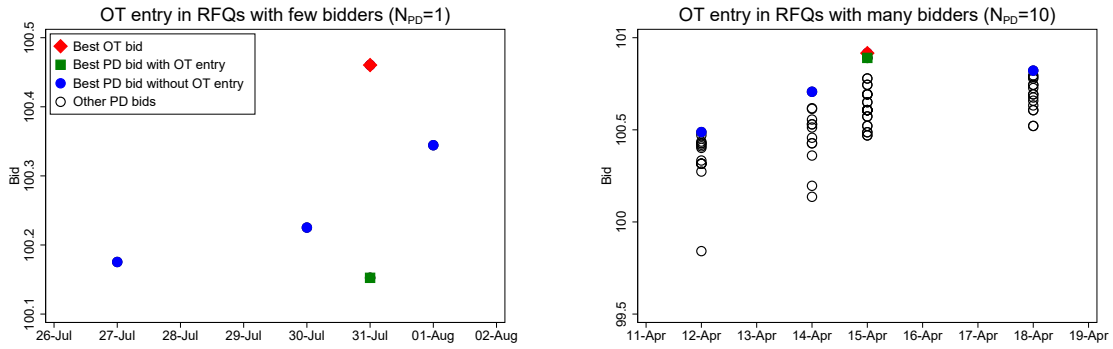


Figure 1: **Example RFQs.** The figures shows example RFQs. The left plot shows an RFQ with low dealer participation. We depict all RFQs in Cusip 02665WCJ8 between July 27 and August 1, 2018. The RFQ with OT entry on July 31 has N_{PD}=1. The right plot shows an RFQ with high dealer participation. We depict all RFQs in Cusip 478160BY9 between April 12 and April 18, 2016. The RFQ with OT entry on July 31 has N_{PD}=10. The red rhombus is the OT bid. The green square and the blue circles are the best bids by permissioned dealers in RFQs with and without OT entry respectively. The black circles are other permissioned dealer bids. The vertical distance between the rhombus and the square captures the entry effect of OT. The vertical distance between the square and the solid circles captures the indirect price improvement (IPI).

improves prices when it wins auctions, referred to as the *entry effect*, and OT can indirectly impact dealers' prices even if OT does not win or even enter. The entry effect observed in the data is based on the best non-OT bid: the highest/lowest bid submitted by all traditional dealers in the case of an RFQ to sell/buy. OT's direct price improvement due to the entry effect is the difference between the winning OT bid and the best non-OT bid, which is the vertical distance between the red rhombus and green square in both subplots of Figure 1. In the figure, the entry effect is non-negative and smaller when the number of permissioned dealer bids, N_{PD}, is large. With a higher N_{PD} the dealer bids are more competitive, leaving less scope for OT to improve on already competitive dealer bids.

During our sample period, the average direct price improvement (DPI) is 1 basis point (bp); however, most trades experience no direct price improvement due to OT either not participating or not winning, resulting in a median DPI of zero. Average DPI increases over our sample period from zero to 1.5bps due to increased OT entry. In RFQs with fewer dealer bids, the DPI is larger and exceeds 4bps at the end of the sample. DPI conditional on OT entry (cDPI) is much larger than DPI and exceeds 10bps in RFQs with fewer dealer bids. Consistent with Figure 1, conditional DPI is lower at only a few basis points in RFQs where the number of dealer bids is large. For fixed N_{PD}, DPI increases while cDPI decreases over time due to increased OT entry.

Unlike direct OT price improvement, which is always positive, indirect OT price improvement (IPI) can be either positive or negative. Two countervailing economic forces shape indirect OT price improvement: the *competition effect* and the *information effect*. Their importance depends on whether RFQs more closely resemble independent private-value or common-value first-price

sealed bid auctions. By entering RFQs, OT adds bidders, thus increasing competition in RFQs. The increased competition makes bidders shade their bids less as each bidder trades off her gains conditional on winning against her chances of winning against more rivals. If bidders' costs of intermediating the trade (i.e., valuations of holding the bond) are independent, IPI is always positive as increased competition is the only indirect effect.

The information effect due to the winner's curse arises in common-value settings because the RFQ winner tends to be the bidder with the most optimistic estimate of the cost of intermediating the trade.[3] Common values and the winner's curse can arise from information about the issuer or resale value in the interdealer market.[4] IPI can turn negative if the information effect outweighs the competition effect, as OT entry causes dealers to bid less aggressively than they would have otherwise.[5]

In Figure 1, the indirect OT price improvement is shown by the vertical distance between the dealer bid in the RFQ with OT entry (green square) and counterfactual dealer bids in RFQs without OT entry (solid blue circles). All solid blue circles are above the green square in the left subplot with a single dealer bid implying a negative IPI. This is consistent with a stronger information effect due to the winner's curse than the competition effect in these RFQs. All solid blue circles are below the green square in the right subplot with ten dealer bids implying a positive IPI. This is consistent with the stronger competition effect than the winner's curse in these RFQs. Figure 1 illustrates how the magnitudes of the information and competition effects and, hence, IPI, can depend on the number of bidders. As Figure 1 also shows, DPI is RFQ-specific and directly quantifiable in the data, while IPI and its components are not and must be estimated.

To estimate and decompose IPI into its competitive and information effects, we model all-to-all RFQs as a sealed-bid first-price auction for a single unit of a generic bond with N_{PD} permissioned dealer bids and random OT entry. In the spirit of Klemperer (1999), dealers and OT are subject to intermediation costs equal to ex-ante baseline costs and a weighted average of private and common cost shocks, with the weights varying with the number of bidders and the probability of OT entry. Common cost shocks give rise to the winner's curse. The model nests the independent private-value case, the pure common-value case, and combinations of these two cases. We solve for a linear symmetric equilibrium in which all bidders use the same bidding functions.[6]

[3] Pinkse and Tan (2000) show that an affiliation effect in affiliated private-values models leads to similar economic implications as those that arise in common-value auctions. Because we cannot distinguish between affiliated private-values and common-value auctions in the data, we interpret our findings using the common-value auction setting. However, similar effects can arise even in private-values settings, as long as signals are affiliated.

[4] The corporate bond market is characterized by active interdealer trading in which other dealers affect the price when laying off inventory or, respectively when filling a short position.

[5] Bulow and Klemperer (2002) discuss the relationship between price and the winner's curse in common-value models. Adding bidders in common-value settings can lead to less aggressive equilibrium bidding and even reduced seller revenue: theoretically in Laffont (1997) and empirically in Hong and Shum (2002) in procurement auctions, and in Compiani, Haile, and Sant'Anna (2020) for U.S. offshore oil and gas lease auctions.

[6] The equilibrium requires OT entrants to lack private information about the success rate of OT entry. It is consistent with the observation that OT entry is dominated by quasi-dealers that provide liquidity by bidding frequently

All three economic forces of OT entry are present and important in our all-to-all RFQ model: entry, competition, and information. By entering RFQs, OT increases the number of bidders from N_{PD} to $N = N_{\text{PD}} + N_{\text{OT}}$. All else equal, this mechanically improves the best bid. Therefore, the model predicts positive direct OT price improvement. The threat of extra competition due to OT entry makes dealers bid more aggressively thus narrowing the spread and leading to a positive competition effect. The information effect arises in the model because of the winner's curse as the RFQ winner tends to be the bidder with the lowest estimate of intermediation costs which may have an ambiguous effect on dealer spreads. Dealers adjust spreads to mitigate the winner's curse by either widening or narrowing them. The relative magnitudes of the competition and information effects depend on the number of bidders and the OT entry rate, leading to a sign switch in the indirect OT price improvement depending on model primitives.

We estimate the model primitives using our granular bidding data based on how the intermediation cost parameters and OT entry determinants affect cDPI and cIPI, respectively, for different values of N_{PD} and OT entry rates, which form the moments in a minimum-distance estimation. We find that the loading on the common cost shock is significantly positive and declines with N_{PD} from an initial value of over 100bps, suggesting that the winner's curse problem is economically relevant in trading corporate bonds. It is the most severe for $N_{\text{PD}} = 1$ where spreads are large, and it diminishes with the number of permissioned dealer bids, consistent with dealers offloading inventory in an imperfectly competitive interdealer market. Essentially, only RFQs with a large number of bidders are private-value auctions.

Next, we find that the loading on the private cost shock is increasing with N_{PD}, suggesting that the private value component becomes more important as the number of bidders increases, and then eventually plateaus for large N_{PD}. This is consistent with the risk-sharing hypothesis. When N is small, dealers can share risk by finding the lowest-cost dealer to trade with, and, hence, individual cost shocks have little impact. When N is large, dealers transact on the interdealer market at a competitive price and thus must rely on their private cost shocks when determining their intermediation costs. As a result, the competition effect of OT is positive and weakest early in the sample and strongest later in the sample, peaking at around 10bps for $N_{\text{PD}} = 10$. The information effect of OT is negative for values of $N_{\text{PD}} < 3$ with the lowest quarterly values of about -30bps for $N_{\text{PD}} = 1$.

The competition and information effects together lead to IPI being negative for $N_{\text{PD}} < 3$ and IPI increasing in N_{PD}. Most trades see a substantial indirect price improvement with a median IPI of 0.8bps. The average IPI is 1.6bps with a low of less than -5bps for $N_{\text{PD}} = 1$ and a high of more than 5bps for $N_{\text{PD}} = 10$ by sample end. Conditional on OT entry, IPI can be as low as -20bps for $N_{\text{PD}} = 1$ and as high as 10bps for $N_{\text{PD}} = 10$ with a mean of 2.8bps. Overall, the information effect increases with N_{PD} and dominates the competition effect for low values of N_{PD}. However,

across different RFQs, similar to permissioned dealers.

the competition effect increases with N_{PD} and dominates the information effect for large values of N_{PD}. IPI therefore increases with N_{PD}. Overall, OT entry can force incumbent dealers to adjust their bidding functions, but entry does not always improve prices.

Total price improvement (TPI) is the sum of the indirect and direct price improvements. TPI is 2.7bps on average with a median of 1.4bps. Compared to O'Hara and Zhou's (2020) estimates for average electronic trading costs, OT's TPI lowers trading costs by 15-30%. Because IPI dominates DPI in the data, the total price improvement behaves similarly to IPI over time and as a function of N_{PD}. In particular, TPI is negative in RFQs with $N_{\text{PD}} < 3$. Ignoring IPI would, hence, significantly misestimate the total impact of OT on trading costs.

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.[7] Our results suggest that investors in corporate bonds prefer intermediation to direct trade.[8] Nonetheless, all-to-all trading can facilitate the entry of new dealers that provide significant liquidity. New entrants can directly improve prices and force incumbents to become more competitive. However, a more severe winner's curse problem counterbalances these positive competition effects. When the number of dealer bids is small, additional competition from OT can impose extra costs by increasing permissioned dealers' costs. Consistent with not all trading occurring on MarketAxess and limited entry into liquidity provision via OT, our findings suggest that despite increased competition, all-to-all trading does not necessarily benefit all trading and all investors as the adverse information effect can be large, especially in RFQs that do not attract much bidding.

We use the model and its estimated primitives to construct three counterfactual experiments where we improve information to eliminate the winner's curse, improve interdealer risk sharing to eliminate private value shocks, and allow dealers to observe OT entry.[9] Eliminating the winner's curse improves prices. This leaves less scope for OT entry to improve prices further. Therefore, DPI, IPI, and TPI decline. Eliminating private cost shocks worsens prices because no dealers have lower costs. This creates more scope for OT entry to improve prices, increasing DPI, IPI, and TPI. Allowing dealers to observe OT entry increases dealer competition, raising IPI and TPI.

[7] 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 (2019) discuss institutions versus retail investors. Lee and Wang (2021) and Dufresne, Hoffmann, and Vogel (2019) discuss informed versus uninformed investors. Dugast, Uslu, and Weill (2022) discuss dealer heterogeneity.

[8] 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

[9] To quantitatively fit the model and analyze potential policies, the model incorporates uncertainty about OT's presence and entry in RFQs. In the model, OT can be present and not bid. If OT is absent, bidders have intermediation costs based on N_{PD}. If OT is present and bids then $N = N_{\text{PD}} + N_{\text{OT}}$. Therefore, the model allows dealers to observe OT's presence and entry imperfectly. This leads to dealers making Type I and II errors about both, which yields a nonzero IPI.

Literature overview. While RFQs resemble auctions, they are a relatively novel innovation in the secondary corporate bonds market generally described in the academic literature as an OTC market where investors sequentially search for the best price. Uslu (2019) shows how investor heterogeneity in an all-to-all search model results in investors with certain characteristics endogenously choosing to become dealers. Our results are consistent with this specialization story, as enabling investor-to-investor trading does not lead to substantial disintermediation of dealers. Also consistent with search models, entry by new quasi-dealers increases competition by improving investors' outside options, leading to direct and indirect price improvement.

Our paper also relates to the literature on competition in market making, RFQ trading in OTC markets, OTC versus centralized trading, 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 (2020) and Dugast, Uslu, and Weill (2022) theoretically examine OTC versus centralized trading. Allen and Wittwer (2023) 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 the cost of trading.[10] 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. Hendershott and Madhavan (2015) examine RFQs on the same platform we study, MarketAxess, before 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. While we focus on liquidity supply by responders in RFQs, Kargar et al. (2023) examine liquidity demand on MarketAxess by estimating the average time to complete a trade for customers initiating repeated RFQs. RFQs have also been studied in other markets. 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 investors

[10] See Menkveld (2013) and Eisfeldt, Herskovic, Rajan, and Siriwardane (2023) for evidence on the importance of individual dealers in the stock and credit default swap markets, respectively.

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.

Finally, our paper relates to the structural auction literature. Our identification assumptions are consistent with the recent literature on the effects of endogenous entry on the equilibrium bidding function (see, e.g., Li and Zheng, 2009; Compiani, Haile, and Sant'Anna, 2020). Li and Zheng (2009) do not make the bidding function conditional on the realized number of bidders including OT entry, hence IPI = 0 by construction in their paper. Compiani et al. (2020) assume the realizations of N are common knowledge among bidders, allowing prices to improve due to incumbents adjusting their bidding functions due to realized OT entry. We follow this and examine bidding outcomes conditional on the number of bidders and the OT entry probability. We find that IPI is nonzero and constitutes a large part of TPI.[11]

1 All-to-All Trading and its Evolution

1.1 Data and descriptive statistics

To study all-to-all trading and its evolution, we analyze comprehensive bidding data from electronic auctions in corporate bonds. 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 platform where investors can trade with 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. In 2012 MarketAxess introduced a new feature called Open Trading (OT), which, by selecting the all-to-all option for the RFQ, allows all platform participants, including institutional investors, traditional dealers, and nontraditional liquidity providers, to trade directly with each other.

Investors and dealers participate in the RFQ by submitting a binding quote. RFQs have a fixed duration, typically 2 to 20 minutes, after which the investor reviews the dealer's 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 a quote system is a sealed bid first-price auction with an undisclosed reserve price. MarketAxess charges a fee, incorporated into the transaction price, for trading. During our sample period, fees for trading with permissioned dealers were approximately 0.2 basis points, while OT trades had fees closer to

[11] Motivated by a recent SEC proposal, Ernst, Spatt, and Sun (2022) theoretically compare welfare in order-by-order exchange auctions versus off-exchange competition by market makers using a model similar to our structural decomposition into information and competition effects. Highlighting the importance of the information effect we find, they show that auctions can lower welfare due to the winner's curse.

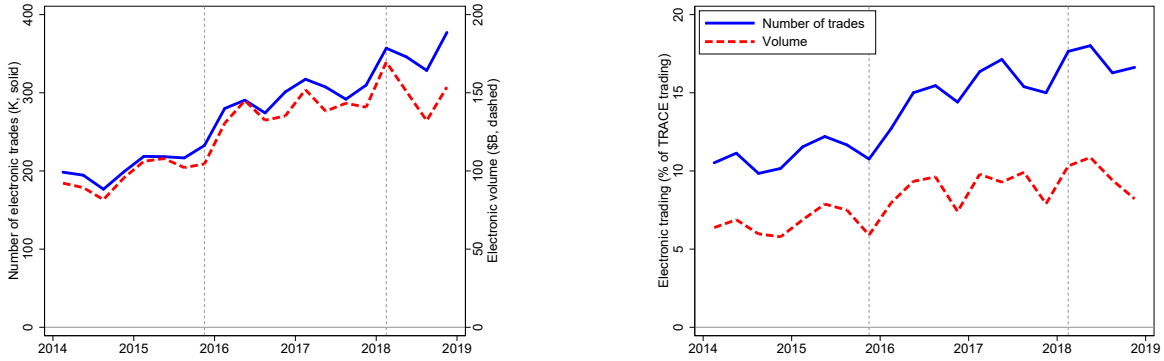


Figure 2: **Electronic trading in corporate bonds on MarketAxess.** The left subplot presents the quarterly trades that are executed on MarketAxess, both in terms of the number of trades (solid line) and total par amount traded (dashed line). The right subplot presents the quarterly average number of electronic trades executed on MarketAxess as a share of TRACE trading, in terms of both the number of trades (solid line) and the total par amount traded (dashed line). Vertical dotted lines mark the increase in OT at the end of 2015 and the beginning of 2018.

1.2 basis points.[12] Our MarketAxess data provide an anonymized identifier for market participants queried and responding, as well as all their bids and the final transaction price.

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 trade data. The final sample contains a total of 7,434,179 RFQs, 5,434,989 of which resulted in a trade, corresponding to a 73% success rate.[13]

Figure 2 documents changes in the electronic trading of corporate bonds on the MarketAxess platform during the sample period (see O'Hara and Zhou (2020) for additional information on trading on MarketAxess during 2010–2017). The left subplot shows the quarterly number of trades (solid line) and the total par amount traded (dashed line). The vertical dotted lines mark the increase in OT at the end of 2015 and the beginning of 2018. The number of electronic trades has steadily increased 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 subplot presents the same data 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 increased from 10% in 2014 to approximately 17% at the end of 2018. The volume of MarketAxess as a fraction of TRACE trading increased from 6% in 2014 to 10% in mid-2018.

[12] 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.

[13] Hendershott and Madhavan (2015) and Kargar et al. (2023) find similar success rates. Hendershott and Madhavan (2015) find evidence that investors whose RFQs fail can 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 CLO RFQs being longer in duration, days versus minutes, and the greater number of dealers in corporate bonds, hundreds versus tens in CLOs.

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	25%	Median	75%
Client buy	46%				
Trade size ($M)	0.46	1.11	0.03	0.12	0.45
Panel B: Bond characteristics					
	Mean	SD	25%	Median	75%
Issue size ($B)	1.46	1.33	0.70	1.00	2.00
Maturity (years)	9.52	9.19	3.34	6.02	9.75
Bond age (years)	3.15	3.02	1.02	2.34	4.33
Coupon rate	0.04	0.02	0.03	0.04	0.05
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
Total no. of trades (K)	5,435	768	886	1,146	1,226	1,409
Trades with OT enabled (K)	4,947	609	757	1,065	1,162	1,354
Share of total trades	91.0%	79.3%	85.5%	92.9%	94.7%	96.1%
OT trades (K)	359	9	25	65	86	174
Share of total trades	6.6%	1.2%	2.8%	5.7%	7.0%	12.4%
Total volume ($B)	2,468	354	415	534	565	600
Volume with OT enabled (K)	2,175	271	346	484	514	560
Share of total volume	88.1%	76.5%	83.3%	90.7%	90.9%	93.4%
OT volume ($B)	123	4	14	29	30	46
Share of total volume	5.0%	1.2%	3.3%	5.4%	5.4%	7.7%
Share of OT trades by type:						
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%

Table 1 reports descriptive statistics on trade (Panel A) and bond (Panel B) characteristics in RFQs that resulted in trades. Panel A shows that buys and sells are about equally split on the platform. The average trade size is $460K, with a median equal to $120K. The bond characteristics documented in Panel B are representative of the U.S. corporate bond universe, with a $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,[14] and 25% covenant-lite. The IG

[14]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

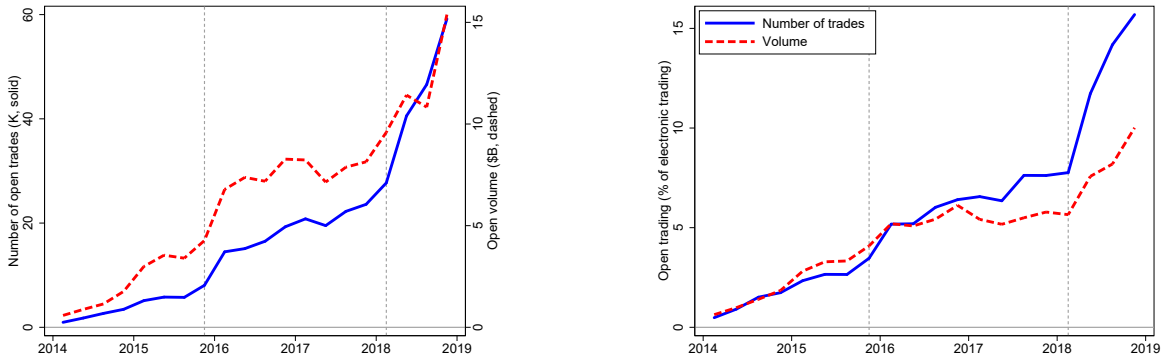


Figure 3: **Open trading on MarketAxess.** The left subplot presents the quarterly open trades that are executed on MarketAxess, both in terms of the number of trades (solid) and the total par amount traded (dash). The right subplot presents the quarterly average open trades that are executed on MarketAxess as a share of electronic trading, both in terms of the number of trades (solid) and the total par amount traded (dash). Vertical dotted lines mark the increase in OT at the end of 2015 and the beginning of 2018.

rating distribution is AAA 1%, AA 14%, A 46%, and BBB 31%.

1.2 Evolution in open trading

In 2012, MarketAxess introduced Open Trading (OT), which, by selecting the all-to-all option for the RFQ, allows all platform participants, including investors and dealers, to trade directly with each other. This is done by MarketAxess, which acts as a counterparty to each side of the trade. The goal of OT is to improve prices and increase trading by expanding the number of potential counterparties. Potential liquidity suppliers could then 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. Analyzing the impact of OT on prices and identifying the role of dealers and non-dealers in influencing them is central to understanding the impact of all-to-all trading.

Using OT in an RFQ is up to 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 suggest that few trades on MarketAxess limit disclosure. Hendershott and Madhavan (2015) provide evidence that investors who want to limit disclosure trade bilaterally with dealers.

