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Quote Competition in Corporate Bonds

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ABSTRACT

Dealer quotes in corporate bonds, though indicative, lower trading costs and increase trading volume. Dealers offering higher quality quotes attract more order flow and execute trades at favorable prices. Dealers advertise quotes to manage their inventories and attract orders from nonrelationship clients. However, quote competition is imperfect. The best quotes often fail to attract orders, and trade-throughs are common. Nevertheless, quote competition is important as clients exploit quotes from other dealers in negotiations, forcing dealers with lower quality quotes to offer price improvements. Quoting is not a zero-sum game, as more active bond-level quoting leads to more bond-level trading.

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UNLIKE SECURITIES TRADED ON CENTRALIZED exchanges, where binding bid and ask quotes are publicly available, corporate bonds are traded on over-the-counter (OTC) markets with limited pre-trade transparency (Bessembinder et al., 2020). In this trading environment, corporate bond dealers play a pivotal role, disseminating indicative quotes—commonly known as "runs"—to potential clients. While theoretical literature often portrays OTC markets as rife with search and matching frictions (e.g., Duffie et al., 2005, 2017) and reliant on client-dealer relationships (e.g., Hendershott et al., 2020), the role of dealer quotes in mitigating these frictions and shaping trading outcomes as well as their broader market impact remains unclear. We address this gap by documenting empirical facts about the relations between dealers' indicative quotes, order flow, and client execution costs using dealer-level quote data in the U.S. corporate bond market.

Dealers email quotes on corporate bonds to clients in "runs" consisting of a list of bonds and the indicative quoted price or yield at which the dealer is willing to buy or sell each bond. However, these data are proprietary and not readily available to the public. Our sample comes from BondCliQ (hereafter, CliQ), a provider that collects quotes from participating dealers by requesting inclusion on each dealer's distribution list for runs and that redistributes the quotes to subscribers for a monthly fee. During our October 2019 to May 2020 sample period, 35 CliQ dealers supplied 8.5 million (bid and/or ask) quotes on roughly 24,000 bonds.[1]

We find that dealers advertise their trading intent with quotes to manage their inventories and attract new institutional clients at the expense of relationship dealers. At the individual dealer level, the decision to quote, the extent of quotation activity, and the quality of quotes are all positively related to the client's order flow. However, quoting is not a zero-sum game between quoting and nonquoting dealers, as we document that active bond-level quoting leads to more bond-level trading. Quoting, therefore, helps alleviate welfare losses stemming from fewer trades being consummated in opaque trading environments that rely on relationships, enhancing the overall functioning of the corporate bond market.

We further find that the competition on indicative quotes is imperfect. Clients who trade with dealers posting better quotes obtain higher execution quality or, equivalently, lower trading costs. Thus, consistent with quote competition, dealers have incentives to post better quality quotes, and clients have incentives to search for better quotes. However, while dealers attract order flow by competing on quotes, they do so imperfectly. First, consistent with the best quotes not being observed by all market participants, the best quotes often fail to attract order flow, and trades frequently occur at prices worse than the best

[1] The CliQ data contain dealer names that we match to the dealers' names in the regulatory TRACE data set to link quoting and trading activity. CliQ did not provide quote data to dealers during our sample period, and several of the largest dealers do not include CliQ on their runs. Notwithstanding, CliQ dealers provide significant liquidity, averaging about 25% of trading volume in all bonds, and their quotes affect trading activity.

quote. Second, while quotes matter for large trades, this does not hold for small trades. Third, clients and dealers appear to exploit the information contained in other dealers' quotes in their negotiations, as dealers with lower quality quotes compared to their peers improve execution prices over their quotes to a greater extent. Thus, quote leakage leads to price-matching behavior similar to that in consumer markets, which reduces dealers' incentives to compete aggressively via quotes.

Our analysis starts by exploring several channels impacting dealers' decisions to post quotes. We find that dealers quote to manage their own inventory levels, but are largely insensitive to changes in the inventory of their connected dealers. Moreover, dealers who serve as a bond's lead underwriter in the primary market exhibit a higher propensity to quote the same bond in the secondary market. Bond characteristics also matter for dealers' quoting decisions. In particular, bonds that are higher rated, longer duration, and older bonds, as well as bonds with larger issuances, are more likely to be quoted. Quoting activity, however, shows no relation to dealers' private information on credit rating changes.

We also find a strong relationship between quoting and trading at the dealer-bond-day level. Quoting increases the dealer's trade probability in the bond by 4.8 percentage points (pps, extensive margin), and the number of trades by the quoting dealer by 4.4% (intensive margin). The presence of a quote improves client execution quality by 6 to 7 basis points (bps).

A natural explanation for quotes attracting order flow and lowering trading costs is that quotes reduce search and matching frictions and help clients trade with dealers who quote better prices irrespective of prior relationships (e.g., Duffie et al., 2005, 2017; Hendershott et al., 2020). While we cannot directly track the clients' search process, we observe institutional investors switching to nonrelationship dealers based on quote activity and quote aggressiveness. Using data on corporate bond trades by insurance companies matched to our quote data, we show that the presence of dealer quotes increases insurers' likelihood of trading with nonrelationship CliQ dealers compared to relationship CliQ dealers, that is, those that receive the largest share of the insurer's past order flow. Nonrelationship dealers handle 23% of trades when they quote, as opposed to 11% when they do not quote. Higher quality quotes increase the switching probability even further. These results indicate that dealer quotes partially substitute for established client-dealer relationships and allow dealers to facilitate bond trades that they otherwise might not have been able to attract.