Figure 3 and Panel C of Table 1 document the evolution of OT trading on MarketAxess during the sample period from January 2014 through December 2018. The left subplot of Figure 3 graphs

periods—six months or a year, rather than the customary two-year period.

quarterly OT trades executed on MarketAxess, both in terms of the number of trades (solid line) and the total par amount traded (dashed line). It shows that at the beginning of the sample period, the number of OT trades is 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 grew, with two notable sharp increases in 2015Q3 and 2018Q1 indicated by the vertical dotted lines. In the last quarter of 2018, there were 60K trades totaling \$15B in volume.

The right subplot of Figure 3 presents the quarterly share OT trades in all electronic trading executed on MarketAxess, both in terms of the number of trades (solid line) and the total par amount traded (dashed line). It shows that 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 2018Q4, the OT share represents 16% of trades and 10% of volume. Panel C of Table 1 further quantifies OT trading. It shows that OT has increased 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.

For a regression analysis of open trading with results documented in Appendix A, we adopt the same panel specification that we employ throughout the paper:

$$Y_{ibt} = \alpha_b + \alpha_t + \boldsymbol{\beta}_1' \mathbb{X}_i + \boldsymbol{\beta}_2' \mathbb{X}_b + \boldsymbol{\beta}_3' \mathbb{X}_t + \epsilon_{ibt}, \tag{1}$$

where α_b and α_t are bond and day fixed effects and $\mathbb{X} = (\mathbb{X}_i, \mathbb{X}_b, \mathbb{X}_t)$ are observables and $\mathbb{X}_i$ are RFQ controls, $\mathbb{X}_b$ are bond controls, and $\mathbb{X}_t$ are time controls whenever we drop α_t. 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 a variable rate, rule 144a, and cov-lite. All reported standard errors are robust to clustering at day and bond levels. All tables presenting multivariate results have the same layout and report four different variants of specification (1) consisting of $\mathbb{X}_i$, and either both day, α_t, and bond, α_b, fixed effects (Column 1), or only day fixed effects (Column 2), or yearly dummies and only bond fixed effects (Column 3), or yearly dummies and bond controls, $\mathbb{X}_b$, (Column 4).

Table A.1, Panel A (Table A.2) reports univariate (multivariate) results for the determinants of OT trading. The rows show that open trades tend to be smaller sales, and open-traded bonds tend to be older and have higher credit ratings, shorter maturity, larger issue, and non-cov-lite bonds. These bonds are also more likely coupon-paying with coupon rates being lower and non-variable. Finally, privately placed bonds are slightly less likely to be open-traded. The results in Table A.2 mostly support the findings from Table A.1 and emphasize OT's growth over time even after controlling for heterogeneity in open trading across bonds and RFQs.

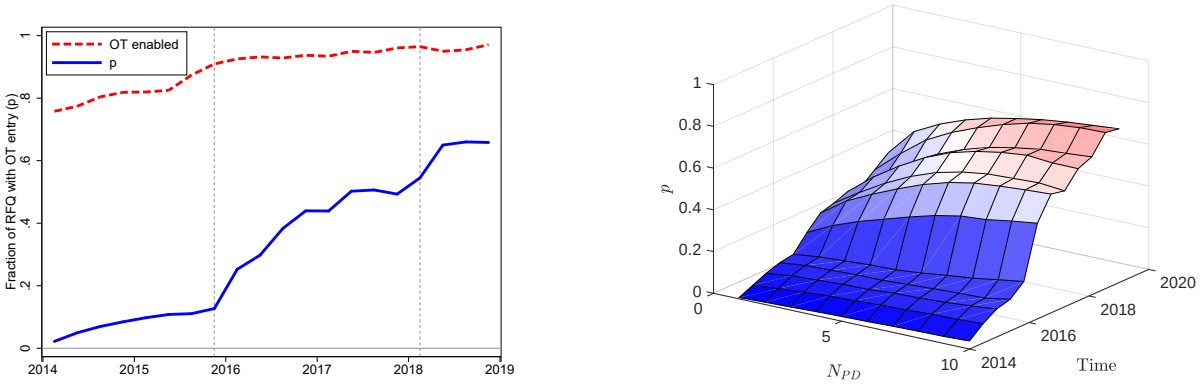


Figure 4: **OT entry rate over time.** The left plot documents the intertemporal variation in the OT entry rate, $p = \Pr(\text{OT entry})$ (solid line). For comparison, we include the fraction of RFQs with OT enabled (dash line). The right plot documents the variation in the OT entry rate across RFQs and over time. The plots report quarterly averages across all RFQs. Vertical dotted lines mark the increase in OT at the end of 2015 and the beginning of 2018.

OT's slow but steady growth facilitates measuring its impact on investors, dealers, and competition to provide liquidity. So far, our analysis has been conditional on RFQs won by OT. However, just by entering and bidding in RFQ, even without winning, OT may impact bidding and trading by other market participants along several channels, which we will discuss later. We, therefore, proceed by studying the OT entry decision. This includes the determinants of the RFQs where OT enters, reported in Appendix A, and OT entry rates which we discuss next.

1.3 Steady rise in OT entry rate

OT's average entry rate rises steadily over time. The left subplot of Figure 4 documents the intertemporal variation in the OT entry rate averaged across all RFQs in a given quarter. For reference, we add the fraction of RFQs with OT enabled as a dashed line. The left subplot of Figure 4 shows that p (solid line) increases with two notable sharp increases in 2015Q3 and 2018Q1 indicated by the vertical dotted lines. OT entry was close to zero at the beginning of 2014. Between 2015Q3 and 2018Q1, p increases from approximately 10% to more than 50%. By the end of 2018, p is about 70%.

The right subplot of Figure 4 documents the intertemporal variation in the OT entry rate conditional on the number of permissioned dealers bidding. It shows that p varies over time and with N_{PD}. For all values of N_{PD}, p increases over time, but must less so for smaller N_{PD}. OT entry is the largest in RFQs with already many permissioned dealer bidders.

OT's impact depends on the probability of OT bidding in an RFQ and the impact conditional on entry/bidding. To allow for variation in OT entry rates across RFQs beyond the binary realized outcome of entry in each RFQ, we estimate the RFQ-specific determinants of the OT entry rates in the RFQ i for the bond b on date t, $p_{ibt} = \Pr(\text{OT entry}_{ibt}|\mathbb{X})$, conditional on the observables

$\mathbb{X} = (\mathbb{X}_i, \mathbb{X}_b, \mathbb{X}_t)$ using Probit regressions.[15] Here the dependent variable Y_{ibt} is the indicator function OT entry$_{ibt}$ equals one if an OT bidder enters and bids in RFQ i for bond b on the day t, and zero otherwise. Trade controls, $\mathbb{X}_i$, include a buy-sell indicator; trade size indicators for odd (\$100K-\$1M), round (\$1M-\$5M), and large (\$5M+) sizes. Bond controls, $\mathbb{X}_b$, include either bond dummies, α_b or such bond characteristics as 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 a variable rate, rule 144a, and cov-lite. Time controls are captured by day fixed effects α_t. Let $p_t = \frac{1}{\#\text{RFQ}_t} \sum_i \sum_b \widehat{p}_{ibt}$, where the predicted OT entry rate, $\widehat{p}_{ibt}$, for RFQ i is calculated according to:

$$\widehat{p}_{ibt} = \Phi(\widehat{\alpha}_t + \widehat{\boldsymbol{\beta}}'_{1t}\mathbb{X}_i + \widehat{\boldsymbol{\beta}}'_{2t}\mathbb{X}_b), \tag{2}$$

where $\widehat{\boldsymbol{\beta}}_{1t}$ and $\widehat{\boldsymbol{\beta}}_{2t}$ are predicted regression coefficients on the RFQ- and bond-specific explanatory variables, respectively.

Table A.1, Panel B reports univariate results for the determinants of OT entry. Table A.3 reports the results of specification (2) and shows that OT is more likely to enter sell RFQs and for smaller trades. OT is also more likely to enter RFQs for bonds with larger issue sizes, shorter maturity, and lower non-variable coupon rates, and for bonds that are older, higher-rated, publicly placed, and cov-lite. The OT entry rates and how they vary over time and across RFQs are essential for understanding the impact of OT on prices. Because OT enters almost all RFQs by the end of the sample, we focus on the time series of OT's entry and its impact on prices.

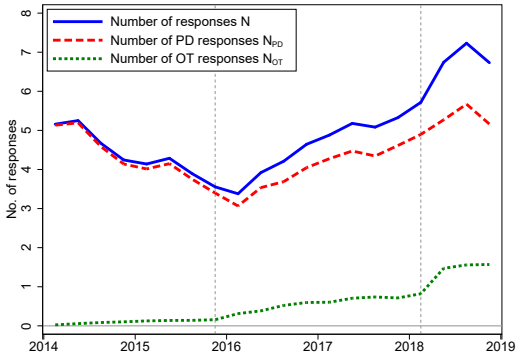
1.4 Variation in bidding by permissioned dealers and OT

We next provide evidence on the variation in the number of RFQ responses by permissioned dealers, N_{PD}, OT, N_{OT}, and the total number of responses, $N = N_{\text{PD}} + N_{\text{OT}}$. N_{PD}, N_{OT}, and N are other key determinants for RFQ outcomes and particularly for the impact of OT on prices.

Figure 5 in Panel A reports the intertemporal variation in RFQ responses. It graphs quarterly values of N (solid line), N_{PD} (dashed line), and N_{OT} (dotted line), each averaged across all RFQs in a given quarter. The intertemporal variation in N_{OT} mirrors the intertemporal variation in the OT entry rate from the left subplot in Figure 4. N_{OT} increases from being barely above zero to 0.2 during 2014Q1–2015Q3 period and then grows sharply to almost 1 during 2015Q4–2018Q1 period. Finally, N_{OT} increases sharply to 1.5 between 2018Q1 and 2018Q3 and remains flat during the last quarter of 2018. The total number of RFQ responses behaves like N_{PD}, since N_{OT} is small, 2014Q1–2016Q1. N_{OT}, however, starts to contribute significantly to the total number of RFQ responses 016Q2 and 2018Q3 with N reaching its highest value of 7.8 in 2018Q3. N declines during the last quarter of 2018 due to a decline in N_{PD}.

[15] Results are similar with a monthly Logit specification or linear probability model and therefore omitted.

Panel A: Responses to RFQs over time



Panel B: Distribution of responses to RFQs

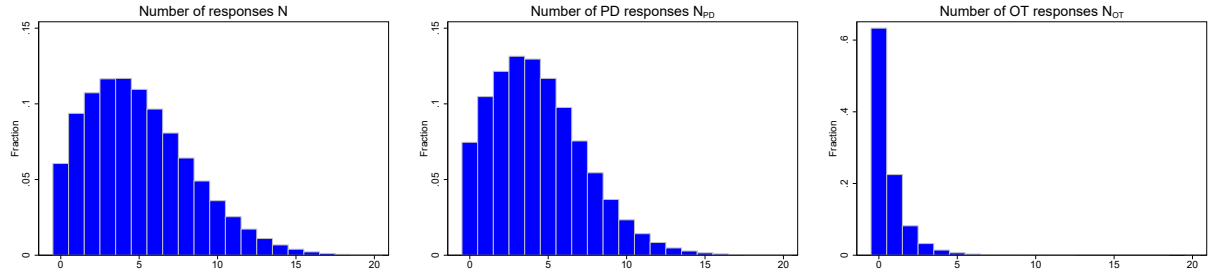


Figure 5: **Distribution of responses to RFQs.** Panel A documents the intertemporal variation in the average number of RFQ responses split by permissioned dealers N_{PD} (dashed line), OT N_{OT} (dotted line), and all liquidity providers N (solid line) on MarketAxess. Panel B documents the distribution of the number of responses to RFQs by all liquidity providers N (left subplot), permissioned dealer responses to RFQs N_{PD} (central subplot), and OT responses to RFQs N_{OT} (right subplot).

Figure 5 in Panel B reports the frequency of the total number of RFQ responses (left subplot), the number of RFQ responses by permissioned dealers (central subplot), and the number of RFQ responses by OT (right subplot).[16] The left subplot shows that while some RFQs get as many as 38 responses in total, the majority of RFQ responses fall between 0 and 10 with a sample average equal to 5.88 and a standard deviation equal to 3.17. The central subplot displays that the majority of N_{PD} also falls between 0 and 10 with a sample average equal to 5.16 and a standard deviation equal to 2.80. The right subplot shows that the average number of OT responses is equal to 0.71 with the standard deviation equal to 1.15. While some RFQs receive up to 20 OT responses, 60% of the time they do not generate OT responses. This evidence suggests that both traditional dealers and OT entrants respond selectively to RFQ queries. It is also consistent with our prior observation that the introduction of OT only slowly increased OT entry.

Table A.1, Panel C reports univariate results for the determinants of N_{PD}. For the multivariate analysis of N_{PD}, we use specification (1) with the number of permissioned dealers' responses in RFQ

[16] 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 the RFQs go to less than 10 dealers.

i for bond b in month t as the response variable to understand the RFQs and bonds favored by permissioned dealers. Table A.4 reports these results and shows that N_{PD} is higher for client sales than buys and for larger trades. It also shows that N_{PD} is higher for bonds with larger issue size, longer maturity, and non-variable coupons, and for bonds that are younger, higher-rated, publicly placed, and Cov-lite.

1.5 Staggered quasi-dealer entry

To assess whether OT bidding is distributed across a diverse set of entrants or dominated by a few participants behaving like traditional dealers, we examine the composition of OT entrants. Entry via OT can occur by existing buy-side institutions trying to earn rather than pay the trading cost. OT can also allow existing permissioned dealers to bid for new customers and, third, for new quasi-dealers to enter. Quasi-dealers are non-traditional dealers that provide liquidity without an existing client-dealer network. To understand how entry via OT occurs on the MarketAxess platform, we split OT bidders into traditional dealers, quasi-dealers, and buy-side institutions based on (i) liquidity supply versus demand and (ii) response activity. Appendix B provides details on our classification. We obtain the following classification:

- N=754 buy-side institutions,
- N=173 traditional dealers (permissioned and non-permissioned),
- N=81 quasi-dealers, with 1 predominant quasi-dealer.

Figure A.1 documents the contribution of non-permissioned dealers, buy-side institutions, and quasi-dealers to OT. The plots show that quasi-dealers are the main force behind the growth in OT, and a large quasi-dealer enters RFQs in a staggered manner and has the largest OT share by the end of the sample period. To sum up, OT is enabled in over 90% of RFQs while OT entry has increased from 1% in 2014 to over 60% by 2018. OT entry occurs more in RFQs with already many permissioned dealers bidding. OT is dominated by quasi-dealers providing liquidity in RFQs without a client-dealer network, with a stable share of non-permissioned dealers and a small, declining share of direct institution-to-institution trading.

2 Price Improvements in All-to-All RFQs

OT's steady expansion and growing prominence highlight the importance of assessing its impact on investors, dealers, and competition in liquidity provision. OT's entry improves prices when it wins RFQs which is OT's entry effect. While the entry effect yields *direct price improvement* (DPI) from OT-winning bids, the threat of OT entry also yields an *indirect price improvement* (IPI) or disimprovement from changes in incumbent dealers' bidding behavior. OT intensifies competition

which may indirectly improve prices—OT's competition effect. However, OT's entry may indirectly worsen prices through its adverse information effect on incumbent dealers. This section shows how DPI and IPI can be measured in our granular RFQ data.

2.1 Price improvements from OT

To fix ideas, assume permissioned dealers bid B_j, $j = 1, ..., N_{\text{PD}}$, in RFQs without OT. OT bidders are present with probability q and enter an all-to-all RFQ with probability $p \leq q$. When OT is present, dealers bid $B_{\text{PD},j}$, $j = 1, ..., N_{\text{PD}}$ and OT bids $B_{\text{OT},j}$, $j = 1, ..., N_{\text{OT}}$ when it enters. In an RFQ to buy (RFQs to sell are treated symmetrically), $B^{l:N-k}$ is the l-highest of $N - k$ bids and $\mathbb{E}_N[B^{l:N-k}] \equiv \mathbb{E}[B^{l:N-k}|\text{no. of bidders} = N]$ is its expectation. The transaction price with OT entry is the highest bid, $B^{1:N} = \max\{B_{\text{PD}}^{1:N_{\text{PD}}}, B_{\text{OT}}^{1:N_{\text{OT}}}\}$, and the expected transaction price changes from $\mathbb{E}_{N_{\text{PD}}}[B^{1:N_{\text{PD}}}]$ to $\mathbb{E}_N[B^{1:N}]$ upon OT entry, which is the total price improvement (TPI). TPI is due to the extra bids received from OT in the RFQ and the fact that the best dealer bid changes to $\mathbb{E}_N[B_{\text{PD}}^{1:N_{\text{PD}}}]$. Throughout, we assume these expectations exist and have a finite value.

The price improvements from OT can be captured by expressing RFQ bids relative to a reference price R that reflects the bond's fair value to control for price levels and comparing different half-spread measures.[17] The expected half-spread S in all-to-all RFQs is a weighted average of spreads dependent on OT entry:

$$\begin{array}{lcll} S & \equiv & p \times S_{\text{cumOT}} + (1-p) S_{\text{noOT}} & \text{(Half-spread)}, \\ S_{\text{cumOT}} & \equiv & R - \mathbb{E}_N[\max\{B_{\text{PD}}^{1:N_{\text{PD}}}, B_{\text{OT}}^{1:N_{\text{OT}}}\}] & \text{(Half-spread with OT entry)}, \\ S_{\text{exOT}} & \equiv & R - \mathbb{E}_N[B_{\text{PD}}^{1:N_{\text{PD}}}] & \text{(PD half-spread with OT entry)}, \\ S_{\text{noOT}} & \equiv & R - \mathbb{E}_{N_{\text{PD}}}[B^{1:N_{\text{PD}}}] & \text{(Half-spread without OT entry)}. \end{array} \tag{3}$$

S_{cumOT} is the half-spread at the best bid price in an all-to-all RFQ with OT entry. S_{exOT} is the half-spread at the best permissioned-dealer bid or the ex-OT half-spread. The half-spread in RFQs without OT entry is S_{noOT}. Computing S requires observing the best bids in all RFQs and the reference price R.

These relations can be used to decompose the total impact of OT on prices. The expected direct price improvement (DPI) and the direct price improvement conditional on OT entry (cDPI) are equal to

$$\begin{array}{rcl} \text{DPI} & \equiv & p \times \text{cDPI}, \\ \text{cDPI} & \equiv & \mathbb{E}_N[\max\{B_{\text{OT}}^{1:N_{\text{OT}}} - B_{\text{PD}}^{1:N_{\text{PD}}}, 0\}] = S_{\text{exOT}} - S_{\text{cumOT}}. \end{array} \tag{4}$$

The indirect effects of OT occur even if OT does not win RFQs because permissioned dealers change their bidding function depending on the number of bidders N_{PD} in response to OT entry and a

[17] This is for bidders buying from the selling RFQ initiator. In buy RFQs, the reference price is subtracted from the expected lowest bid. In our empirical implementation, R is the last interdealer price from TRACE, see Hendershott and Madhavan (2015) and O'Hara and Zhou (2020).

higher entry probability p. The expected indirect price improvement (IPI) and the indirect price improvement conditional on OT entry (cIPI) can be measured by

$$\begin{aligned} \text{IPI} &\equiv p \times \text{cIPI}, \\ \text{cIPI} &\equiv \mathbb{E}_N[B_{\text{PD}}^{1:N_{\text{PD}}}] - \mathbb{E}_{N_{\text{PD}}}[B^{1:N_{\text{PD}}}] = S_{\text{noOT}} - S_{\text{exOT}}. \end{aligned} \tag{5}$$

While DPI and cDPI are always positive, IPI and cIPI may be negative depending on whether the information effect is larger than the competition effect of OT's presence. The expected total price improvement, TPI = DPI + IPI, and the total OT price improvement conditional on OT entry, cTPI = cDPI + cIPI, aggregate the direct and indirect effects:

$$\begin{aligned} \text{TPI} &\equiv p \times \text{cTPI}, \\ \text{cTPI} &\equiv \underbrace{\mathbb{E}_N[\max\{B_{\text{OT}}^{1:N_{\text{OT}}} - B_{\text{PD}}^{1:N_{\text{PD}}}, 0\}]}_{\text{Holding bidding distribution fixed}} + \underbrace{\mathbb{E}_N[B_{\text{PD}}^{1:N_{\text{PD}}}] - \mathbb{E}_{N_{\text{PD}}}[B^{1:N_{\text{PD}}}]}_{\substack{\text{Changing bidding distribution,} \\ \text{holding no. bidders fixed at } N_{\text{PD}}}} \\ &= \mathbb{E}_N[B^{1:N}] - \mathbb{E}_{N_{\text{PD}}}[B^{1:N_{\text{PD}}}] = S_{\text{noOT}} - S_{\text{cumOT}}. \end{aligned} \tag{6}$$

Relation (6) compares a counterfactual half-spread without OT present, S_{noOT}, to a half-spread with OT entry, S_{cumOT}, with the latter capturing that OT entry changes the best bid if OT wins and the distribution of bids, that is, bidders change their bidding strategies.

Total price improvement is an important seller's welfare metric. In a perfectly competitive auction ($N_{\text{PD}} \to \infty$) the seller receives the bond's fundamental value. The difference between the bond's value and the expected best bid when only a single dealer participates in the auction equals the dealer's surplus. TPI captures changes in dealers' ex-ante surplus from adding extra bidders to an RFQ with N_{PD} permissioned dealers. Correspondingly, price improvement's elasticity with respect to the number of bidders captures the marginal change in dealers' ex-ante surplus from adding extra bidders to an RFQ with N_{PD} bidders. Combining cDPI $= S_{\text{exOT}} - S_{\text{cumOT}}$ and cIPI $= S_{\text{noOT}} - S_{\text{exOT}}$ with a definition of the half-spread $S = p \times S_{\text{cumOT}} + (1-p)S_{\text{noOT}}$ yields a more convenient expression for the half-spread $S = S_{\text{exOT}} - p \times \text{cDPI} + (1-p)\text{cIPI}$, which ties observed spreads and direct price improvement to unobserved indirect price improvement. It can be rearranged for cIPI such that the unconditional indirect price improvement, IPI, can be written in terms of observables so long as $p < 1$, thus leading to a convenient decomposition for the total OT price improvement irrespective of the parametric assumptions made.

PROPOSITION 1: *The total price improvement from OT entry is*

$$\text{TPI} = \frac{1+p}{1-p}\left(\frac{1}{1+p}\text{DPI} - \frac{p}{1+p}(S_{\text{exOT}} - S)\right) \lesseqgtr 0, \tag{7}$$

with direct price improvement DPI $= p(S_{\text{exOT}} - S_{\text{cumOT}})$ *and indirect price improvement* IPI $=$

$\frac{p}{1-p}(S - S_{\text{exOT}} + \text{DPI})$.

Proposition 1 shows how one can measure TPI (and also DPI and IPI) in the data. Expression (7) has an intuitive interpretation. In the limit $p \to 0$, TPI is zero. When $p > 0$, TPI has two components. The first term is the direct price improvement from OT winning, which is always positive and has weight $\frac{1}{1+p}$. The second term is the change in half-spreads due to OT entry, which can be positive or negative and has weight $\frac{p}{1+p}$. For small p, DPI hence dominates the total price improvement. In the limit $p \to 1$, both terms receive the same weight.

2.2 Quantifying the entry effect of OT

Using our granular RFQ data, we can quantify the entry effect of OT on prices for each RFQ without a model. The direct price improvement from OT in RFQ i for bond b on date t is the difference between the winning bid and the best bid by traditional dealers excluding all OT bids. Accordingly, the direct price improvement from OT conditional on entry in buy and, respectively, sell RFQ i for bond b on date t is given in the data by

$$\text{cDPI}_{ibt} = \begin{cases} \frac{\text{Bid price}_{ibt} - \max_j(\text{Non-OT bid}_{ijbt})}{\text{Par}_{ibt}} \geq 0, & \text{if Buy}_{ibt} = 0 \text{ and OT entry}_{ibt} = 1, \\ \frac{\text{Ask price}_{ibt} - \min_j(\text{Non-OT ask}_{ijbt})}{\text{Par}_{ibt}} \geq 0, & \text{if Buy}_{ibt} = 1 \text{ and OT entry}_{ibt} = 1. \end{cases} \tag{8}$$

In the data, cDPI is undefined in RFQs that OT does not enter and equals zero if OT enters but does not win. In expression (8), Bid price_{ibt} is the highest bid in the RFQ, and Non-OT bid_{ijbt} are the bids submitted by traditional dealers on the RFQ, indexed by j. Ask price_{ibt} is the lowest bid in the RFQ and Non-OT bid_{ijbt} 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.[18] The expected DPI relates to cDPI via OT's entry rate according to

$$\text{DPI}_{ibt} = p_{ibt} \times \text{cDPI}_{ibt}. \tag{9}$$

Table 2 quantifies the estimates for the price improvement from OT. The summary statistics for all bonds in Panel A reveal that the direct price improvement conditional on entry (cDPI) averages 3bps, with a high standard deviation of 13bps, indicating a sizable mean with substantial variation around it. Most trades see no direct price improvement, i.e., median cDPI equals zero, because OT winning RFQs are initially limited. The unconditional direct price improvement (DPI) is smaller, averaging 1bp with a standard deviation of 4bps.[19] These results highlight that OT can

[18] 9.7% of RFQs with OT bids have no non-OT bids. Definition (8) cannot measure price improvement on these trades and does not capture the benefits of OT for these trades. Thus, our DPI is a conservative measure of the direct price improvement from OT.

[19] While unreported, the 95th percentile shows significant direct price improvements of 19bps for cDPI and 6.6bps for DPi, respectively.

Table 2: **Price improvement from OT over time.** The table documents the price improvement from OT. We decompose the total impact into direct and indirect impacts, respectively. DPI is the direct price improvement from OT winning, computed in the data using equation (8). IPI is the indirect price improvement from OT impacting dealers' bidding functions, computed using expression (7). TPI is the total price improvement from OT entry, computed using expression (7). Panel A reports summary statistics. Panel B reports annual averages for all bonds. The number of RFQs with OT entry is 1,065,500.

Panel A: Price improvement from OT

	Mean	SD	25%	Median	75%
cDPI (bps)	3.24	12.61	0.00	0.00	0.00
DPI (bps)	1.05	4.09	0.00	0.00	0.00
cIPI (bps)	2.77	69.47	-21.90	2.73	27.47
IPI (bps)	1.64	27.51	-8.36	0.83	10.99
cTPI (bps)	6.02	68.31	-19.12	4.40	29.62
TPI (bps)	2.68	27.24	-7.31	1.39	11.79

Panel B: Price improvement from OT over time (bps)

	cDPI	DPI	cIPI	IPI	cTPI	TPI
Total	3.24	1.05	2.77	1.64	6.02	2.68
2014	2.97	0.22	0.34	0.11	3.31	0.33
2015	4.40	0.56	0.91	0.29	5.32	0.85
2016	3.81	1.07	4.08	2.12	7.89	3.19
2017	2.33	0.83	2.06	1.18	4.38	2.02
2018	3.07	1.51	3.04	2.23	6.12	3.74

yield notable direct price improvements when successful.

Table 2, Panel B documents trends for cDPI and DPI across years. cDPI starts at 3bps in 2014, peaking at 4.4bps in 2015, and then stabilizes around 2–3bps in subsequent years, reflecting a declining but persistent impact of OT when it enters RFQs. Meanwhile, the unconditional DPI shows a steady increase over time, rising from 0.2bps in 2014 to 1.5bps in 2018 in line with the increase in OT entry documented in Figure 4.

Since the variation in price improvement can be attributed to the variation of N_{PD} and p across RFQs, we next explore the dependence of (c)DPI on (N_{PD}, p). Later in the paper, we develop a model of all-to-all RFQ for a generic bond to quantify the economic channels of the OT price improvement. With the model in mind, we construct $\widehat{\text{cDPI}}(N_{\text{PD}}, p)$ for a generic bond by fitting the shape of the functional form as polynomials. To do this we set p to the predicted OT entry rate from specification (2) and control for bond fixed effects α_b to capture deviations from a generic bond, such that $\mathbb{E}[\text{cDPI}_{ibt} - \alpha_b - \widehat{\text{cDPI}}(N_{\text{PD}}, p)] = 0$, with general polynomial form

$$\widehat{\text{cDPI}}(N_{\text{PD}}, p) = \sum_{l=1}^{L} (a_l + \sum_{k=1}^{K} b_{kl} \times p^k) \times \mathbf{1}\{N_{\text{PD}} = l\}, \tag{10}$$

and parameters (a_l, b_{kl}) for $(K, L) \in \mathbb{N}^2$. Similarly, $\widehat{\text{DPI}}(N_{\text{PD}}, p) = p \times \widehat{\text{cDPI}}(N_{\text{PD}}, p)$. The reported results are obtained under the assumption of the simplest polynomial form with $K = 1$ and $L = 11$. Table A.5 documents $\widehat{\text{cDPI}}$ and $\widehat{\text{DPI}}$ across years and shows that both measures closely track cDPI and DPI, respectively, for all bonds. We will use the generic bond in our model.

Figure 6, Panel A reports average quarterly DPI (left subplot) and cDPI (right subplot) as a function of the number of permissioned dealer bidders, N_{PD}, and time for a generic bond. We construct it by creating bins for $N_{\text{PD}} = \{1, ..., 10, 11+\}$ in each quarter and computing the average (c)DPI for a generic bond in each bin. The plots clearly show that the direct price improvement is a non-negative and decreasing function of N_{PD}. The latter relation helps in explaining the annual variation in Panel B of Table 2 and is because as N_{PD} increases it is harder for OT to improve on the already competitive dealer bids.

2.3 OT's total price impact

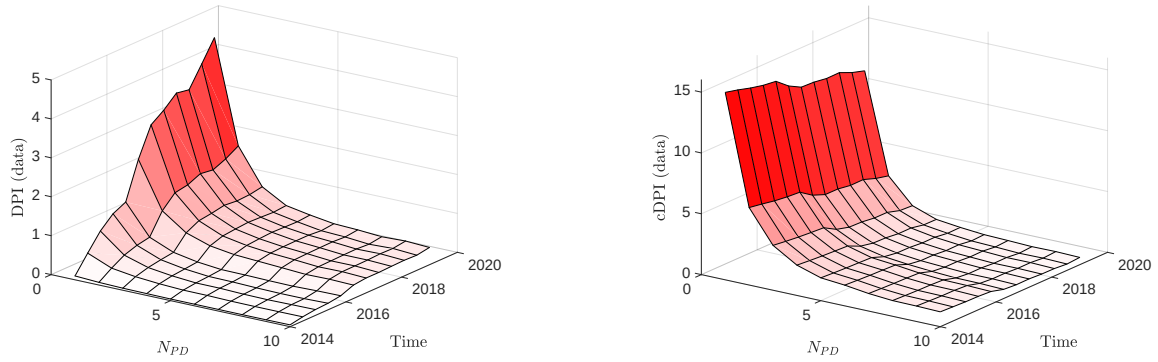
While the direct OT price improvement can be observed in the data, the total OT price improvement includes the indirect price improvement that is not directly observable. We proceed as follows.

Proposition 1 provides the basis to estimate indirect price improvement as a function of OT entry and the number of bidders. TPI in (7) depends on the OT entry rate p which we characterize in Section 1.3, the direct OT price improvement DPI which we characterize in Section 2.2, and the difference in half-spreads with and without OT bids. When measuring the expected half-spread S, we can use a regression approach or capture cohort-specific variation in TPI by defining a suitable control group of RFQs. For the latter, we can again proceed in different ways. We can compare RFQs in the same bond at the same time with and without OT entry. Or, we exploit the staggered OT entry documented in Section 1.5 and use the matched-sample approach described in Appendix C. The identifying assumption here is that while OT entry can be endogenous the exact order in which the large quasi-dealer entered different RFQs depends on the sequence of bonds being sold and bought. This is random once we condition on observables. Using this procedure, we obtain the direct and indirect OT price improvement, $\text{cDPI}_{ibt}/\text{cIPI}_{ibt}$, in RFQ i for bond b in month t.

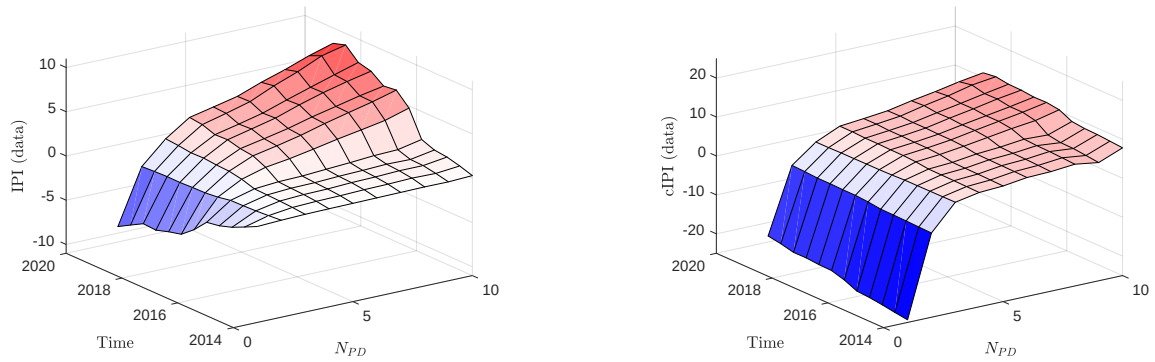
Figure 6, Panels B and C plot the variation in (c)IPI and (c)TPI with the number of permissioned dealers, N_{PD}, over time. For each plot, we follow the same procedure we use for (c)DPI by estimating the relation between price improvement, N_{PD}, and time for a generic bond by controlling for bond fixed effects in regressions of price improvement on p for each realization of N_{PD} as outlined in expression (10). We report the average price improvement for each bin. Panel B of Figure 6 reports estimated indirect OT price improvement, IPI, left subplot, and the indirect OT price improvement conditional on OT entry, cIPI, right subplot. Panel C of Figure 6 reports estimated TPI, left subplot, and cTPI, right subplot.

An important result is the blue region present throughout the sample period indicating that cIPI, and correspondingly IPI, can be negative and as low as -20bps thus implying that OT entry

Panel A: Direct OT price improvement (left = DPI, right = cDPI)



Panel B: Indirect OT price improvement (left = IPI, right = cIPI)



Panel C: Total OT price improvement (left = TPI, right = cTPI)

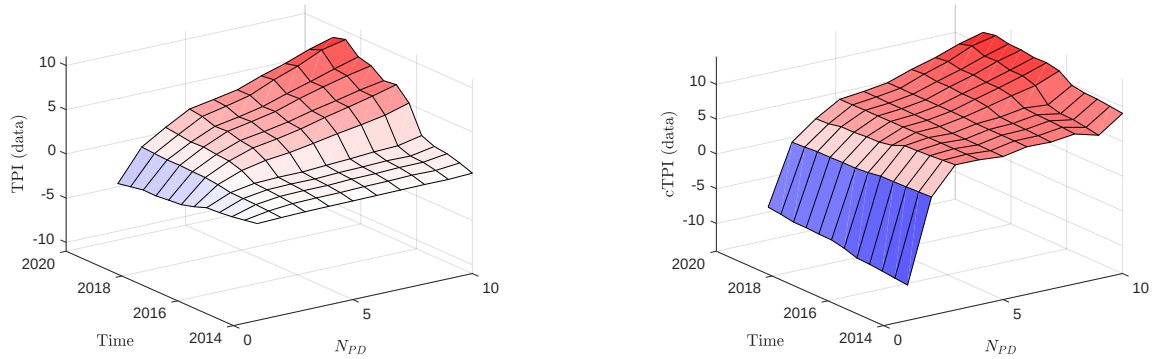


Figure 6: **OT price improvement depending on the number of RFQ responses and OT entry rate.** The left plots show the price improvement from OT as a function of the number of RFQ responses by the permissioned dealers, N_{PD}, over time. The right plots show the price improvement conditional on OT entry as a function of N_{PD} over time. All plots are constructed by estimating the relation between price improvement, N_{PD}, and time for a generic bond by controlling for bond fixed effects in regressions of price improvement on p for each realization of N_{PD}. We then report the average price improvement for each bin.

worsened prices. Negative (c)IPI means the corporate bonds RFQs are common-value auctions. Fixing time, both cIPI and IPI increase with N_{PD}, and they switch from negative values for $N_{\text{PD}} < 3$ to positive values. This indicates that OT entry indirectly improves prices when the number of incumbent bidders is already large. Fixing N_{PD}, cIPI is slowly increasing over time. Since the entry rate p increases over time, IPI becomes more negative over time for $N_{\text{PD}} < 3$ and IPI is positive and increasing over time for $N_{\text{PD}} > 3$. cIPI is negative for $N_{\text{PD}} < 3$ and it is positive for $N_{\text{PD}} \geq 3$ in the data for all values of the entry probability p. These patterns are robust to alternative approaches of computing (c)IPI (Appendix C provides additional details).

Total OT price improvement equals the sum of the direct and indirect OT price improvements. The total price improvement in Panel C is negative when the number of incumbent bidders is low, $N_{\text{PD}} < 3$, due to the entry effect being weaker than the indirect price improvement. OT improves prices for $N_{\text{PD}} \geq 3$. RFQs where IPI is the largest also experience the largest total price improvement. Hence, DPI alone is a misleading indicator for the total price improvement from OT since IPI can be large and switch signs.

Panel A of Table 2 reports summary statistics for cIPI/IPI and cTPI/TPI. The summary statistics for all bonds show that cIPI/IPI averages 2.8bps/1.6bps, with a high standard deviation of 69bps/28bps. cIPI/IPI can be quite negative with a lower quartile of -22bps/-8bps indicating the presence of the winner's curse. Most trades see a substantial indirect price improvement, i.e., median cIPI/IPI equals 2.7bps/0.8bps, while the upper quartile shows a very large cIPI/IPI of 28bps/11bps. These results highlight that the threat of OT entry can force incumbent dealers to substantially adjust their bidding functions. The total price improvement is the sum of the indirect and direct price improvements which is reflected in its summary statistics. The mean cTPI/TPI of 6bps/2.7bps is the sum of means for cDPI/DPI and cIPI/IPI. The rest of the statistics for cTPI/TPI is dominated by the statistics for cIPI/IPI. Of note is that most trades see a total price improvement of 4.4bps/1.4bps (median cTPI/TPI).

Table 2, Panel B documents trends for cIPI/IPI and cTPI/TPI across years. Much of the variation in price improvement can be linked to Figure 6. TPI was as low as 0.3bps in 2014 mostly because the OT entry rate was low. For the same reason, DPI (0.2bps) and IPI (0.1bps) were also small in 2014. N_{PD} declined in 2015. Therefore, cDPI/DPI increased to 4.4bps/0.6bps, while cIPI/IPI increased to 0.9bps/0.3bps. Correspondingly, cTPI increased to 5.3bps mostly because cDPI increased to 4.4bps. As the OT entry rate went up in 2015, TPI also increased to 0.9bps. cIPI increased to 4bps in 2016, while cDPI decreased to 3.8bps. Therefore, cTPI/TPI was quite high at 7.8bps/3.2bps. N_{PD} increased in 2017 and then declined in 2018. Therefore, cDPI/DPI declined to 2.3bps/0.8bp in 2017 and then increased to 3.1bps/1.5bps in 2018. cIPI/IPI declined to 2.1bps/1.2bps in 2017 and then increased to 3bps/2.2bps in 2018. Since cIPI/IPI and cDPI/DPI contributed almost equally to cTPI/TPI during 2017 and 2018, cTPI/TPI mirrored their behavior. cTPI/TPI declined to 4.4bps/2bps in 2017 and increased to 6.1bps/3.7bps in 2018.

To gain further economic intuition about price improvements from OT entry, we develop a model of all-to-all RFQs in the next section.

3 Model of All-to-All RFQs

To decompose the total price improvement from OT into entry, competition, and information effects, we consider the following framework based on standard assumptions in the auction literature. Since the traded quantity equals the requested quantity in 98.9% of trades on MarketAxess, an all-to-all RFQ is a sealed-bid first-price auction for a single unit of bond with a reference value of R which is common knowledge. The model allows for Type I and II errors in bidding.

3.1 Model setup and equilibrium spreads

To generate direct and indirect price improvements from OT consistent with the data, we assume there are three scenarios: (i) OT is present, i.e., it is enabled by the RFQ initiator, and enters the RFQ; (ii) OT is present but does not enter the RFQ; (iii) OT is not present, i.e., it is not enabled by the RFQ initiator. Figure 7 illustrates the scenarios, bidding functions, and observed half-spreads in all-to-all RFQs. From the discussion in Section 2.1, OT is present with probability q which depends, for instance, on the adoption of OT by market participants, whether OT is enabled, and the number of bidders, N_{PD}. When OT is present, we assume it can enter the RFQ with probability λ which depends, for instance, on the speed with which OT can prepare a bid, how many concurrent tasks OT has to perform, and how many other bidders are trying to enter the RFQ, N_{PD}. The ex-ante probability of OT entry is $p = \lambda q$, which is documented in Section 1.3. Accordingly, N_{PD} permissioned dealers and, depending on realized OT entry, $N_{\text{OT}} \geq 1$ OT entrants are bidding to buy the bond; the case for bidding to sell the bond is symmetric.[20] The total number of bidders is equal to $N_{\text{PD}} \geq 2$ without and $N = N_{\text{PD}} + N_{\text{OT}}$ with OT entry. Since we observe RFQs with $N_{\text{PD}} = 1$ in the data, we assume that a monopolist dealer bids its outside option. For q, λ, and p we drop the dependence on N to shorten the notation.

While we can quantify (c)DPI, (c)IPI, and (c)TPI without parametric assumptions (Proposition 1), to decompose the price improvement from OT into its entry effect, competition effect, and information effect, we make the following additional assumptions to complete the model. Dealers and OT receive privately observed cost shocks t_j, $j = 1, ..., N$ and are subject to intermediation costs $\xi_j(N)$. When OT is enabled, which occurs with probability q, dealers and OT face intermediation costs $\xi_j(N)$. In contrast, dealers face intermediation costs $\xi_j(N_{\text{PD}})$ when OT is not enabled.

[20] The empirical framework will allow for heterogeneity across RFQs i and bidders j. In RFQ i, there are $N_{\text{PD},i}$ permissioned dealers and $N_{\text{OT},i}$ OT bidders, for a total of $N_i = N_{\text{PD},i} + N_{\text{OT},i}$, with $N_{\text{PD},i}$ and $N_{\text{OT},i}$ known, which is a standard assumption in the auction literature (Levin and Smith, 1994). This assumption is without loss of generality as it can be relaxed. However, Figure 5 documents that conditional on OT entry in more than 50% of RFQs a single OT bidder enters. That is, typically $N_{\text{OT}} = 1$ in the data.

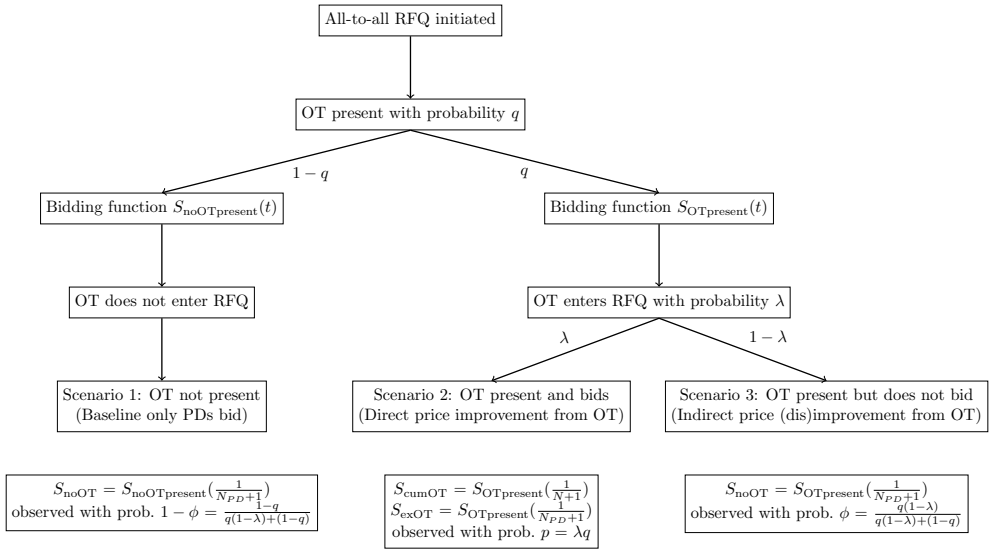


Figure 7: **Model of all-to-all RFQs**. The diagram summarizes bidding outcomes in the RFQ with an all-to-all option model.

Intermediation costs $\xi_j(N)$ are subject to common and private shocks:

$$\xi_j(N) \quad = \quad \xi + \alpha_N \sum_{\substack{k=1 \\ k\neq j}}^{N} (t_k - \mathbb{E}[t_k]) + \beta_N (t_j - \mathbb{E}[t_j]), \tag{11}$$

where the constant term ξ captures the ex-ante expected costs. The second term in (11) is the aggregate cost shock shared by all bidders from j's perspective. It gives rise to the winner's curse in the model. The third term in (11) is the private cost shock known only by bidder j. α_N captures the degree of commonality, with $\alpha_N = 0$ implying the independent private value (IPV) model and $\alpha_N = \beta_N$ implying a pure common value (PCV) model. Coefficients α_N and β_N are functions of N (see, e.g., Klemperer (1999, p. 259), Ernst *et al.* (2023)) such that $\lim_{N\to\infty} N \cdot \alpha_N$ and $\lim_{N\to\infty} \beta_N = \beta_\infty$ are finite. We do not make any other assumptions about α_N and β_N and let the data determine α_N and β_N as functions of N.

After privately observing their costs, bidders simultaneously submit bids from one of two bidding functions; at a spread $S_j = S_{\text{OTpresent}}(t; N_{\text{PD}}, N, \lambda)$ relative to the reference price R when OT is enabled, and $S_j = S_{\text{noOTpresent}}(t; N_{\text{PD}})$ when OT is not enabled. No bidder can condition bids on realized OT entry, thus leading to Type I/II errors in bidding.[21] The bid with the lowest discount

[21] The auction literature typically assumes that only bidders incurring entry costs can submit bids (see, e.g., Levin and Smith, 1994; Li and Zheng, 2009; Athey, Levin, and Seira, 2011; Krasnokutskaya and Seim, 2011; Bhattacharya, Roberts, and Sweeting, 2014; and Gentry and Li, 2014). We follow the literature by assuming that the distribution of realizations of N is common knowledge among bidders (Compiani, Haile, and Sant'Anna, 2020), thus allowing for the possibility that prices improve due to incumbents adjusting their bidding functions in response to realized OT entry. OT entry can be exogenous or endogenous in the model when the OT option is selected (which we take as given). Dealers bid without knowing whether OT entry occurs based on the ex-ante probabilities of OT being present, q, and

wins the RFQ. In the case of a tie, the winner is chosen randomly among those who submit the same lowest discount. We consider symmetric equilibria in which all bidders use the same bidding functions.

Equilibrium bidding functions. Appendix D characterizes the optimal bidding functions in an all-to-all RFQ depending on OT presence and shows that under the standard assumption $t_j \sim U[0,1]$ (Klemperer (1999), Ernst *et al.* (2023)), for which $\mathbb{E}[t_k] = \frac{1}{2}$ for all $k = 1, ..., N$, there exists a linear symmetric equilibrium summarized by the following proposition.

PROPOSITION 2: *There exists a unique linear symmetric equilibrium in the bidding game with intermediation costs given by (11) in which the equilibrium bidding functions can be decomposed into dealer costs and markups:*

$$\begin{aligned} S_{\text{noOTpresent}}(t; N_{\text{PD}}) &= c_{\text{noOTpresent}}(t; N_{\text{PD}}) + m_{\text{noOTpresent}}(t; N_{\text{PD}}), \\ S_{\text{OTpresent}}(t; N_{\text{PD}}, N, \lambda) &= c_{\text{OTpresent}}(t; N_{\text{PD}}, N, \lambda) + m_{\text{OTpresent}}(t; N_{\text{PD}}, N, \lambda), \end{aligned} \tag{12}$$

with the dealer costs given by

$$\begin{aligned} c_{\text{noOTpresent}}(t; N_{\text{PD}}) &= \xi - \tfrac{\alpha_{N_{\text{PD}}}}{2}(1 - N_{\text{PD}} \cdot t) - \beta_{N_{\text{PD}}}\left(\tfrac{1}{2} - t\right), \\ c_{\text{OTpresent}}(t; N_{\text{PD}}, N, \lambda) &= \xi - \tfrac{\alpha_N}{2}(1 - N \cdot t) - \beta_N\left(\tfrac{1}{2} - t\right) - (1-\lambda) \underbrace{\alpha_N \frac{N - N_{\text{PD}}}{2} t}_{\text{Type II error in cost}}, \end{aligned} \tag{13}$$

and the dealer markups given by

$$\begin{aligned} m_{\text{noOTpresent}}(t; N_{\text{PD}}) &= (\alpha_{N_{\text{PD}}} \tfrac{N_{\text{PD}}}{2} + \beta_{N_{\text{PD}}}) \tfrac{1-t}{N_{\text{PD}}}, \\ m_{\text{OTpresent}}(t; N_{\text{PD}}, N, \lambda) &= (\alpha_N \tfrac{N}{2} + \beta_N) \tfrac{1-t}{N} + (1-\lambda) \underbrace{\frac{N - N_{\text{PD}}}{N_{\text{PD}}} \beta_N \frac{1-t}{N}}_{\text{Type II error in markup}}. \end{aligned} \tag{14}$$

For $N_{\text{PD}} = 1$, we assume that a monopolist dealer with a private cost shock t has an outside option $R - S_{\text{noOTpresent}}(t; 1)$. Relations (12) show that $S_{\text{noOTpresent}}(t; N_{\text{PD}})$ depends on the number of dealers, N_{PD}, only while $S_{\text{OTpresent}}(t; N_{\text{PD}}, N, \lambda)$ depends on the possible number of bidders, N_{PD} and N, and the probability that OT bids in the RFQ, λ when OT is present. With probability $1 - \lambda$, bidders make a Type II error when they do not expect OT entry into the RFQ but it takes place. Bidders make Type II errors in RFQs with OT present by underestimating costs, $-\alpha_N \frac{N - N_{\text{PD}}}{2} t$, believing that the winner's curse is less severe than it is, and by overestimating markups, $\frac{N - N_{\text{PD}}}{N_{\text{PD}}} \beta_N \frac{1-t}{N}$, believing that the competition is weaker than it is. As the number of

OT entering RFQ, λ.

bidders used to calculate the expected cost shock increases from N_{PD} to N, the Type II error in costs shrinks while it increases for markups.

It follows from expressions (13) that since the expected shock of the winning bidder is less than the average shock as we will see below, the expected dealer costs are below the ex-ante costs ξ. Dealer markups are always positive except for the bidder with the worst signal $t = 1$. Furthermore, dealer costs are increasing with the cost shock t while markups are declining. In order to compare $c/m_{\text{noOTpresent}}(t; N_{\text{PD}})$ and $c/m_{\text{OTpresent}}(t; N_{\text{PD}}, N, \lambda)$ holding t fixed we need to know how α_N and β_N depend on the number of bidders N.

Mapping model to data—equilibrium half-spreads and price improvements. To calculate the half-spreads observed in the data, let $t^{N+1-j:N}$ be the jst lowest of the N independently drawn cost t_j with an expected value equal to the first moment of the order statistic for the standard uniform distribution: $\mathbb{E}[t^{N+1-j:N}] = \frac{j}{N+1}$ for $j = 1, ..., N$. The bidder who wins the RFQ with OT entry has the lowest signal, $t^{N:N}$, resulting in transaction price $B^{1:N} = R - S_{\text{OTpresent}}(t^{N:N})$, while the best bid among the permissioned dealers is equal to $B^{1:N_{\text{PD}}} = R - S_{\text{OTpresent}}(t^{N_{\text{PD}}:N_{\text{PD}}})$. The bidder who wins the RFQ without OT presence has the lowest signal, $t^{N_{\text{PD}}:N_{\text{PD}}}$, resulting in transaction price $B^{1:N_{\text{PD}}} = R - S_{\text{noOTpresent}}(t^{N_{\text{PD}}:N_{\text{PD}}})$. Since all bids are linear in the signal t calculating expected spreads amounts to calculating the appropriate order statistic. We can now calculate the observed spreads and price improvements.

Using the identities (4)–(6), price improvements from OT equal cDPI $= S_{\text{exOT}} - S_{\text{cumOT}}$ and cIPI $= S_{\text{noOT}} - S_{\text{exOT}} = (1 - \phi)(S_{\text{noOTpresent}} - S_{\text{exOT}})$, respectively. The observed spread in RFQs with OT entry, $S_{\text{cumOT}}(N_{\text{PD}}, N, \lambda)$, is equal to

$$\begin{aligned} S_{\text{cumOT}}(N_{\text{PD}}, N, \lambda) &= S_{\text{OTpresent}}(\tfrac{1}{N+1}; N_{\text{PD}}, N, \lambda) = \\ &= c_{\text{OTpresent}}(\tfrac{1}{N+1}; N_{\text{PD}}, N, \lambda) + m_{\text{OTpresent}}(\tfrac{1}{N+1}; N_{\text{PD}}, N, \lambda) = \\ &= \xi + \alpha_N\big(\tfrac{N}{N+1} - \tfrac{1}{2}\big) + \beta_N\big(\tfrac{2}{N+1} - \tfrac{1}{2}\big) - \\ &\qquad -(1-\lambda)\tfrac{N-N_{\text{PD}}}{N_{\text{PD}}(N+1)}\big(\tfrac{\alpha_N}{2}N_{\text{PD}} - \beta_N\big), \end{aligned} \tag{15}$$

where the last term captures the Type II error of the dealers. The first component of dealers' Type II error is the underestimation of their expected costs by $\frac{\alpha_N}{2}\frac{N-N_{\text{PD}}}{N+1}$. This error component narrows $S_{\text{cumOT}}(N_{\text{PD}}, N, \lambda)$ thus improving the bid. The second component of dealers' Type II error is the overestimation of their expected markups by $\beta_N \frac{N-N_{\text{PD}}}{N_{\text{PD}}(N+1)}$. This error component widens $S_{\text{cumOT}}(N_{\text{PD}}, N, \lambda)$ thus worsening the bid. The net effect of the dealers underestimating

the threat of OT entry on $S_{\text{cumOT}}(N_{\text{PD}}, N, \lambda)$ depends on the sign of $\frac{\alpha_N}{2} N_{\text{PD}} - \beta_N$. Correspondingly,

$$\begin{aligned} S_{\text{exOT}}(N_{\text{PD}}, N, \lambda) &= S_{\text{OTpresent}}(\tfrac{1}{N_{\text{PD}}+1}; N_{\text{PD}}, N, \lambda) = \\ &= c_{\text{OTpresent}}(\tfrac{1}{N_{\text{PD}}+1}; N_{\text{PD}}, N, \lambda) + m_{\text{OTpresent}}(\tfrac{1}{N_{\text{PD}}+1}; N_{\text{PD}}, N, \lambda) = \\ &= \xi + \tfrac{\alpha_N}{2}\big(\tfrac{N_{\text{PD}}+N}{N_{\text{PD}}+1} - 1\big) + \beta_N\big(\tfrac{N_{\text{PD}}+N}{N(N_{\text{PD}}+1)} - \tfrac{1}{2}\big) \\ &\qquad -(1-\lambda)\tfrac{N-N_{\text{PD}}}{N(N_{\text{PD}}+1)}\big(\tfrac{\alpha_N}{2} N - \beta_N\big). \end{aligned} \tag{16}$$

The equilibrium spreads observed in an RFQ with no OT is a weighted average of the spread when OT is not present (Scenario 1 in Figure 7), which occurs with probability $1-\phi = \frac{1-q}{q(1-\lambda)+(1-q)}$, and the spread when OT entry does not take place (Scenario 3 in Figure 7), which occurs with probability $\phi = \frac{q(1-\lambda)}{q(1-\lambda)+(1-q)}$. It is equal to

$$\begin{aligned} S_{\text{noOT}}(N_{\text{PD}}, N, \lambda, q) &= \phi S_{\text{exOT}}(N_{\text{PD}}, N, \lambda) + (1-\phi) S_{\text{noOTpresent}}(\tfrac{1}{N_{\text{PD}}+1}; N_{\text{PD}}) = \\ &= S_{\text{noOTpresent}}(\tfrac{1}{N_{\text{PD}}+1}; N_{\text{PD}}) - \phi\big(S_{\text{noOTpresent}}(\tfrac{1}{N_{\text{PD}}+1}; N_{\text{PD}}) \\ &\quad - S_{\text{exOT}}(N_{\text{PD}}, N, \lambda)\big) = \xi + \alpha_{(N_{\text{PD}},\phi)}\big(\tfrac{N_{\text{PD}}}{N_{\text{PD}}+1} - \tfrac{1}{2}\big) + \\ &\quad + \beta_{(N_{\text{PD}},\phi)}\big(\tfrac{2}{N_{\text{PD}}+1} - \tfrac{1}{2}\big) + \phi\lambda\underbrace{\big(\frac{\alpha_N}{2} - \frac{\beta_N}{N}\big)\frac{N - N_{\text{PD}}}{N_{\text{PD}}+1}}_{\text{Type I error}}, \end{aligned} \tag{17}$$

where $(\alpha, \beta)_{(N_{\text{PD}},\phi)} \equiv \phi \times (\alpha, \beta)_N + (1-\phi) \times (\alpha, \beta)_{N_{\text{PD}}}$. The term $S_{\text{noOTpresent}}(\frac{1}{N_{\text{PD}}+1}; N_{\text{PD}}) - S_{\text{exOT}}(N_{\text{PD}}, N, \lambda)$ captures the Type I error of the dealers as they bid more aggressively projecting that OT may enter but it does not.

3.2 Model estimation

The model can be estimated with our granular bidding data using the identities (4)–(6) and expressions (15)–(17). Combined with observed OT entry decisions, they allow to back out the probability of OT non-entry in RFQs, ϕ, probability of OT presence in RFQs, $q = p + \phi(1-p)$, and probability of OT entering RFQs conditional on OT being present, $\lambda = p/q$, and α_N and β_N as functions of N and over time.

All three economic forces of OT, entry, competition, and information, are present in the model and affect cDPI and cIPI differently depending on N_{PD} and p and the model parameters. While cDPI and DPI are always positive, cIPI and IPI may be negative depending on parameter values. Finding negative IPI in the data suggests that RFQs reflect a common value environment subjecting dealers to the winner's curse. The model nests independent private and pure common values. With independent private values ($\alpha_N = 0, \beta_N > 0$), it predicts that cDPI, cIPI, and cTPI should all be positive and decrease with the number of bidders when holding the entry probability fixed. The shape of β_N determines how fast price improvement changes with N and whether it remains

significantly positive for large N. The RFQ model with common-value component ($\alpha_N > 0$) predicts that holding the entry probability fixed, cDPI is positive and cIPI can be either negative or positive depending on the model's primitives. Depending on the relative magnitudes of cDPI and cIPI, the total price improvement can be either positive or negative. We use these model-implied relations to identify the determinants of (α_N, β_N) in (11) and ϕ in (17). By focusing on spreads, we can ignore all variation due to changes in intermediation cost ξ in (11).

Estimating the model parameters in our granular RFQ data requires making several empirical choices. The analysis in Section 2 suggests that the price improvement from OT entry and its components depend on N_{PD} and p. We therefore use the fitted shapes of the functional forms $\widehat{\text{cDPI}}(N_{\text{PD}}, p)$ and $\widehat{\text{cIPI}}(N_{\text{PD}}, p)$ as in (10), create bins for $N_{\text{PD}} = \{1, ..., 10, 11+\}$ in each quarter, and use these to construct moments to be matched. In the reported results, we assume the simplest polynomial form with $K = 1$ and $L = 11$. We then treat the observed $\widehat{\text{cDPI}}$ and $\widehat{\text{cIPI}}$ for each N_{PD} and every quarter between 2014 and 2019 capturing a generic bond as moments that we want to match. Last, we need to specify functional forms for α_N, β_N, and ϕ in (11). The most natural flexible specifications are

$$\begin{aligned}
\alpha_N &= \exp(\textstyle\sum_{l=0}^{L}\sum_{k=0}^{K}\alpha_{kl} \times N^l \times p^k), s.t.\ \alpha_N \geq 0, \\
\beta_N &= \exp(\textstyle\sum_{l=0}^{L}\sum_{k=0}^{K}\beta_{kl} \times N^l \times p^k), s.t.\ \beta_N \geq 0, \\
\phi &= \Phi(\textstyle\sum_{l=0}^{L}\sum_{k=0}^{K}\gamma_{kl} \times N_{\text{PD}}^l \times p^k), s.t.\ \phi \in (0,1), \\
q &= p + \phi(1-p) \in (0,1), \\
\lambda &= p/q \in (0,1),
\end{aligned} \tag{18}$$

where $\Phi(\cdot)$ is the normal cdf and $(K, L) \in \mathbb{N}^2$ depend on how one models post-RFQ trading (see, e.g., Klemperer (1999, p. 259), Ernst *et al.* (2023)). With the parameter estimates from (10), we estimate the parameters in specification (11) and (18) by minimizing the distance between the observed $\widehat{\text{cDPI}}$ and $\widehat{\text{cIPI}}$ and the model-implied $\text{cDPI}(\alpha, \beta, \gamma)$ and $\text{cIPI}(\alpha, \beta, \gamma)$ from Proposition 1 for all $N_{\text{PD}} \times$ quarter bins. Given the order of expansion $(K, L) \in \mathbb{N}^2$, we minimize the weighted distance over the $3(K+1)(L+1)$ cost coefficients $(\alpha_{kl}, \beta_{kl}, \gamma_{kl})_{k=0,...,K, l=0,...,L}$:

$$\min_{\substack{\alpha_{kl},\beta_{kl},\gamma_{kl} \\ k=0,...,K \\ l=0,...,L}} \mathcal{D}(\alpha, \beta, \gamma; \omega) = \omega \left|\left|\widehat{\text{cDPI}} - \text{cDPI}(\alpha, \beta, \gamma)\right|\right| + (1-\omega) \left|\left|\widehat{\text{cIPI}} - \text{cIPI}(\alpha, \beta, \gamma)\right|\right|. \tag{19}$$

In our implementation, we measure the distance between the model-implied price improvement and the one observed in the data by

$$\left|\left|\widehat{\text{PI}} - \text{PI}(\alpha, \beta, \gamma)\right|\right| = \sum_{\#N_{\text{PD}} \times \text{quarter}} \left(\widehat{\text{PI}}(N_{\text{PD}}, \text{quarter}) - \text{PI}(\alpha, \beta, \gamma; N_{\text{PD}}, \text{quarter})\right)^2,$$

and use $\omega = 0.5$ in the base case. In alternative specifications we use different orders (K, L) and

either the observed $\widehat{\text{cDPI}}$, $\widehat{\text{cTPI}}$, or $\widehat{\text{cIPI}}$ to estimate the parameters, by setting $\omega \gtreqless 0.5$.

Parameter identification. The model is formally identified so long as number of moments, $40L$, exceeds the number of cost coefficients, $3(K+1)(L+1)$. The intuition for identification stems from the model solution (15)–(17) and cDPI $= S_{\text{exOT}} - S_{\text{cumOT}}$ and cIPI $= S_{\text{noOT}} - S_{\text{exOT}} = (1-\phi)(S_{\text{noOTpresent}} - S_{\text{exOT}})$, respectively. cDPI (cIPI) depends on the β_N more (less) than the α_N coefficients. When the β_N coefficients are all zero, cIPI becomes hump-shaped and converges to zero for large N_{PD} which is inconsistent with the data. When the α_N coefficients are all zero, cIPI cannot become negative for small N_{PD}. Also, for cIPI to be non-zero, ϕ cannot be one. However, cIPI becomes larger than observed for large N_{PD} when $\phi = 0$. As a result, α_N, β_N, and ϕ affect cDPI and cIPI differently for different values of N_{PD} and over time.

Model fit. Table A.6 summarizes the parameter estimates for different specifications. Specification (3) provides the best fit. In this specification with $K = L = 1$ and $\omega = 0.5$, all common value parameters α_{kl} and all private value parameters β_{kl} are statistically significant. The participation parameters γ_{kl} are not all significant, with only the intercept γ_{00} and the interaction with N_{PD} being statistically significant. The tightest fit has a mean-squared error of 0.92 (AIC=5.16, BIC=45.88) which corresponds to an average error of less than 1bp for each bin ($=\sqrt{0.92}$).

Figure A.3 illustrates the model fit. The plots show the fit of cDPI (Panel A), cIPI (B), and cTPI (C) by comparing predicted to actual values for each value of N_{PD} and each quarter. The plots illustrate that the fit is tight. The only exception is the largest values of cDPI for all quarters which occur for $N_{\text{PD}} = 1$. Here, the model underpredicts the magnitude of cDPI in the data by several basis points. For all other moments, the fit is close. We can improve the fit for cDPI($N_{\text{PD}} = 1$) by putting higher weight $\omega > 0.5$ on matching cDPI than cIPI (specification 4), in which case the procedure does not attempt to minimize cTPI but a weighted average of cDPI and cIPI.

Figure A.4 illustrates the model parameters. The left subplot in Panel A shows that the common value parameters α_{kl} are such that α_N declines rapidly with N from an initial value of over 100bps, suggesting that the winner's curse problem is the most severe for $N_{\text{PD}} = 1$ and declines with the number of bidders, which is qualitatively similar to findings of Ernst *et al.* (2023). This finding is consistent with dealers having inventory costs quadratic in the cost shock so that the marginal inventory costs are linear in the cost shock. The dealer can manage the inventory shock by trading with other dealers on the interdealer market where $N-1$ dealers compete to fill the order by charging $a_N t_j$, $j = 1, ..., N-1$, with a_N declining with N due to competition. The plot also shows that the winner's curse problem becomes less severe over time as p increases.

The right subplot in Panel A of Figure A.4 shows that the private value parameters β_{kl} make β_N an increasing function of N. β_N increases with N suggesting the private value component becomes more important as the number of bidders increases; it eventually plateaus for large N in

agreement with the assumption that $\lim_{N\to\infty}\beta_N$ is finite. This result is consistent with the risk-sharing by dealers and differs from the one in Ernst *et al.* (2023) where β_N is a constant. When N is small, dealers can share risk across the market by finding the lowest-cost dealer to trade with, and individual cost signals have less impact. When N is large, dealers transact on the interdealer market at a competitive price and thus must rely more heavily on their private cost shocks when determining their intermediation costs.

Panel B of Figure A.4 shows that the participation parameters γ_{kl} are such that ϕ is close to zero and λ is close to one so long as N_{PD} is less than 5. For N_{PD} larger than 5, ϕ increases up to more than 30% while λ drops to less than 50% for $N_{\text{PD}} = 10$. These results imply that Type I and Type II errors are economically important in RFQs with many bidders.

Table A.5, Panel B reports the model-implied price improvement from OT, allowing for a comparison with Panel A. Over the sample period, the average model-implied cDPI=3.6bps, DPI=1.1bps, cIPI=2.5bps, IPI=1.7bps, cTPI=6bps, TPI=2.8bps. The reported statistics show that the model-implied values align with the observed data-generated price improvements, with close approximations for direct and indirect price improvements across the sample period. Specifically, while the model estimates tend to be slightly higher than the observed values, they follow similar trends year-by-year, particularly in the non-monotone behavior of cDPI and cIPI from 2014 to 2018. For instance, in 2018, Panel B shows model-implied cDPI/cIPI of 2.9/3.6bps, respectively, which closely reflect the observed values in Panel A of 2.2/3.9bps.

The model-implied TPI values also track the observed TPI but tend to be marginally higher. This suggests that while the model accurately captures the general dynamics of price improvement, it slightly overestimates the net impact of OT entry under some market conditions. For instance, in 2017 (2018), the model implies a TPI of 3.5bps (4.3bps) compared to the observed TPI of 3.3bps (4.1bps). These comparisons suggest the model captures key price improvement dynamics while the small residual differences may arise from unmodeled market conditions or bidder behavior.

4 Entry, Competition, and Information Effects from OT

Here we use the model to quantify three economic channels via which OT affects prices in RFQs: entry, competition, and information. In the model, dealers' bids are based on their expected costs of intermediating the trade and their ability to charge a markup by shading their bids below/above their intermediation costs when buying/selling. Correspondingly, entry, competition, and information effects can all be split into costs and markups which, in turn, depend on the sensitivities of dealers' intermediation costs to their common, α_N, and private, β_N, cost shocks. It is natural to consider that dealers *compete* on their private cost shocks and we, therefore, classify dealers' bid adjustments scaled by β_N as the competition effect in the model, which we expect to improve RFQ prices. The common shock to dealers' intermediation costs leads to the winner's curse. The threat

of OT entry changes the severity of the winner's curse which we term the information effect in the model and associate dealers' bid adjustments scaled by α_N with it.

4.1 Entry effect from OT

The entry effect manifests via the direct price improvement from OT which is straightforward to construct in the model using expressions for equilibrium spreads (15)–(17) leading to the following decomposition.

CHANNEL 1 (Entry effect): *OT directly improves prices directly when it wins RFQs. The direct price improvement conditional on OT entry* (cDPI) *and the expected direct price improvement* (DPI $\equiv p \times$ cDPI) *are equal to:*

$$\begin{aligned} \text{cDPI} \;\equiv\; & \mathbb{E}_N[\max\{B_{\text{OT}}^{1:N_{\text{OT}}} - B_{\text{PD}}^{1:N_{\text{PD}}}, 0\}] = S_{\text{exOT}} - S_{\text{cumOT}} = \\ = \; & \underbrace{\frac{(N - N_{\text{PD}})}{(N_{\text{PD}}+1)(N+1)}\left[\alpha_N \frac{N}{2} + \beta_N - (1-\lambda)\frac{N - N_{\text{PD}}}{2}\alpha_N\right]}_{\text{Entry effect on cost } \geq 0} \\ & \underbrace{-\frac{(N - N_{\text{PD}})}{N(N_{\text{PD}}+1)(N+1)}\left[\alpha_N \frac{N}{2} + \beta_N + (1-\lambda)\frac{N - N_{\text{PD}}}{N_{\text{PD}}}\beta_N\right]}_{\text{Entry effect on markup } \leq 0}. \end{aligned} \tag{20}$$

Expression (20) illustrates that the entry effect can be decomposed into the cost, the first term in relation (20), and markup, the second term in (20), components. Both components have Type II errors scaled by the probability of non-entry into the RFQ when OT is present, $1-\lambda$, where setting $\lambda = 1$ corresponds to the case of dealers perfectly observing OT entry. Following the intuition from expressions (13) and (14), dealers underestimate the effect of OT entry on costs resulting in the negative error in the cost term, and overestimate the effect of OT entry on markups, resulting in the positive error in the markup term. The entry effect on costs is non-negative. This is because the winning bidder with a lower cost shock offers a higher cost discount relative to the baseline costs ξ. The entry effect on markups is non-positive, i.e. widening the spread. This is because the winning bidder with a lower cost shock charges a higher markup.

Figure 8 illustrates the entry effect of OT as a function of the number of RFQ responses by the permissioned dealers, N_{PD}, over time. In Panel B, the top/bottom plot shows the entry effect due to cost/markup as a function of N_{PD} over time. All plots are constructed by estimating the model in the data using the procedure outlined in Section 3.2. Panel A shows the model-implied entry effect captured by cDPI. It is very close to its data counterpart from the right subplot of Figure 6, Panel A. Panel B plots the cost, top subplot, and markup, bottom subplot, components of the entry effect. The cost component of the entry effect is positive and a decreasing function of N_{PD}. The cost component was as high as 25bps in 2014 for $N_{\text{PD}} = 1$. The markup component of

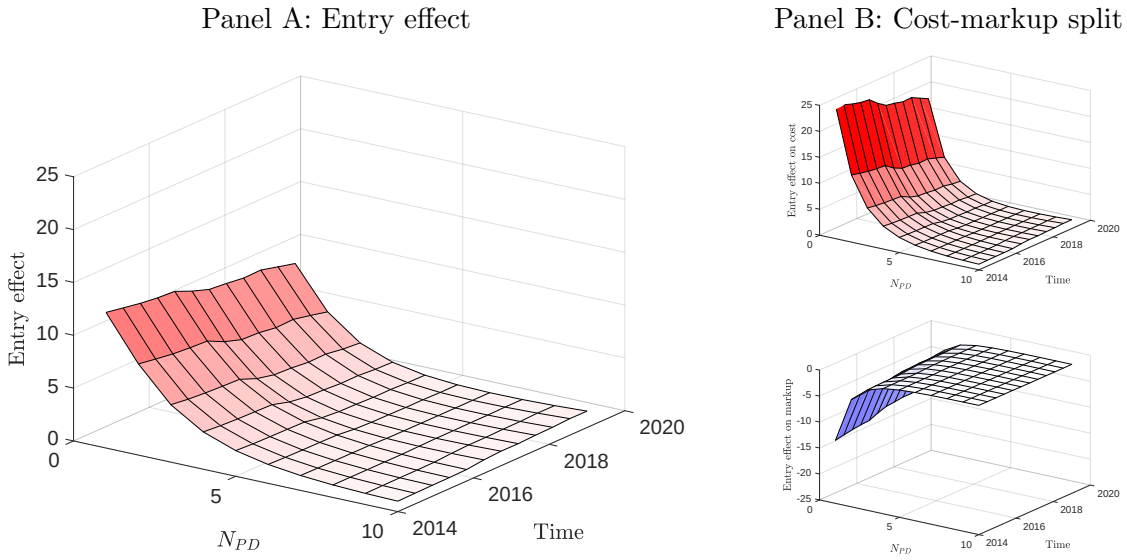


Figure 8: **Entry effect** Panel A shows the entry effect of OT from relation (20) as a function of the number of RFQ responses by the permissioned dealers, N_{PD}, over time. In Panel B, the top/bottom plot shows the cost/markup component of the entry effect as a function of N_{PD} over time. All plots are constructed by estimating the model in the data using the procedure outlined in Section 3.2.

the entry effect is a negative and increasing function of N_{PD}. Its lowest value was about -12bps in 2014 for $N_{\text{PD}} = 1$. It is clear from Panel B that the cost component is responsible for the time variation in cDPI since the markup component does not vary much over time.

4.2 Competition effect from OT entry

The competition effect is the second channel of OT price improvement in RFQs and it is the only indirect price improvement channel if bidders are independently privately informed ($\alpha_{N_{\text{PD}}} = \alpha_N = 0$). Since OT does not bid, the expected cost shock of the winning bidder remains the same at $\frac{1}{N_{\text{PD}}+1}$ and below the unconditional mean cost shock of $\frac{1}{2}$ in these analyses.

CHANNEL 2 (Competition effect): *OT indirectly affects prices by making permissioned dealers bid more aggressively on their private cost shocks as measured by*

$$\text{Competition effect} = \underbrace{(1-\phi)(\beta_N - \beta_{N_{\text{PD}}})\left(\frac{1}{2} - \frac{1}{N_{\text{PD}}+1}\right)}_{\text{Competition effect on cost } \geq 0 \text{ if } \beta_N > \beta_{N_{\text{PD}}}} + \underbrace{(1-\phi)\left(\beta_{N_{\text{PD}}} - \beta_N \frac{N_{\text{PD}}}{N} - (1-\lambda)\beta_N\left(1 - \frac{N_{\text{PD}}}{N}\right)\right)\frac{1}{N_{\text{PD}}+1}}_{\text{Competition effect on markup } \gtreqless 0}. \quad (21)$$

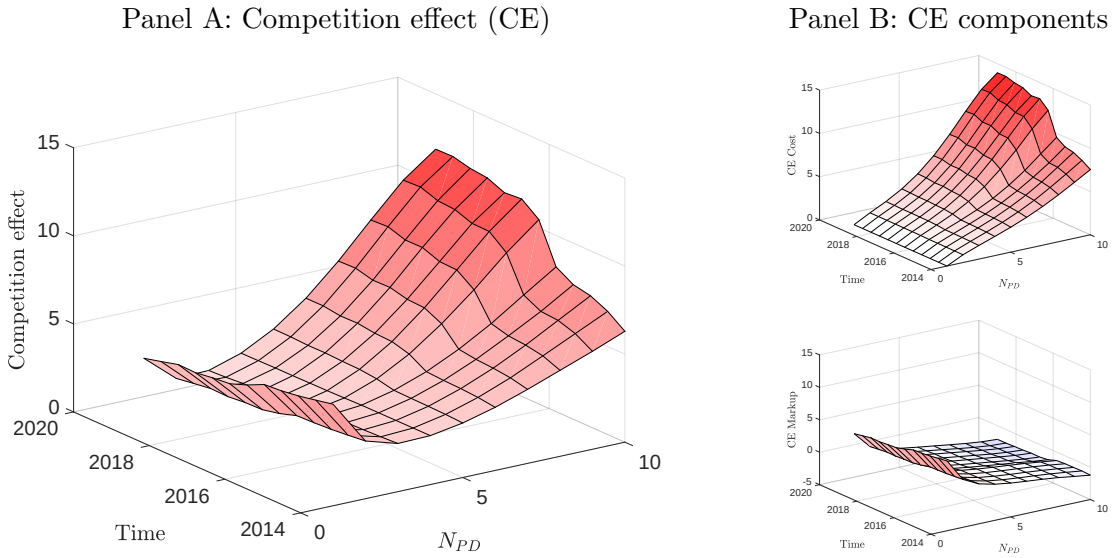


Figure 9: **Competition effect** Panel A shows the competition effect of OT from relation (21) as a function of the number of RFQ responses by the permissioned dealers, N_{PD}, over time. In Panel B, the top/bottom plot shows the cost/markup component of the competition effect as a function of N_{PD} over time. All plots are constructed by estimating the model in the data using the procedure outlined in Section 3.2.

The competition effect of OT entry affects prices via changes in dealers' costs and markups. Since our estimation results show that β_N increases with N, it follows from relations (13) that the threat of competing with OT makes dealers discount their costs relative to ξ more aggressively by switching from $\beta_{N_{\text{PD}}}$ to β_N. Relations (14) indicate that a threat of competing with OT on markups results in switching from $\beta_{N_{\text{PD}}}/N_{\text{PD}}$ to β_N/N and overestimating markups due to a Type II error and thus it cannot be signed. Intuitively, one would expect the total competition effect to be positive.

Figure 9 documents the competition effect of OT entry via heat maps constructed using the same approach used for heat maps from Figure 6. The plots report both effects as a function of the number of RFQ responses by the permissioned dealers, N_{PD}, and time. Panel A confirms that the competition effect of OT entry is positive and weakly U-shaped in N_{PD} for all times. The competition effect is weakest early in the sample and strongest later in the sample peaking at over 10bps for $N_{\text{PD}} = 10$.

To fully explore the sources of variation in the competition effect, we use the model to decompose them into cost and markup components according to relation (21). Figure 9, Panel B documents the cost and markup components of the competition effect of OT entry as a function of N_{PD} and time, constructed using the same approach as in Figure 6. By the first term in relation (21), the cost component of the competition effect is non-negative as long as $\beta_{N_{\text{PD}}}$ increases with N_{PD} which is the case in the data. Correspondingly, the top subplot shows that the cost component of the competition effect is non-negative in the data. Also consistent with the first term in relation (21),

the cost component of the competition effect increases with N_{PD}. The second term in relation (21) captures the markup component of the competition effect and its sign is ambiguous. The bottom subplot shows that the markup component of the competition effect is positive and largest for $N_{\text{PD}} = 1$ and then slowly declines with N_{PD} becoming slightly negative (light blue areas) for large values of N_{PD} in the data. Combined, these results explain that the competition effect is U-shaped in N_{PD} in the data. In terms of magnitudes, somewhat surprisingly, the cost effect from increased competition is larger than the markup effect from increased competition. Hence, OT entry strongly affects lowering costs, more so than lowering dealer markups.

4.3 Information effect from OT entry

The information effect is the third and final channel of OT price improvement in RFQs.

CHANNEL 3 (Information effect): *OT indirectly affects prices by impacting permissioned dealers' bidding on the common component of their intermediation costs, i.e., their winner's curse, which can be measured by*

$$\text{Information effect} = \underbrace{(1-\phi)\left[\frac{\alpha_N}{2}\left(1-\frac{N}{N_{\text{PD}}+1}\right)-\frac{\alpha_{N_{\text{PD}}}}{2}\frac{1}{N_{\text{PD}}+1}+(1-\lambda)\frac{\alpha_N}{2}\frac{N-N_{\text{PD}}}{N_{\text{PD}}+1}\right]}_{\text{Information effect on cost } \leq 0 \text{ if } N \geq N_{\text{PD}}+1 \text{ and } \alpha_{N_{\text{PD}}} > \alpha_N} + \underbrace{(1-\phi)(\alpha_{N_{\text{PD}}}-\alpha_N)\frac{N_{\text{PD}}}{2}\frac{1}{N_{\text{PD}}+1}}_{\text{Information effect on markup } >0 \text{ if } \alpha_{N_{\text{PD}}} > \alpha_N}. \quad (22)$$

The information effect of OT entry also affects prices via changes in dealers' costs and markups. It follows from relations (13) that a threat of OT entry makes dealers discount their costs relative to ξ less aggressively, i.e., reduce their winner's curse, by switching from $\frac{\alpha_{N_{\text{PD}}}}{2}\left(1-\frac{N_{\text{PD}}}{N_{\text{PD}}+1}\right)$ to $\frac{\alpha_N}{2}\left(1-\frac{N}{N_{\text{PD}}+1}\right)$ because the second term is non-positive for $N \geq N_{\text{PD}}+1$. Incumbent dealers also underestimate their costs due to their Type II error which can make the total information effect on costs positive. However, the total information effect on costs is non-positive if α_N decreases with N, $\alpha_{N_{\text{PD}}} > \alpha_N$, as is in our case. Relations (14) show that the threat of OT entry reduces markups since $\alpha_{N_{\text{PD}}} > \alpha_N$. Ultimately, the sign of the information effect can be both negative and positive depending on the deep model parameters that we estimate in the data.

Figure 10, Panel A shows that the information effect of OT entry is negative for values of $N_{\text{PD}} < 3$ and it is slightly hump-shaped, i.e., it increases sharply for values of $N_{\text{PD}} < 4$ and then declines slowly, in N_{PD} for all times. The information effect is the most negative, about -30bps, for $N_{\text{PD}} = 1$ early in the sample. Panel B of Figure 10 shows the components of the information

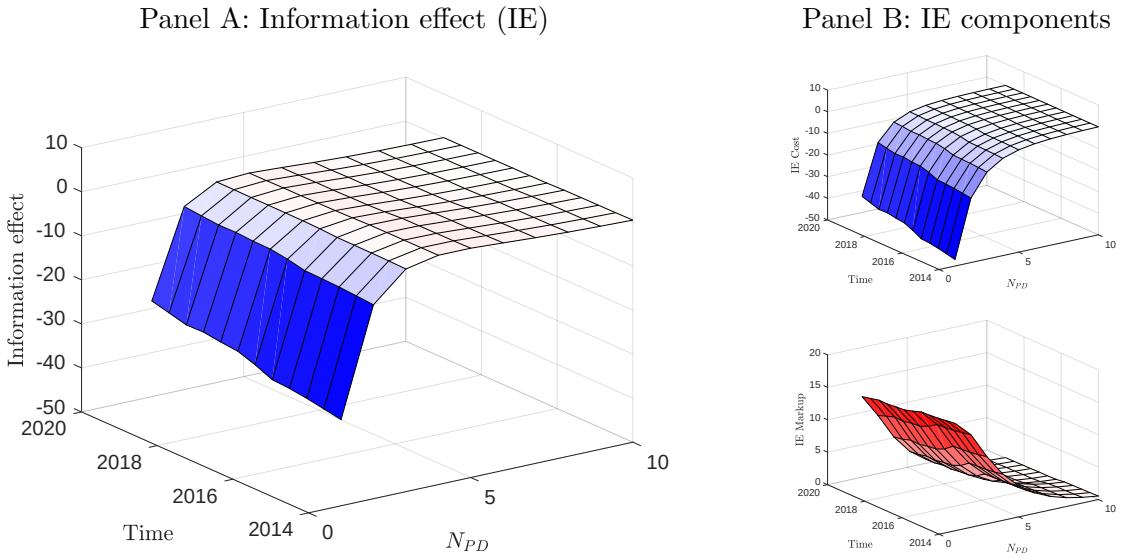


Figure 10: **Information effect** Panel A shows the information effect of OT from relation (22) as a function of the number of RFQ responses by the permissioned dealers, N_{PD}, over time. In Panel B, the top/bottom plot shows the cost/markup component of the information effect as a function of N_{PD} over time. All plots are constructed by estimating the model in the data using the procedure outlined in Section 3.2.

effect. The first term in relation (22) capturing the cost component of the information effect is non-negative as long as $\alpha_{N_{\text{PD}}}$ decreases with N_{PD} which is also the case in the data. Correspondingly, the top subplot shows that the cost component of the information effect is non-positive in the data. The behavior of the cost component of the information effect as a function of N_{PD} is ambiguous but the data shows that it increases with N_{PD}. The second term in relation (22) captures the markup component of the information effect. It has to be non-negative as long as $\alpha_{N_{\text{PD}}}$ decreases with N_{PD}. The bottom subplot shows that, in agreement with the model, the markup component of the competition effect is positive. It also decreases with $N_{\text{PD}} = 1$ implying that $\alpha_{N_{\text{PD}}} - \alpha_N$ decreases faster with N_{PD} than its factor $N_{\text{PD}}/(N_{\text{PD}} + 1)$ increases with N_{PD}. Taken together, the cost component dominates the information effect for values of $N_{\text{PD}} < 4$ making it negative and increasing in $N_{\text{PD}} < 4$ but then the markup component kicks in resulting in the hump-shaped function of N_{PD}. Overall, OT entry strongly affects increasing costs due to information, more so than lowering dealer markups.

4.4 Components of the competition and information effects over time

Table 3 documents annual averages for the competition and information effects from OT entry. Panel A shows that competition and information effects have become larger than the entry effect in recent years. The competition effect, which represents increased dealer bidding aggressiveness, is partially offset by the information effect, which captures the cost of adverse selection as OT participants bring new information into the market. This trend is evident particularly from 2016

Table 3: **Competition and information effect from OT over time.** The table documents the decomposition of the indirect price improvement from OT over time. Panel A decomposes the indirect impact into competition effect (CE) and information effect (IE). Panel B decomposes the indirect impact into cost and markup components due to competition and information effects. We report annual averages.

Panel A: Competition and information effect from OT (bps)

	Competition effect (CE)	Information effect (IE)	$p\times$CE	$p\times$IE
Total	4.36	-1.90	1.94	-0.26
2014	4.34	-0.99	0.33	-0.03
2015	4.00	-2.68	0.51	-0.23
2016	4.06	-2.42	1.58	-0.34
2017	4.58	-1.58	2.45	-0.25
2018	4.80	-1.21	3.05	-0.21

Panel B: Components of competition and information effect from OT (bps)

					$p\times$			
	CE Cost	CE Markup	IE Cost	IE Markup	CE Cost	CE Markup	IE Cost	IE Markup
Total	4.13	0.23	-7.65	5.76	2.03	-0.09	-2.06	1.80
2014	4.02	0.32	-6.28	5.29	0.32	0.01	-0.38	0.35
2015	3.16	0.84	-9.84	7.15	0.44	0.07	-0.98	0.76
2016	3.58	0.48	-8.95	6.52	1.55	0.03	-2.25	1.91
2017	4.59	-0.01	-6.73	5.15	2.61	-0.16	-2.33	2.07
2018	5.03	-0.23	-5.80	4.60	3.35	-0.30	-2.40	2.19

onward, when IPI (indirect price improvement) surpasses DPI (direct price improvement). As a result, OT entry continues to have a net positive impact on prices because the entry effect (DPI) and competition effect more than offset the adverse selection effect in the information effect. By the end of the sample period, total price improvement (TPI) reached 4bps, with three-quarters of this improvement attributed to the indirect effects (IPI) and the remaining quarter to direct effects (DPI). These findings highlight OT's significant impact on reducing trading costs. For example, compared to O'Hara and Zhou's (2020) estimate of average electronic trading costs of 10-20bps in 2017, OT reduces costs by economically significant amounts.

As shown in Table 3, the information effect is -1.9bps over the sample period. It began at -1bps in 2014 and initially became more negative, reaching -2.7bps in 2015 and -2.4bps in 2016, reflecting higher adverse selection costs as OT entry remained low. However, as OT entry and trading frequency increased, the information effect improved to -1.6bps in 2017 and further to -1.2bps in 2018, indicating reduced adverse selection costs in later years. Meanwhile, the competition effect was relatively strong at 4.4bps throughout the sample period, starting at 4.3bps in 2014, decreasing to 4bps in 2015, and then slightly increasing to 4.6bps in 2017 and continued to rise to 4.8bps in 2018. The competition effect consistently remains sufficiently high to offset the negative impact of the information effect each year, resulting in a net positive cIPI of 2.5bps across the sample period.

Table 3, Panel B decomposes the competition and information effects into their cost and markup components, revealing how OT entry impacts dealers' pricing strategies at a more granular level. The competition effect is primarily driven by reductions in dealer costs, which align with increased competitive pressure. Interestingly, while dealer markups decline due to competition from Ot during 2014-6, they increase after 2016 which limits the scope for further price improvements. In contrast, the information effect stems from both adjustments in adverse selection costs and markups based on new information introduced by OT entrants. The information effect shows a significant increase in costs of 7.7bps on average (-6.3bps in 2014 and -5.8bps in 2018) as dealers face hightened adverse selection risks. Significant reductions to markups of 5.8bps on average (5.3bps in 2014 and 4.6bps in 2018) partially offset this effect, softening its negative impact on the total price improvement. These components confirm that while OT reduces dealer costs and markups through competition, it also leads to adverse selection costs reflected in the information effect, counterbalanced by markup adjustments. This decomposition provides a clearer picture of the underlying dynamics contributing to OT's overall price improvement effect in the corporate bond market than Panel A.

Overall, the evidence is consistent with the permissioned dealers responding to OT entry by adjusting their bidding strategies. As electronic trading is expected to continue growing over time, the effects we document will likely remain and become more significant for determining transaction costs in corporate bonds. Moreover, ignoring IPI would underestimate the OT entry effect on making RFQ prices less or more competitive.

5 Counterfactual Policy Experiments

We construct three counterfactual experiments that modify the information environment, market structure, and RFQ trading protocol to assess how transparency, interdealer risk sharing, and the information available to bidders during the RFQ affect prices. We take the RFQ initiator's need to trade as given in all counterfactual experiments.

5.1 Transparency counterfactual

We set $\alpha_N^{cf} = 0$ in the IPV counterfactual thus hypothetically eliminating the winner's curse, where the highest bidder overpays due to limited information. Under this counterfactual RFQs are pure independent private values, IPV, auctions implying that bidders have independent inventory cost shocks and there is no risk of overpaying due to private information. An alternate related counterfactual would be that transparency increases but only partially solves the problem, implying a residual risk of overpaying. For instance, a counterfactual with $\alpha_N^{cf} = \alpha_N/2$ assumes a partial improvement in transparency. Alternatively, we can adjust $\alpha_N^{cf} = \alpha_{10+N_{\text{OT}}}$ to match a larger number of primary dealers (e.g., $N_{PD} = 10$), meaning the winner's curse is reduced but not eliminated, as if the market had more participants or smaller information asymmetries.

The results for this transparency counterfactual are reported in Panel A of Table 4, with Table 2 reporting the baseline estimates. The comparison between Panel A of Table 4 and Table 2 illustrates that removing the winner's curse (via $\alpha_N^{cf} = 0$) leads to a shift in the composition of price improvements. Direct price improvements decrease due to reduced valuation uncertainty, as bidders face fewer risks of overpaying. The plot for the counterfactual cDPI in Figure A.5, Panel A illustrates that this is due to significantly reduced direct improvements for low N_{PD}, as cDPI drops from over 10bps to below 3bps for all RFQs.

Indirect price improvements increase, suggesting that transparency intensifies competition by narrowing bid dispersion. The plot for the counterfactual cIPI in Figure A.5, Panel B illustrates that this is due to significantly larger and now non-negative indirect improvements for low N_{PD}, as cIPI rises from less than -20bps to above 0bps for all RFQs.

Total price improvements decline slightly overall, indicating that while transparency enhances indirect gains, the overall improvement potential is reduced without private information asymmetries driving up dispersion. Thus, the IPV counterfactual shows that while transparency promotes competition, it may also limit price improvement potential by diminishing the role of private information in shaping bid behavior.

5.2 Risk sharing counterfactual

We set $\beta_N^{cf} = \alpha_N$ in the PCV counterfactual. The PCV counterfactual assumes perfect risk sharing within the interdealer market by eliminating private cost shocks and making all dealer intermediation costs common. Under this setup, dealers would care equally about the values of other participants, ensuring that any price reflects a shared valuation across the interdealer market. This counterfactual allows us to explore how market structure and risk-sharing affect RFQ outcomes by simulating cases with differing levels of risk-sharing and information asymmetry across bidders.

Panel B of Table 4 reports the results under the perfect risk-sharing counterfactual. The comparison between Panel B of Tables 4 and 2 highlights that direct price improvements are slightly reduced or remain similar under a common valuation setting, as participants no longer adjust bids based on individual private valuations. The homogeneity in valuation reduces the room for price adjustments based solely on OT entry. The plot for the counterfactual cDPI in Figure A.5, Panel B illustrates that this is due to slightly lower direct improvements for all values of N_{PD}. Indirect price improvements increase significantly under the PCV scenario, as a shared valuation intensifies bidding competition and narrows bid dispersion. The uniformity in valuations yields stronger competitive forces, resulting in higher indirect price gains. The plot for the counterfactual cIPI in Panel B of Figure A.5 illustrates that this is due to significantly increased indirect improvements for low N_{PD}, as cIPI rises from less than -20bps, in the baseline case reported in Panel B of Figure A.3, to more than 20bps for $N_{\text{PD}} = 1$.

Total price improvements remain high under the PCV setting, exceeding the baseline in the

Table 4: **Counterfactual analysis.** The table documents counterfactual price improvement from OT for three counterfactual experiments. Across columns (1)2, (3)4, and (5)6, we report the (c)DPI, (c)IPI, and (c)TPI. In Panel A, we report the counterfactual price improvement from OT if the all-to-all RFQ was an independent private value setting. In Panel B, we report the counterfactual price improvement from OT if the all-to-all RFQ was a pure common value setting. In Panel C, we report the counterfactual price improvement from OT if permissioned dealers made no Type I and Type II errors.

	cDPI	DPI	cIPI	IPI	cTPI	TPI
			Panel A: IPV ($\alpha_N^{cf} = 0$)			
2014	1.30	0.09	4.34	0.33	5.64	0.43
2015	1.46	0.17	4.00	0.51	5.46	0.68
2016	1.42	0.48	4.06	1.58	5.48	2.06
2017	1.34	0.64	4.58	2.45	5.92	3.09
2018	1.32	0.75	4.80	3.05	6.11	3.81
			Panel B: PCV ($\beta_N^{cf} = \alpha_N$)			
2014	3.24	0.20	3.32	0.19	6.56	0.40
2015	4.90	0.50	5.61	0.55	10.50	1.04
2016	4.32	1.12	5.47	1.31	9.79	2.43
2017	3.21	1.14	4.23	1.39	7.44	2.54
2018	2.75	1.17	3.71	1.46	6.46	2.63
			Panel C: No Type I and II errors ($\lambda^{cf} = 1, \phi^{cf} = 0$)			
2014	3.28	0.24	3.66	0.51	6.94	0.75
2015	4.36	0.48	1.49	0.43	5.85	0.90
2016	3.94	1.17	1.94	1.53	5.88	2.71
2017	3.23	1.36	3.67	2.86	6.90	4.22
2018	2.94	1.49	4.58	3.83	7.52	5.32

earlier years when p was still low, as increased indirect competition offsets the reduced role of direct price adjustments. The plot for the counterfactual cTPI in Figure A.5, Panel B illustrates that cTPI is now almost entirely driven by low N_{PD} RFQs. In summary, the PCV counterfactual suggests that if interdealer markets operated under perfect risk-sharing, indirect price improvements would likely dominate, driven by tougher competition around a common valuation. While direct improvements may decline, the intensified competition under a common value setting maintains or even increases total price improvements from OT entry.

5.3 Dealer accuracy counterfactual

The third counterfactual, where permissioned dealers make no Type I and Type II errors concerning OT entry, involves setting $\lambda^{cf} = 1$. This eliminates Type II errors (false positive dealer beliefs about RFQ entry), meaning that permissioned dealers never fail to anticipate OT entry into the market. It also involves setting $\phi^{cf} = 0$. This eliminates Type I errors (false negative dealer beliefs about RFQ entry), meaning permissioned dealers never erroneously assume OT does not

enter RFQs. In this setup, the OT entry rate changes to $p^{cf} = q$, and permissioned dealers perfectly discriminate between entry and non-entry, which assumes perfect knowledge of dealers about the bidding process in the RFQs. This counterfactual allows for examining how perfect decision-making by permissioned dealers affects market dynamics, potentially influencing the risk of market distortion, dealers' valuation uncertainty, and ultimately price efficiency in the corporate bond market.

Table 4, Panel C presents the results under the dealer accuracy counterfactual, where $\lambda^{cf} = 1$ and $\phi^{cf} = 0$, assuming permissioned dealers make no Type I and Type II errors in assessing OT entry decisions. The comparison between Panel C of Table 4 and Table 2 highlights that direct price improvements do not benefit from accurate dealer decisions. Indirect price improvements see more notable gains under the dealer accuracy scenario, as accurate entry decisions amplify competitive responses from other market participants, enhancing overall market efficiency and pushing indirect price improvement higher. The plot for the counterfactual cIPI in Figure A.5, Panel C illustrates that this is due to increased indirect improvements for large N_{PD}, as cIPI rises from about 10bps to almost 20bps for $N_{\text{PD}} = 10$.

Total price improvements are consistently higher in the dealer accuracy scenario, with indirect improvements benefiting from the absence of Type I and II errors in RFQs with many bidders. In summary, the dealer accuracy experiment shows that if dealers had had perfect entry assessment capabilities, the market would experience the largest TPI driven largely by indirect channels. Removing entry misjudgments enables a more predictable and competitive bidding environment, leading to more efficient pricing outcomes in the corporate bond market.

6 Conclusion

We examine the introduction of all-to-all trading, called Open Trading or OT, in the OTC market for corporate bonds. Because OT was added in an already centralized request-for-quote (RFQ) market, broadening the scope to bidding by buy-side institutions and quasi-dealers, its usage provides direct evidence of whether investors provide liquidity to each other, eliminating dealer intermediation, or prefer to trade with dealers. Following its introduction in 2012, OT steadily increased to win 12% of trades on the platform by 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 OT comes from the entry of new liquidity providers that act like dealers in 7% of trades. While 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.

All-to-all trading also provides evidence on the impact of OT on prices. We find that the average direct price improvement, DPI, is equal to 1.0bp reflecting the *entry effect* of OT. While DPI is

observed in the data, the indirect OT price improvement, IPI, is not and must be estimated. We develop a framework to estimate IPI that relies on granular data about bidder identities, RFQ bids, and transaction prices. Inconsistent with OT having only a *competition effect*, IPI is negative when the number of bidders is low. IPI increases in the number of bids indicating the presence of an *information effect* due to the winner's curse in corporate bond trading.

Over the sample period, all-to-all trading improves prices by 2.7bps on average and 6.0bps conditional on OT entry. When comparing this number with O'Hara and Zhou's (2020) estimate of average electronic trading costs, OT's total impact lowers trading costs by 15-30 percent. To further explore the channels through which OT impacts prices, we develop a structural auction model to decompose OT's indirect impact into components due to the competition effect of OT entry and the information effect due to the winner's curse. The entry effect of adding extra bidders accounts for 0.8-1.0bps (2.9-3.2bps conditional on OT entry) while the indirect effect from adapted bidding behavior adds another 1.6-1.8bps (2.6-2.8bps conditional on OT entry). The competition effect is large with OT entry improving prices by 4.4bps conditional on OT entry. But OT entry also imposes significant adverse information effects on dealers thus increasing their costs by 1.9bps, resulting in an average model-implied indirect price improvement of 1.7bps.

In our all-to-all setting, search and network frictions are largely eliminated.[22] This raises the question of why intermediation remains central and what drives specialization in liquidity provision. While we cannot rule out other frictions, our results highlight a significant increase in competition and the winner's curse due to OT entry. This may inhibit investors from bidding in RFQs and disintermediating dealers. In counterfactual experiments, we find that if dealers had perfect entry assessment capabilities, the corporate bond market would experience the largest TPI driven largely by indirect channels, while improved transparency and risk sharing would yield smaller TPI but would eliminate all price disimprovements for RFQs with a low number of bidders.

Our results potentially shed light on liquidity provision more generally. A single large quasi-dealer who makes up the majority of OT trades at the end of our sample is a high-tech trading firm (Wirz (2019)). Such firms play increasingly important roles in markets in all asset classes (Franklin and Mourselas (2024)). Our findings are consistent with high-tech firms being able to automate liquidity provision in illiquid markets with limited market data. Consistent with the entry of high-tech liquidity providers being associated with improved liquidity in many markets, we find that OT entry is beneficial as it increases competition and improves prices. However, technologically enabled entry can impose the winner's curse on assets with few liquidity providers. For instance, automation in stock trading failing to improve liquidity in small stocks motivated the SEC's tick size pilot. Our results provide additional insights into why automation is more likely to improve liquidity in more liquid assets than in less liquid ones.

[22] Weill (2020) emphasizes that most theoretical analyses of OTC markets rely on tools from either search or network theory. Uslu (2019) proposes non-informational investor heterogeneity such as preferences and meeting intensities while Glode and Opp (2020) highlight the informational costs of bidding and the associated required expertise.

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Appendix

The Appendix reports determinants of open trading, classifies the types of OT entrants, describes the empirical measurement of price improvement in all-to-all RFQs, and contains proofs.

Appendix A Determinants of open trading

Table A.1 reports univariate results for the determinants of OT trading. We start our analysis by splitting the sample into terciles along a given sorting characteristic and then report the percent of the variable of interest in the low and high terciles. Sorting characteristics consist of the trade direction (buy/sell), trade size, bond issue size, bond maturity, bond age, bond rating, bond coupon rate, whether it is a variable rate, bond's placement (private/public), and whether it is a cov-lite bond. Reported t-statistics allow for unequal variance across the terciles. The first two rows of Table A.1 show that open trades tend to be smaller sales. The rest of Table A.1 indicates that open-traded bonds tend to be older and have higher credit ratings, shorter maturity, larger issue size, and non-cov-lite bonds. These bonds are also more likely coupon-paying with coupon rates being lower and non-variable. Finally, privately placed bonds are slightly less likely to be open-traded.

Table A.2 reports multivariate results to further understand the determinants of OT trading. We replace Y_{ibt} in specification (1) with an indicator function Open trade$_{ibt}$ equal to one if OT provides the best bid in trade i in bond b on the day t, and zero otherwise, is the response variable of interest in specification (1). Multivariate results from Table A.2 mostly support our univariate findings from Table A.1 and we focus our discussion on the notable differences between them. The regression coefficient on the coupon rate is positive and both statistically and economically significant in specifications 2 and 4. It indicates that unlike univariate sorts find, open-traded bonds pay higher coupon rates than non-open-traded bonds. Furthermore, the regression coefficients on investment grade, zero coupon, and cov-lite dummies are not statistically significant, indicating that, unlike in the univariate case, these bond characteristics are not important determinants of OT.

Appendix B Types of OT entrants

We designate a liquidity supplier as a dealer or quasi-dealer if across all her MarketAxess 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 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 in more than 1,000 RFQs, and the fraction of non-OT RFQs to total RFQs (that is, RFQ plus OT) exceeds 1/3. The others are *quasi-dealers*. The results are not very sensitive to the exact thresholds. We obtain the following classification:

- N=754 buy-side institutions,
- N=173 traditional dealers (permissioned and non-permissioned),
- N=81 quasi-dealers, with 1 predominant quasi-dealer.

Traditional dealers can trade as both permissioned dealers and non-permissioned dealers depending on the RFQ. Permissioned dealers trade directly with customers with whom they have a credit relationship for lower fees. Non-permissioned dealers trade with customers they do not have a credit relationship; in these non-permissioned OT trades MarketAxess acts as the counterparty to both sides of the trade.

Figure A.1 documents the contribution of non-permissioned dealers, buy-side institutions, and quasi-dealers to OT. Panel A illustrates the number (left subplot) and the share (right subplot) of quarterly open trades by liquidity provider type. The left subplot shows that all types of liquidity providers increased their OT trading, with quasi-dealers showing the largest increase. The right subplot 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 at <1/3 share for the remainder. Buy-side institutions were the main liquidity providers in OT trading in 2014, comprising almost 90% of all open trading. Their share shows a steady decline to 12% by the end of 2018.[1]

[1] Alternatively, we have graphed the par amount and share of quarterly OT volume by liquidity provider type.

Panel B of Figure A.1 splits open trades and open volume by quasi-dealers into a single large quasi-dealer and all other quasi-dealers. It shows that the large quasi-dealer entered RFQs in a staggered manner. At the end of 2015, other quasi-dealers handled the majority of open trades and volume. While trades by quasi-dealers rose throughout, the large quasi-dealer by Q3 of 2016 started overtaking all other 80 quasi-dealers combined. At the beginning of 2018, the large quasi-dealer ramps up bidding and winning even further and, as a result, more than doubled trades during 2018 to over 25K trades and $4B per quarter.

Appendix C Empirical measurement of TPI

We use alternative approaches to empirically measure the total price improvement from OT. Results are comparable across the approaches. In the following we describe the measurement based on expression (7) and definition (5), respectively. In the reported results, we use expression (5).

Measurement based on Proposition 1. To take expression (7) from Proposition 1 to the data, we need to measure p, DPI, the half-spread without OT bids, S_{exOT}, and the expected half-spread S. We construct the OT entry rate as the predicted value $\widehat{p}_{ibt} = \Pr(\text{OT entry}_{ibt}|\mathbb{X})$ as a function of the characteristics $\mathbb{X} = (\mathbb{X}_i, \mathbb{X}_b, \mathbb{X}_t)$ from relation (2). We run these as Probit regressions each quarter. DPI is computed using the approach in Section 2.2.

Next, we compute half-spreads. For the reference price R, we use the last interdealer price from TRACE (results are robust to variations on R). To ensure that RFQs with and without entry are as comparable as possible, we restrict the sample to RFQs with OT entry and RFQs without OT entry in comparable bonds. S_{exOT} is the half-spread without OT bids in the RFQs with OT entry. S is the half-spread across all these RFQs.

Measurement based on Definition (5). To ensure that we compute the no-OT half-spread S_{noOT} in comparable RFQs, we relate RFQs with OT entry in a given month to RFQs without OT entry from a suitable control group in the same month with the same number of non-OT bids and matched on characteristics $\mathbb{X} = (\mathbb{X}_i, \mathbb{X}_b, \mathbb{X}_t)$. Here, we use for $\mathbb{X}$ a buy-sell indicator, trade size, bond size, maturity, age, rating, coupon rate, rule 144a status, and covlite status.

To define the control group, we exploit the staggered entry of a single large quasi-dealer. As depicted in Figure 4, a single large quasi-dealer entered OT trading at the end of 2015 and increased participation at the beginning of 2018. Across different bonds, the large quasi-dealer's entry occurred in a staggered manner depending on which bonds where available via RFQs. To determine the treatment status of an RFQ, we compute the earliest time when the large quasi-dealer bids on the bond being RFQed, as identified by its CUSIP. This time is designated as the bond-specific OT entry date. The identifying assumption here is that after controlling for $\mathbb{X}$, the exact timing of entry in a specific bond is random.

To address the issue that standard difference-in-difference estimates with staggered treatment timing may not causally identify treatment effects even under random assignment (e.g., de Chaisemartin and D'Haultføeuille, 2020; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021; Baker, Larcker, and Wang, 2022), we compute cohort-specific price improvements and adopt the approach from Callaway and Sant'Anna (2021) in which control units can only be ones that have not yet received treatment, which in our setting means the large quasi-dealer has never before bid on this bond but does so eventually. We eliminate all bonds that have already received treatment at least once before and the ones that never received treatment since they are likely different from the rest for some reason. Figure A.2 plots the number of RFQs without OT entry in a given month that are eligible for the control group (1) and non-eligible (0). The treatment date is here the bond-specific OT entry date by the large quasi-dealer.

For each RFQ with OT entry, we then compute the half-spreads S_{cumOT} and S_{exOT}, respectively, and place them into an appropriate bin based on the same number of non-OT bids and terciles of the controls. Results are qualitatively similar when we place them into an appropriate bin based on the number of non-OT bids and predicted OT entry rate. Results are also qualitatively similar when we compare RFQs with OT entry in a given month to all RFQs in the same bond-month with the same number of non-OT bids irrespective of other controls. To each RFQ with OT entry, we match RFQs without OT entry from the control group in the same month and bin. For each RFQ

Consistent with the right subplot 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 subplot of Panel A, 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.

in the control group without OT entry, we compute the half-spread S_{noOT} and average across these RFQs. Finally, we compute expression (5).

This approach captures changes in the permission dealers' bidding strategies caused by OT entry by the difference in half-spreads between RFQs with and without OT entry that are similar in terms of N_{PD} and other characteristics and that are drawn among those RFQs that are for bonds on which the large quasi-dealer has not yet bid or never bids. The identifying assumption here is that after controlling for observables $\mathbb{X} = (\mathbb{X}_i, \mathbb{X}_b, \mathbb{X}_t)$, the exact timing of entry in a specific bond is uncorrelated with the difference between trading costs without OT in the treatment and control groups. If OT enters RFQs where trading costs increase then this approach underestimates IPI.

Appendix D Proof of Proposition 2

1. OT entry: Consider the case with OT entry in the RFQ. We need to compute dealer j's expected costs when the lowest cost among the N bidders is $s \in [0,1]$. To do so we calculate the expectation $\mathbb{E}[t_j | \min\{t_1, ..., t_N\} = s]$ $\forall j = 1, ..., N$. Let $y_{-j} \equiv \min_{k \neq j} t_k$, where $-j$ stands for indices other than j, and write the expectation as

$$\mathbb{E}[t_j | \min\{t_1, ..., t_N\} = s] = \mathbb{E}[t_j | \min\{t_j, y_{-j}\} = s] = \mathbb{E}[t_j | t_j = s] \Pr(t_j \leq y_{-j}) + \\ + \mathbb{E}[t_j | t_j > y_{-j} = s] \Pr(t_j > y_{-j}) = s\frac{1}{N} + \frac{1+s}{2}\frac{N-1}{N}. \quad \text{(A1)}$$

With the help of this expression, we can calculate the dealer's cost

$$\begin{aligned}
\Xi_{\text{cumOT}}(s,t;N) &\equiv \mathbb{E}[\xi_j | y_{-j} = s, t_j = t] = \\
&= \xi + \alpha_N \sum_{k \neq j} \mathbb{E}[t_k - \frac{1}{2} | y_{-j} = s, t_j = t] + \beta_N \underbrace{\mathbb{E}[t_j - \frac{1}{2} | y_{-j} = s, t_j = t]}_{= t - \frac{1}{2}} = \\
&= \xi + \alpha_N \sum_{k \neq j} \Big(\mathbb{E}[t_k - \frac{1}{2} | t_k = y_{-j} = s] \frac{1}{N-1} + \\
&\qquad + \mathbb{E}[t_k - \frac{1}{2} | t_k > y_{-j} = s] \frac{N-2}{N-1} \Big) + \beta_N (t - \frac{1}{2}) = \\
&= \xi + \alpha_N \left(s\frac{N}{2} - \frac{1}{2} \right) + \beta_N (t - \frac{1}{2}). \quad \text{(A2)}
\end{aligned}$$

Imposing truthful revelation in equilibrium, $s = t$ in (A2), we obtain the bidders' cost function:

$$c_{\text{cumOT}}(t;N) \equiv \Xi_{\text{cumOT}}(t,t;N) = \underbrace{\xi - \frac{1}{2}(\alpha_N + \beta_N)}_{\equiv \alpha_{\text{cumOT}}(N)} + \underbrace{\left(\alpha_N \frac{N}{2} + \beta_N \right)}_{\equiv \beta_{\text{cumOT}}(N)} t, \quad \text{(A3)}$$

where the first term captures the dealer's cost due to the aggregate cost, while the second term is as in Klemperer (1999) and captures the dealer's exposure to her private cost. The larger importance of the aggregate cost (α_N) increases both dealers' aggregate costs and their sensitivity to their own costs. Since we have set the lowest cost among the other $N-1$ dealers to the dealer j's private cost $t_j = t$, the sensitivity of dealer j's average costs to her private cost, $\beta_{\text{cumOT}}(N)$, implicitly depends on α_N.

We consider symmetric equilibria in which all bidders use the same bidding function or the half-spread of their reported cost s, $S_{\text{cumOT}}(s;N)$. The winning bidder with cost t who reports cost s and submits a bid with half-spread $S_{\text{cumOT}}(s;N)$ receives the following expected profits $\Pi_{\text{cumOT}}(s,t)$

$$\begin{aligned}
\Pi_{\text{cumOT}}(s,t) &= \pi_{\text{cumOT}}(s,t) \left[S_{\text{cumOT}}(s;N) - \mathbb{E}[\xi_j | s \leq y_{-j}, t_j = t] \right] = \\
&= \pi_{\text{cumOT}}(s,t) \left[S_{\text{cumOT}}(s;N) - \frac{1}{\pi_{\text{cumOT}}(s,t)} \int_s^1 (N-1)(1-x)^{N-2} \Xi_{\text{cumOT}}(x,t) dx \right] = \\
&= \pi_{\text{cumOT}}(s,t) S_{\text{cumOT}}(s;N) - \int_s^1 (N-1)(1-x)^{N-2} \Xi_{\text{cumOT}}(x,t) dx, \quad \text{(A4)}
\end{aligned}$$

where the probability of winning the auction when bidder j with cost $t_j = t$ and reports cost $t_j = s$ is equal to

$\Pr(y_{-j} \geq s | t_j = t) \equiv \pi_{\text{cumOT}}(s,t) = (1-s)^{N-1}$. Symmetric bidders maximize their expected profits by choosing the private cost to report

$$\left.\frac{\partial \Pi_{\text{cumOT}}(s,t)}{\partial s}\right|_{s=t} = 0,$$

which yields the following first-order condition:

$$(1-t)^{N-1} S'_{\text{cumOT}}(t;N) - (N-1)(1-t)^{N-2} S_{\text{cumOT}}(t;N) + (N-1)(1-t)^{N-2} \Xi_{\text{cumOT}}(t,t) = 0, \tag{A5}$$

which can be immediately reduced to a linear ordinary differential equation

$$(1-t) S'_{\text{cumOT}}(t;N) + (N-1)[\Xi_{\text{cumOT}}(t,t) - S_{\text{cumOT}}(t;N)] = 0. \tag{A6}$$

We can pick as a candidate solution $S_{\text{cumOT}}(t;N) = S^0_{\text{cumOT}}(N) + S^1_{\text{cumOT}}(N)t$, and substitute it into the ODE (A6)

$$(1-t) S^1_{\text{cumOT}}(N) + (N-1)[\Xi_{\text{cumOT}}(t,t) - S^0_{\text{cumOT}}(N) - S^1_{\text{cumOT}}(N)t] = 0,$$

$\Leftrightarrow$

$$\alpha_{\text{cumOT}}(N) - S^0_{\text{cumOT}}(N) + S^1_{\text{cumOT}}(N)\frac{1}{N-1} + \left[\beta_{\text{cumOT}}(N) - S^1_{\text{cumOT}}(N)\frac{N}{N-1}\right] t = 0,$$

from which we immediately obtain

$$\begin{aligned} S^0_{\text{cumOT}}(N) &= \underbrace{\alpha_{\text{cumOT}}(N) + \beta_{\text{cumOT}}(N)\frac{1}{N}}_{=\Xi_{\text{cumOT}}(\frac{1}{N},\frac{1}{N})} &&= \xi + \beta_N(\tfrac{1}{N} - \tfrac{1}{2}), \\ S^1_{\text{cumOT}}(N) &= \beta_{\text{cumOT}}(N)\tfrac{N-1}{N} &&= (\tfrac{\alpha_N}{2} + \tfrac{\beta_N}{N})(N-1). \end{aligned} \tag{A7}$$

Using the above expressions and rearranging terms yields that the dealer bids $S_{\text{cumOT}}(t;N) = c_{\text{cumOT}}(t;N) + m_{\text{cumOT}}(t;N)$ with a markup

$$m_{\text{cumOT}}(t;N) = \beta_{\text{cumOT}}(N)\frac{1-t}{N}. \tag{A8}$$

2. No OT entry: When OT is present, the cost function ξ_j remains unchanged irrespective of OT entry since OT is present in post-RFQ trading, but dealers' bidding function changes since OT does not bid in the RFQ. We make this assumption to focus on the extra signal revealed by OT entry. Dealer j's expected cost when receiving cost $t_j = t$ while the lowest cost among the other $N_{\text{PD}} - 1$ dealers is $s \in [0,1]$

$$\begin{aligned} &\Xi_{\text{noOTentry}}(s,t;N_{\text{PD}},N) \equiv \mathbb{E}[\xi_j | \min_{k\neq j,\text{OT}} t_k = s, t_j = t] = \\ &= \xi + \alpha_N \sum_{k\neq j,\text{OT}} \mathbb{E}\left[t_k - \frac{1}{2} | \min_{k\neq j,\text{OT}} t_k = s, t_j = t\right] + \\ &\quad + \alpha_N \mathbb{E}\left[t_{\text{OT}} - \frac{1}{2}\right] + \beta_N \underbrace{\mathbb{E}\left[t_j - \frac{1}{2} | \min_{k\neq j,\text{OT}} t_k = s, t_j = t\right]}_{=t-\frac{1}{2}} = \\ &= \xi + \alpha_N\left(s\frac{N_{\text{PD}}}{2} - \frac{1}{2}\right) + \beta_N\left(t - \frac{1}{2}\right). \end{aligned} \tag{A9}$$

By setting $s = t$ in (A9), we obtain the dealers' no-OT cost function:

$$\begin{aligned} c_{\text{noOTentry}}(t;N_{\text{PD}},N) &\equiv \Xi_{\text{noOTentry}}(t,t;N_{\text{PD}},N) = \\ &= \underbrace{\xi - \frac{1}{2}(\alpha_N + \beta_N)}_{\equiv\alpha_{\text{noOTentry}}(N_{\text{PD}},N)=\alpha_{\text{cumOT}}(N)} + \underbrace{\left(\alpha_N\frac{N_{\text{PD}}}{2} + \beta_N\right)}_{\equiv\beta_{\text{noOTentry}}(N_{\text{PD}},N)} t. \end{aligned} \tag{A10}$$

The dealers' cost functions thus have different sensitivities to their own costs but the same sensitivities to aggregate cost components depending on OT entry. *Importantly, the dealers' cost function sensitivity to their own costs increases if OT enters:* $\alpha_{\text{cumOT}}(N) = \alpha_{\text{noOTentry}}(N_{\text{PD}},N)$ *and* $\beta_{\text{cumOT}}(N) \geq \beta_{\text{noOTentry}}(N_{\text{PD}},N)$.

We again consider symmetric equilibria in which all dealers use the same bidding function of their reported cost s, $S_{\text{noOTentry}}(s; N_{\text{PD}}, N)$. The winning bidder with cost t who reports cost s and submits a bid with half-spread $S_{\text{noOTentry}}(s; N_{\text{PD}}, N)$, receives the following expected profits $\Pi_{\text{noOTentry}}(s,t)$

$$\begin{aligned}\Pi_{\text{noOTentry}}(s,t) &= \pi_{\text{noOTentry}}(s,t)\left[S_{\text{noOTentry}}(s; N_{\text{PD}}, N) - \mathbb{E}[\xi_j | \min_{k\neq j,\text{OT}} t_k \geq s, t_j = t]\right] = \\ &= \pi_{\text{noOTentry}}(s,t)\left[S_{\text{noOTentry}}(s; N_{\text{PD}}, N) - \frac{1}{\pi_{\text{noOTentry}}(s,t)}\int_s^1 (N_{\text{PD}}-1)(1-x)^{N_{\text{PD}}-2}\Xi_{\text{noOTentry}}(x,t)dx\right] = \\ &= \pi_{\text{noOTentry}}(s,t)S_{\text{noOTentry}}(s; N_{\text{PD}}, N) - \int_s^1 (N_{\text{PD}}-1)(1-x)^{N_{\text{PD}}-2}\Xi_{\text{noOTentry}}(x,t)dx, \qquad \text{(A11)}\end{aligned}$$

where the probability of winning the RFQ when dealer j receives signal $t_j = t$ and reports signal $t_j = s$ is equal to $\Pr(\min_{k\neq j,\text{OT}} t_k \geq s | t_j = t) \equiv \pi_{\text{noOTentry}}(s,t) = (1-s)^{N_{\text{PD}}-1}$. Symmetric bidders maximize their expected profits by choosing the signal to report, $\frac{\partial \Pi_{\text{noOT}}(s,t)}{\partial s}|_{s=t} = 0$, which yields the following first-order conditions

$$\begin{aligned}(1-t)^{N_{\text{PD}}-1}S'_{\text{noOTentry}}(t; N_{\text{PD}}, N) - (N_{\text{PD}}-1)(1-t)^{N_{\text{PD}}-2}S_{\text{noOTentry}}(t; N_{\text{PD}}, N) + \\ + (N_{\text{PD}}-1)(1-t)^{N_{\text{PD}}-2}\Xi_{\text{noOTentry}}(t,t) = 0, \qquad \text{(A12)}\end{aligned}$$

which can be immediately reduced to the following ordinary differential equation

$$(1-t)S'_{\text{noOTentry}}(t; N_{\text{PD}}, N) + (N_{\text{PD}}-1)[\Xi_{\text{noOTentry}}(t,t) - S_{\text{noOTentry}}(t; N_{\text{PD}}, N)] = 0. \qquad \text{(A13)}$$

We can pick as a candidate solution $S_{\text{noOTentry}}(t; N_{\text{PD}}, N) = S^0_{\text{noOTentry}}(N_{\text{PD}}, N) + S^1_{\text{noOTentry}}(N_{\text{PD}}, N)t$, and substitute it into the ODE (A13)

$$(1-t)S^1_{\text{noOTentry}}(N_{\text{PD}}, N) + (N_{\text{PD}}-1)[\Xi_{\text{noOTentry}}(t,t) - S^0_{\text{noOTentry}}(N_{\text{PD}}, N) - S^1_{\text{noOTentry}}(N_{\text{PD}}, N)t] = 0,$$

$\Leftrightarrow$

$$\begin{aligned}\alpha_{\text{noOTentry}}(N_{\text{PD}}, N) - S^0_{\text{noOTentry}}(N_{\text{PD}}, N) + S^1_{\text{noOTentry}}(N_{\text{PD}}, N)\frac{1}{N_{\text{PD}}-1} + \\ + [\beta_{\text{noOTentry}}(N_{\text{PD}}, N) - S^1_{\text{noOTentry}}(N_{\text{PD}}, N)\frac{N_{\text{PD}}}{N_{\text{PD}}-1}]t = 0,\end{aligned}$$

from which we immediately obtain:

$$\begin{aligned}S^0_{\text{noOTentry}}(N_{\text{PD}}, N) &= \alpha_{\text{noOTentry}}(N_{\text{PD}}, N) + \beta_{\text{noOTentry}}(N_{\text{PD}}, N)\tfrac{1}{N_{\text{PD}}} = \xi + \beta_N(\tfrac{1}{N_{\text{PD}}} - \tfrac{1}{2}), \\ S^1_{\text{noOTentry}}(N_{\text{PD}}, N) &= \beta_{\text{noOTentry}}(N_{\text{PD}}, N)\tfrac{N_{\text{PD}}-1}{N_{\text{PD}}} = \left(\tfrac{\alpha_N}{2} + \tfrac{\beta_N}{N_{\text{PD}}}\right)(N_{\text{PD}}-1).\end{aligned} \qquad \text{(A14)}$$

Using the above expressions and rearranging terms yields that the dealer bids $S_{\text{noOTentry}}(t; N_{\text{PD}}, N) = c_{\text{noOTentry}}(t; N_{\text{PD}}, N) + m_{\text{noOTentry}}(t; N_{\text{PD}}, N)$ with a markup

$$m_{\text{noOTentry}}(t; N_{\text{PD}}, N) = \beta_{\text{noOTentry}}(N_{\text{PD}}, N)\frac{1-t}{N_{\text{PD}}}. \qquad \text{(A15)}$$

Since the dealer does not know if OT entry will take place or not, they bid $S_{\text{OTpresent}}(t; N_{\text{PD}}, N)$ given in (A16) conditional on OT being present in the market.

When OT is present the dealers bid $S_{\text{cumOT}}(t; N)$ with probability λ and $S_{\text{noOTentry}}(t; N_{\text{PD}}, N)$ with probability $1-\lambda$ resulting in the spread from Proposition 1

$$\begin{aligned}S_{\text{OTpresent}}(t; N_{\text{PD}}, N, \lambda) &= \lambda\big(S^0_{\text{cumOT}}(N) + S^1_{\text{cumOT}}(N)t\big) \\ &\quad + (1-\lambda)\big(S^0_{\text{noOTentry}}(N_{\text{PD}}) + S^1_{\text{noOTentry}}(N_{\text{PD}})t\big). \qquad \text{(A16)}\end{aligned}$$

3. No OT presence:

Now consider the scenario with no OT presence. The cost function ξ_j corresponds to the one from the first

scenario but with N_{PD} dealers. Hence,

$$c_{\mathrm{noOTpresent}}(t;N_{\mathrm{PD}}) = \underbrace{\xi-\frac{1}{2}(\alpha_{N_{\mathrm{PD}}}+\beta_{N_{\mathrm{PD}}})}_{\equiv\alpha_{\mathrm{noOTpresent}}(N_{\mathrm{PD}})=\alpha_{\mathrm{cumOT}}(N_{\mathrm{PD}})} + \underbrace{\left(\alpha_{N_{\mathrm{PD}}}\frac{N_{\mathrm{PD}}}{2}+\beta_{N_{\mathrm{PD}}}\right)}_{\equiv\beta_{\mathrm{noOTpresent}}(N_{\mathrm{PD}})=\beta_{\mathrm{cumOT}}(N_{\mathrm{PD}})} t, \tag{A17}$$

$$m_{\mathrm{noOTpresent}}(t;N_{\mathrm{PD}}) = \beta_{\mathrm{noOTpresent}}(N_{\mathrm{PD}})\frac{1-t}{N_{\mathrm{PD}}}, \tag{A18}$$

The dealers' cost functions have different sensitivities to their own costs and aggregate cost components depending on OT entry. *Importantly, the dealers' cost function sensitivity increases if OT enters:* $\alpha_{\mathrm{cumOT}}(N)\geq\alpha_{\mathrm{noOTpresent}}(N_{\mathrm{PD}})$ *and* $\beta_{\mathrm{cumOT}}(N)\geq\beta_{\mathrm{noOTpresent}}(N_{\mathrm{PD}})$.

Table A.1: **Determinants of open trading, OT entry, and number of permissioned dealer bids—univariate sorts.** The table documents the determinants of open trading, OT entry, and number of permissioned dealer bids using univariate sorts. We split the sample into terciles along the sorting variable and report the low and high tercile averages of the sorting variable. t-statistics are robust to clustering at day and bond levels.

Panel A: Open trades as percent of all trades				
Sorting variable	LO	HI	Δ	(t-stat)
Client buy	6.83	6.36	-0.47	(-5.06)
Trade size	6.50	5.59	-0.91	(-5.98)
Bond size	6.03	6.68	0.64	(5.19)
Maturity	7.21	5.18	-2.03	(-14.46)
Bond age	5.14	7.65	2.50	(16.86)
Rating	6.29	7.48	1.19	(9.66)
Coupon rate	6.63	5.76	-0.87	(-7.19)
Variable rate	6.62	5.85	-0.77	(-2.49)
Rule 144a	6.65	5.69	-0.96	(-5.76)
Cov-lite	6.66	6.44	-0.22	(-1.93)
Panel B: OT entry as percent of all-to-all RFQs				
Sorting variable	LO	HI	Δ	(t-stat)
Client buy	43.68	37.95	-5.73	(-19.17)
Trade size	43.90	36.05	-7.85	(-15.02)
Bond size	29.60	49.79	20.19	(27.29)
Maturity	42.51	36.46	-6.05	(-6.92)
Bond age	37.27	42.11	4.84	(5.75)
Rating	42.45	39.79	-2.66	(-3.61)
Coupon rate	43.81	32.97	-10.84	(-13.17)
Variable rate	41.05	38.16	-2.89	(-1.82)
Rule 144a	41.50	29.21	-12.29	(-12.25)
Cov-lite	40.61	42.24	1.63	(2.12)
Panel C: Number of permissioned dealer bids				
Sorting variable	LO	HI	Δ	(t-stat)
Client buy	5.66	4.59	-1.06	(-33.05)
Trade size	4.88	5.59	0.71	(25.14)
Bond size	4.11	6.17	2.06	(51.55)
Maturity	4.77	5.42	0.65	(13.16)
Bond age	5.45	4.74	-0.71	(-16.96)
Rating	5.47	4.71	-0.75	(-16.34)
Coupon rate	5.18	4.78	-0.40	(-6.83)
Variable rate	5.16	5.89	0.73	(4.64)
Rule 144a	5.21	3.94	-1.27	(-21.17)
Cov-lite	5.09	5.39	0.30	(5.60)

Table A.2: **Determinants of open trading—regression analysis.** The table documents the determinants of open trading using regression analysis. 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, and large; issue size indicators for medium, large, and giant; maturity indicators for intermediate and long; bond age; an indicator for investment-grade rating; coupon rate; indicators for a 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**	-0.31***	-0.29***	-0.38***
	(0.09)	(0.09)	(0.09)	(0.09)
Odd (100K-1M)	1.03***	1.16***	0.96***	1.14***
	(0.10)	(0.10)	(0.10)	(0.10)
Round (1M-5M)	-0.89***	-0.75***	-0.97***	-0.79***
	(0.14)	(0.13)	(0.14)	(0.13)
Large (5M+)	-2.31***	-2.15***	-2.52***	-2.32***
	(0.17)	(0.16)	(0.17)	(0.16)
Size medium		-3.92***		-3.70***
		(0.59)		(0.59)
Size large		-3.48***		-3.25***
		(0.59)		(0.59)
Size giant		-4.25***		-3.93***
		(0.67)		(0.67)
Maturity intermediate		-0.27***		-0.27***
		(0.09)		(0.09)
Maturity long		-2.20***		-2.20***
		(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		14.32***		10.20***
		(3.44)		(3.46)
Variable rate		-4.51***		-4.15***
		(0.37)		(0.36)
Rule 144a		-0.39***		-0.43***
		(0.15)		(0.15)
Cov-lite		-0.04		-0.03
		(0.11)		(0.12)
2015.year			1.83***	1.69***
			(0.07)	(0.07)
2016.year			4.97***	4.60***
			(0.10)	(0.10)
2017.year			6.64***	5.95***
			(0.13)	(0.12)
2018.year			12.18***	11.27***
			(0.27)	(0.26)
Constant	6.38***	9.51***	0.47***	3.96***
	(0.06)	(0.62)	(0.10)	(0.63)
Day FE	Yes	Yes	No	No
Bond FE	Yes	No	Yes	No
Bond controls	No	Yes	No	Yes
R^2	0.052	0.035	0.045	0.028
N	5,432,393	5,289,627	5,432,394	5,289,628

Table A.3: **Determinants of OT entry—regression analysis.** The table documents the determinants of OT entry using regression analysis. 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, and large; issue size indicators for medium, large, and giant; maturity indicators for intermediate and long; bond age; an indicator for investment-grade rating; coupon rate; indicators for a 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	-6.80***	-6.57***	-6.92***	-6.58***
	(0.23)	(0.24)	(0.25)	(0.25)
Odd (100K-1M)	2.15***	1.53***	1.88***	1.34***
	(0.23)	(0.25)	(0.23)	(0.26)
Round (1M-5M)	-3.75***	-4.63***	-4.09***	-4.86***
	(0.36)	(0.38)	(0.36)	(0.39)
Large (5M+)	-17.60***	-18.73***	-18.05***	-19.10***
	(0.63)	(0.66)	(0.64)	(0.67)
Size medium		-5.82***		-5.44***
		(1.29)		(1.28)
Size large		8.58***		8.96***
		(1.34)		(1.33)
Size giant		16.72***		17.30***
		(1.86)		(1.83)
Maturity intermediate		0.71**		0.77**
		(0.36)		(0.37)
Maturity long		-5.05***		-4.94***
		(0.48)		(0.48)
Bond age		0.17***		0.24***
		(0.06)		(0.06)
Investment grade		1.31**		1.18*
		(0.59)		(0.61)
Coupon rate		-27.67**		-43.75***
		(13.79)		(13.98)
Variable rate		-27.91***		-27.17***
		(1.66)		(1.65)
Rule 144a		-10.26***		-10.17***
		(0.69)		(0.69)
Cov-lite		1.45***		1.48***
		(0.51)		(0.52)
2015.year			5.11***	5.86***
			(0.30)	(0.31)
2016.year			30.44***	32.48***
			(0.72)	(0.69)
2017.year			45.67***	47.35***
			(0.63)	(0.58)
2018.year			60.04***	61.40***
			(0.64)	(0.59)
Constant	43.92***	41.26***	11.02***	7.36***
	(0.18)	(1.48)	(0.42)	(1.52)
Day FE	Yes	Yes	No	No
Bond FE	Yes	No	Yes	No
Bond controls	No	Yes	No	Yes
R^2	0.319	0.277	0.303	0.261
N	5,432,393	5,289,627	5,432,394	5,289,628

Table A.4: **Number of permissioned dealer bids—regression analysis.** The table documents the number of permissioned dealer bids and their 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, and large; issue size indicators for medium, large, and giant; maturity indicators for intermediate and long; bond age; an indicator for investment-grade rating; coupon rate; indicators for a 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	-1.34***	-1.26***	-1.34***	-1.26***
	(0.03)	(0.03)	(0.03)	(0.03)
Odd (100K-1M)	0.67***	0.56***	0.67***	0.56***
	(0.02)	(0.02)	(0.02)	(0.02)
Round (1M-5M)	1.19***	1.07***	1.19***	1.07***
	(0.03)	(0.03)	(0.03)	(0.03)
Large (5M+)	2.04***	1.90***	2.04***	1.90***
	(0.04)	(0.04)	(0.04)	(0.05)
Size medium		0.87***		0.84***
		(0.09)		(0.09)
Size large		2.41***		2.37***
		(0.10)		(0.10)
Size giant		3.85***		3.82***
		(0.16)		(0.16)
Maturity intermediate		0.64***		0.63***
		(0.03)		(0.03)
Maturity long		0.53***		0.51***
		(0.04)		(0.04)
Bond age		-0.10***		-0.10***
		(0.01)		(0.01)
Investment grade		0.12**		0.11**
		(0.05)		(0.05)
Coupon rate		-1.37		-1.27
		(1.33)		(1.33)
Variable rate		-0.66***		-0.63***
		(0.13)		(0.13)
Rule 144a		-1.73***		-1.72***
		(0.05)		(0.05)
Cov-lite		0.27***		0.26***
		(0.05)		(0.05)
2015.year			-1.36***	-1.10***
			(0.06)	(0.06)
2016.year			-1.86***	-1.30***
			(0.06)	(0.06)
2017.year			-1.20***	-0.45***
			(0.06)	(0.06)
2018.year			-0.62***	0.30***
			(0.07)	(0.07)
Constant	5.33***	3.46***	6.38***	4.00***
	(0.01)	(0.12)	(0.06)	(0.12)
Day FE	Yes	Yes	No	No
Bond FE	Yes	No	Yes	No
Bond controls	No	Yes	No	Yes
R^2	0.376	0.265	0.344	0.234
N	5,432,393	5,289,627	5,432,394	5,289,628

Table A.5: **Price improvement from OT over time—data vs. model.** The table documents the price improvement from OT. We decompose the total impact into direct and indirect impacts, respectively. DPI is the direct price improvement from OT winning, computed in the data using equation (8). IPI is the indirect price improvement from OT impacting dealers' bidding functions, computed using expression (7). TPI is the total price improvement from OT entry, computed using expression (7). Panel A reports annual averages for a generic bond constructed from (10), Panel B for the model-implied price improvement from OT, allowing for a comparison between the model and data. The number of RFQs with OT entry is 1,065,500.

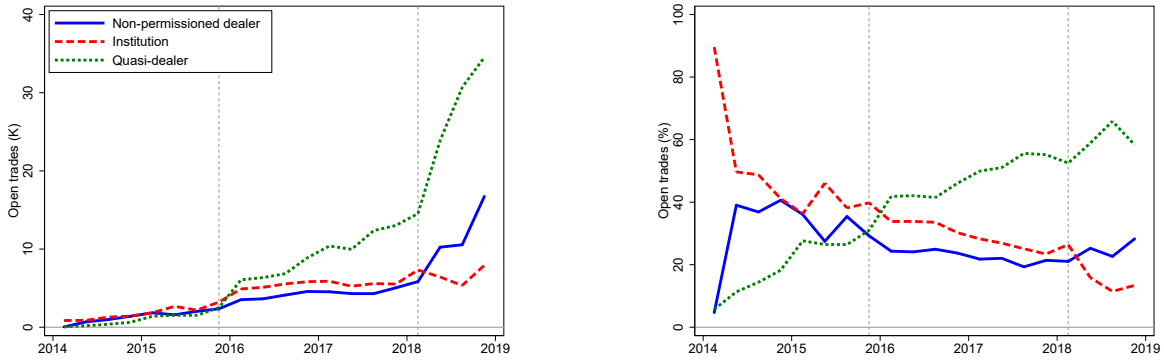
	cDPI	DPI	cIPI	IPI	cTPI	TPI
Panel A: Data for generic bond, constructed from (10)						
Total	2.89	0.84	2.61	1.79	5.50	2.63
2014	2.88	0.19	3.27	0.30	6.15	0.49
2015	3.81	0.40	1.18	0.27	4.99	0.67
2016	3.25	0.89	1.74	1.30	4.99	2.18
2017	2.57	0.98	3.21	2.34	5.79	3.32
2018	2.18	0.98	3.93	3.09	6.11	4.07
Panel B: Model-implied price improvement from OT						
Total	3.55	1.14	2.47	1.68	6.02	2.82
2014	3.28	0.22	3.36	0.30	6.64	0.52
2015	4.36	0.46	1.32	0.28	5.68	0.75
2016	3.94	1.16	1.63	1.24	5.58	2.40
2017	3.23	1.34	3.01	2.20	6.23	3.53
2018	2.94	1.47	3.59	2.85	6.53	4.31

Table A.6: Intermediation cost estimates and model fit

The table provides the intermediation cost parameters and statistics about model fit. Standard errors are reported in parenthesis.

	(1)	(2)	(3)	(4)
α_{00}	-34.13	5.68***	5.67***	5.81***
	(156.05)	(0.03)	(0.03)	(0.03)
α_{10}		-0.54***	-0.49***	-0.49***
		(0.12)	(0.13)	(0.13)
α_{01}		-0.44***	-0.43***	-0.48***
		(0.01)	(0.01)	(0.01)
α_{11}		-0.07	-0.15***	-0.18***
		(0.05)	(0.05)	(0.06)
β_{00}	4.84***	3.06***	3.17***	3.27***
	(0.26)	(0.06)	(0.07)	(0.06)
β_{10}		-0.03	-1.16***	-1.61***
		(0.17)	(0.25)	(0.25)
β_{10}		0.16***	0.15***	0.14***
		(0.00)	(0.01)	(0.01)
β_{11}		0.05***	0.17***	0.2***
		(0.01)	(0.03)	(0.03)
γ_{00}	20.57***		-6.34***	-8.61***
	(0.87)		(1.92)	(2.25)
γ_{10}			3.02	4.87
			(3.26)	(4.58)
γ_{01}			0.47***	0.65***
			(0.18)	(0.22)
γ_{11}			-0.12	-0.27
			(0.31)	(0.45)
MSE	51.41	1.16	0.92	1.08
AIC	872.76	48.20	5.16	40.79
BIC	882.94	75.35	45.88	81.52
ω	0.50	0.50	0.50	0.75
No. parameters	3	8	12	12
No. moments	220	220	220	220

Panel A. Open trades split by type of liquidity provider



Panel B. Large quasi-dealer open trades and open volume

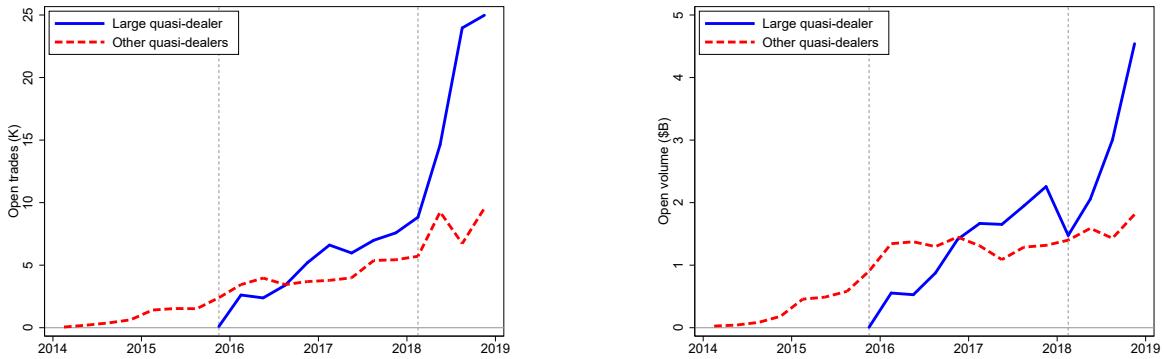
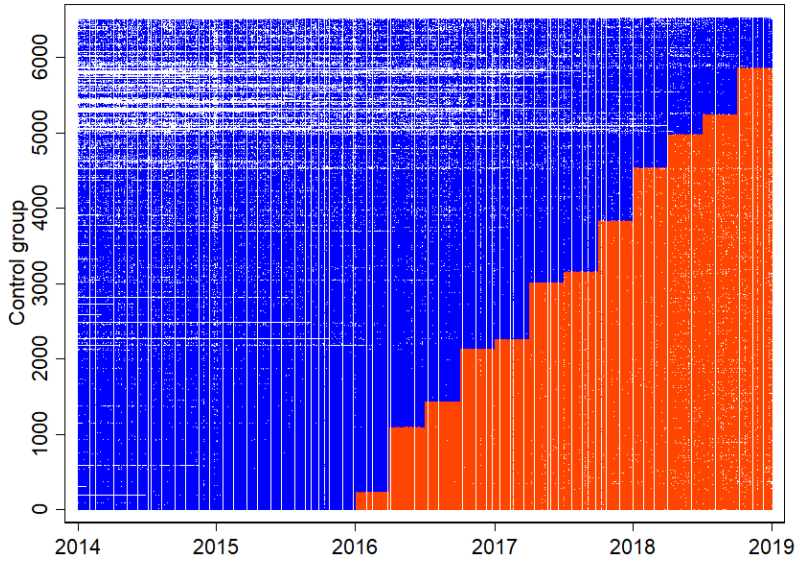


Figure A.1: **OT liquidity providers by type.** Panel A presents the number of trades by type of liquidity provider. The left subplots present the quarterly open trades executed on MarketAxess, split by liquidity provider type into non-permissioned dealer, buy-side institution, and quasi-dealer. The right subplots present the shares of OT by each liquidity provider. The OT types considered are non-permissioned dealers, buy-side institutions, and quasi-dealers. Panel B splits open trades and open volume by quasi-dealers into the single large quasi-dealer entering at the end of 2015 and all other quasi-dealers. Vertical dotted lines mark the increase in OT at the end of 2015 and the beginning of 2018.

Panel A: Control group of bonds.



Panel B: Number of RFQs per month without OT entry in the control group of bonds.

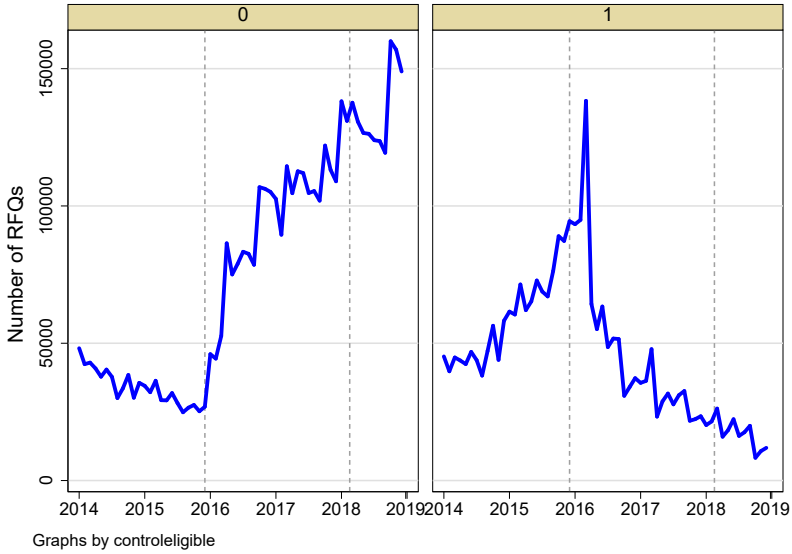
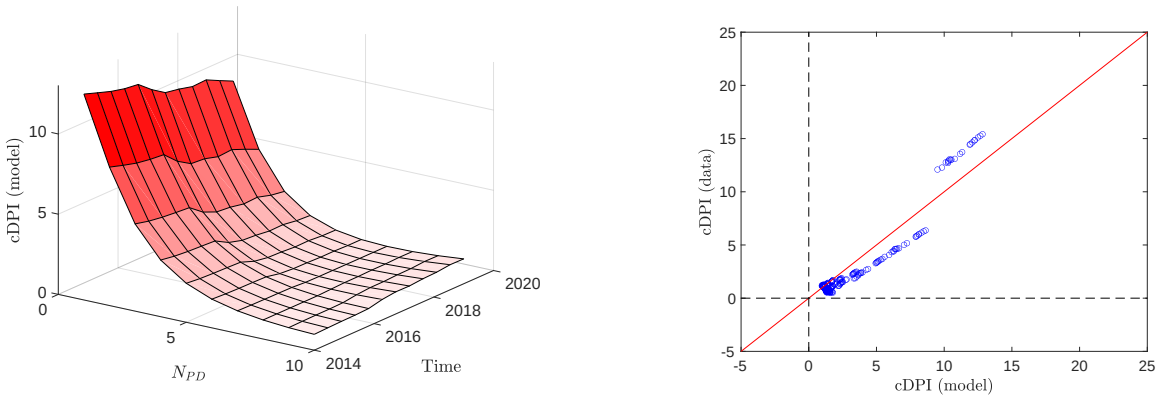
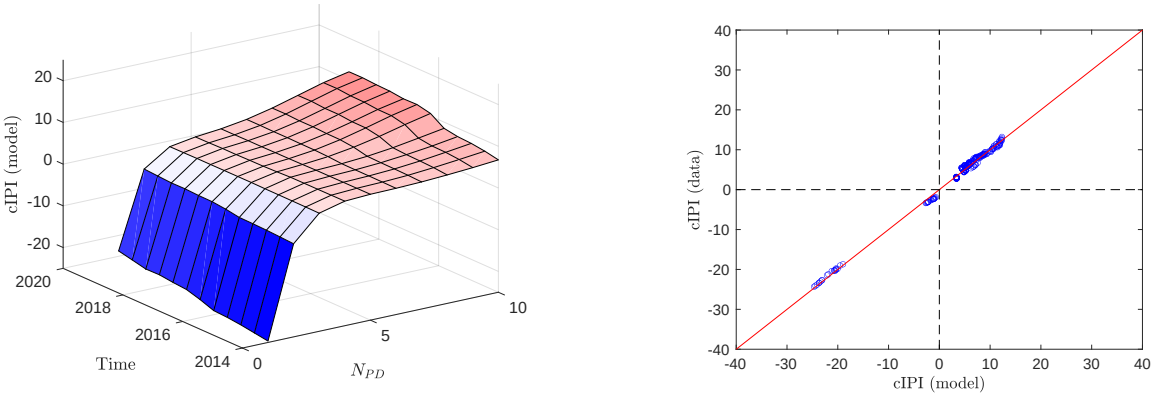


Figure A.2: **Control group of bonds and number of RFQs without OT entry in the control group.** Panel A documents the control group of bonds and RFQ activity in each control bond. Control bonds are sorted by the date of large quasi-dealer entry on the vertical axis. Each dot represents an RFQs without OT entry eligible for the control group. Panel B documents the number of RFQs per month without OT entry eligible for the control group (1) and non-eligible (0). In both panels, eligibility is based on the approach from Callaway and Sant'Anna (2021) in which control units can only not have yet received treatment, i.e., the large quasi-dealer has never before bid on this bond. We eliminate all bonds that have already received treatment at least once before and those that never received treatment since they are likely different from the rest for some reason. The treatment date is the bond-specific OT entry date by the large quasi-dealer.

Panel A: Model-based cDPI



Panel B: Model-based cIPI



Panel C: Model-based cTPI

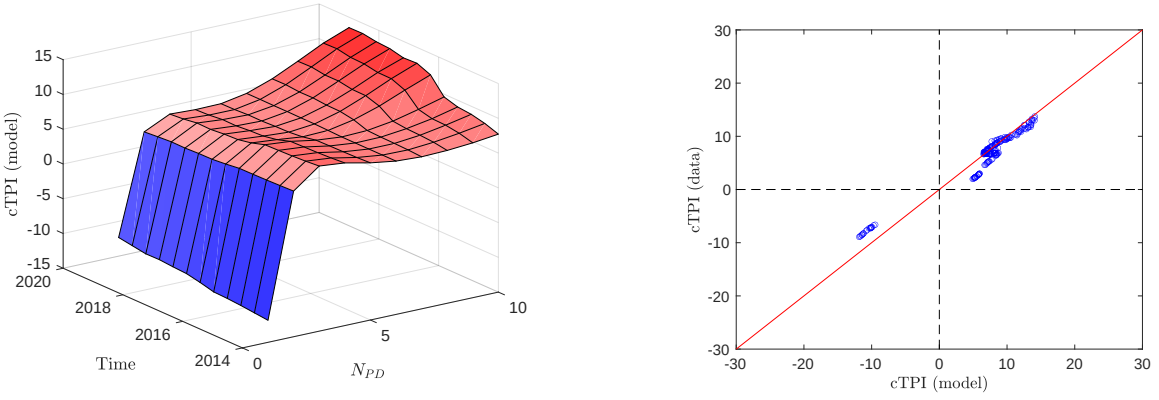
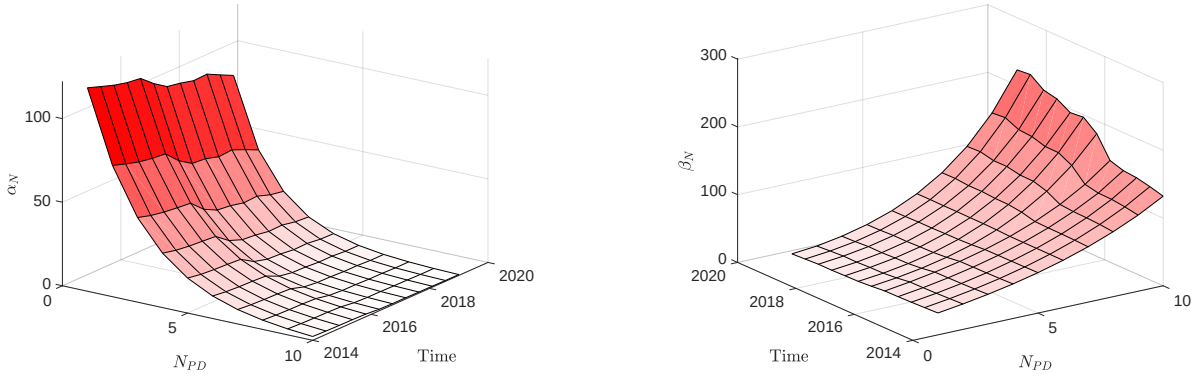


Figure A.3: **Model fit.** The plots document the model fit for cDPI (Panel A), cIPI (Panel B), and cTPI (Panel C) by comparing predicted to actual values for each value of N_{PD} and each quarter.

Panel A: α_N (left) and β_N (right)



Panel B: λ (left) and ϕ (right)

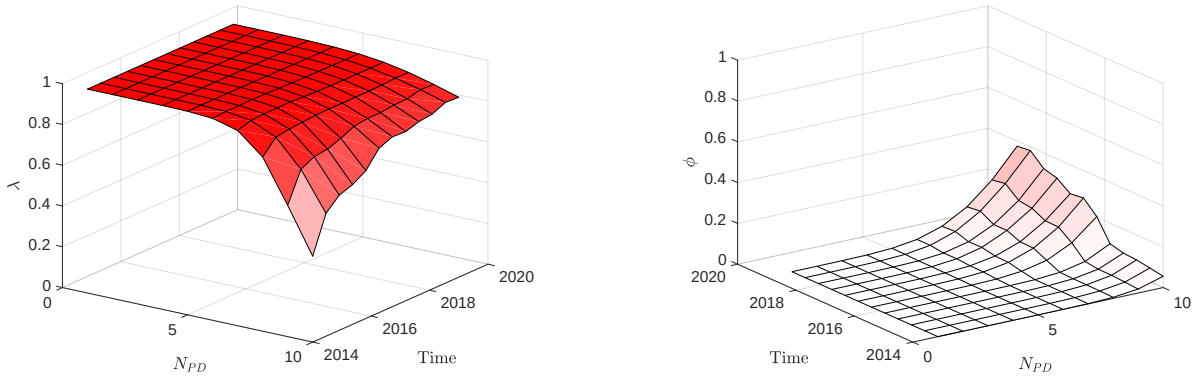
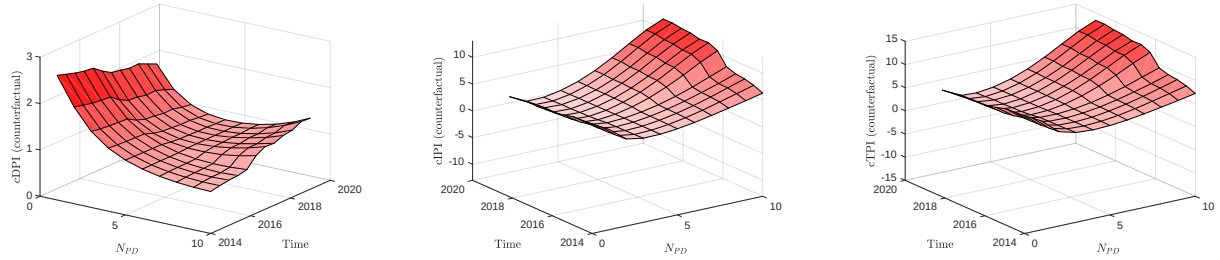
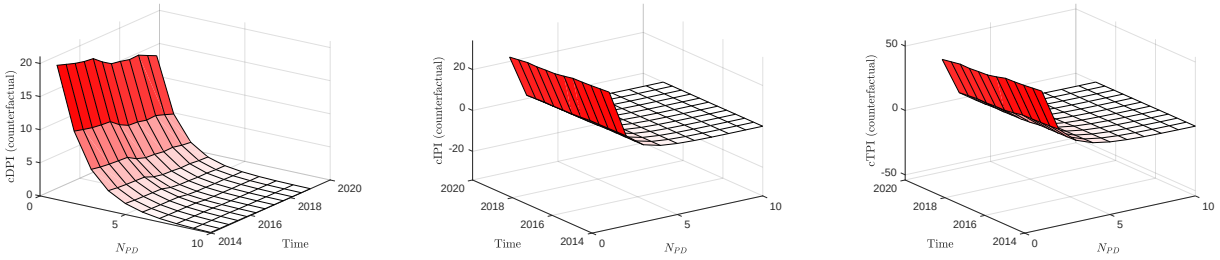


Figure A.4: **Model parameters.** The plots document the estimated model parameters. Panel A plots α_N (left) and β_N as functions of N_{PD} and each quarter. Panel B plots λ (left) and ϕ (right) as functions of N_{PD} and each quarter.

Panel A: Counterfactual IPV ($\alpha_N^{cf} = 0$)



Panel B: Counterfactual PCV ($\beta_N^{cf} = \alpha_N$)



Panel C: Counterfactual no Type I and II errors ($\lambda^{cf} = 1, \phi^{cf} = 0$)

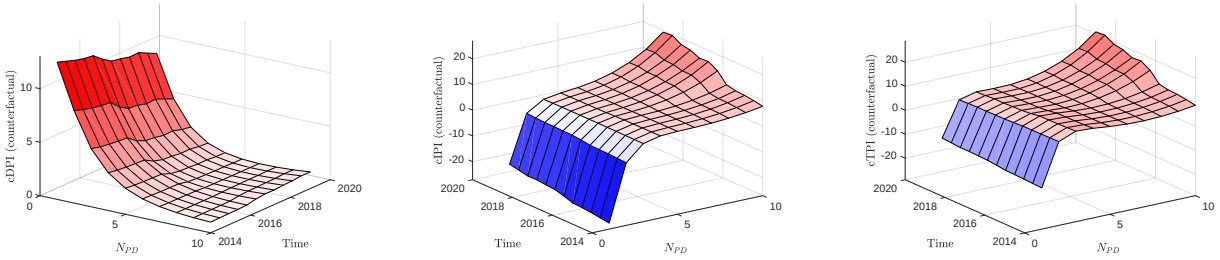


Figure A.5: **Counterfactual analysis.** The plots document the counterfactual cDPI (left), cIPI (middle), and cTPI (right) as functions of N_{PD} and each quarter.