However, the best quotes often fail to attract order flow, and trades frequently occur at prices worse than the best indicative quotes, which does not happen in centralized equity markets (Stoll and Schenzler, 2006).[2] Focusing on CliQ dealers, the dealer with the best quotes attracts only 15% of trades, and more than 30% of trades with dealers not quoting the best price occur at prices

[2] Harris (2015) refers to trades that occur at prices worse than the best available quotes as trade-throughs.

worse than the best quote. Better quote quality, measured as the dealer's ask and bid quotes relative to their respective benchmarks, is passed through 84% to execution quality, with the majority of the effect driven by positive quote quality, that is, quotes better than the benchmark, and large trades.[3] In contrast, negative quote quality, that is, quotes worse than the benchmark, does not materially affect execution quality. These results suggest that competition based on nonbinding quotes is imperfect because dealers posting worse quotes can improve bilaterally negotiated prices ex post.

Do our results establish whether quotes causally impact order flow and execution quality? We find that dealers use quotes to manage their inventories and relationships. In a general sense, this implies a causal interpretation of our results as institutions can more easily find a dealer interested in trading at better prices. However, if the view is that trading generated by quoting arises only from quoting for reasons unrelated to dealers' or customers' interest in trading, our evidence so far is less convincing as it is difficult to find variation in quoting at the dealer-bond-day level that is unrelated to dealers' potential interest in trading.

To show that quoting increases trading at the aggregate bond-day level and does not simply redistribute order flow across dealers, we construct shift-share instruments in the spirit of Bartik (1991). The granularity of our quoting data allows us to isolate the variation in quoting activity due to the differential impact of common shocks on CliQ dealers from unobserved shocks to trading incentives. In constructing our instrument, we exploit the heterogeneity in dealers' prior propensity to trade certain bonds due to information, issuer-dealer relationships, dealer-client relationships, and other factors. Following Goldsmith-Pinkham, Sorkin, and Swift (2020) and Borusyak, Hull, and Jaravel (2022, 2024), we aggregate a dealer's quoting activity on a given day across all bonds to capture the extensive and intensive margins of quote supply. The predicted quote supply in a bond across all dealers is a weighted average of market-wide shocks to quoting rates of each dealer ("shift"), with weights depending on the past distribution of institutional trading activity ("shares"). We find in ordinary least squares (OLS) and instrumental variables regressions that aggregate quote supply increases trading volume and lowers trading costs. A one standard deviation (1-SD) increase in quote supply increases CliQ dealers' market share in the bond on that day by 2.9pps (2.1pps) using OLS (IV), while the same shock increases total trading activity by 3.9% (4.7%). Bond-level execution quality improves by 2.3bps for a 1-SD increase in quote supply. Thus, quote competition is not a "zero-sum game" between dealers whereby one dealer wins order flow at the expense of another. Rather overall trading activity benefits from dealers' quoting activity, which is important for investor welfare.

[3] Because retail clients do not directly access CliQ quotes and may only receive a subset through their brokers, the relationship between quotes and trades should be more pronounced for institutional trades than for retail trades. Indeed, when we separately analyze the relationship between quotes and order flow for large trades (≥\$100K) and small trades (<\$100K), we find that the quote-trade relationship is statistically and economically significant only for large trades.

Literature. While the literature on OTC markets generally does not consider dealer quotes, Duffie, Dworczak, and Zhu (2017) theoretically examine pre-trade transparency in OTC markets as a single market-wide benchmark.[4] Chen and Zhong (2017) model OTC market opacity as a search without knowing the distribution of dealers' quotes and find that NYSE pre-trade transparency favors investors at the expense of dealers by enhancing investors' bargaining power. Vairo and Dworczak (2023) model pre-trade transparency as traders' ability to request firm quotes from multiple dealers simultaneously, lowering search costs in a dynamic model with adverse selection. If indicative dealer quotes are informative about potential terms of trade, then quotes provide pre-trade transparency beyond a benchmark by fostering quote competition. We document quote competition in corporate bonds by showing that higher quote quality attracts more order flow.

By examining the link between quotes by individual dealers and trades, we relate the nature of quote competition observed in the market to that envisioned in theoretical models. Dealers use indicative quotes to broadcast their desire to trade, which can be reinterpreted as an increase in meeting intensity within the context of random search models (Duffie et al., 2005; Chen and Zhong, 2017; Hugonnier et al., 2020; Weill, 2020). We document that trading activity is positively related to quoting activity and quote quality, suggesting that clients respond to dealers' signals of trading interest, consistent with advertising models (Stigler, 1961; Nelson, 1974). Better quoted prices are passed through to trade prices received by clients. However, while quotes matter, trades often occur at a price worse than the best quote (16% to 40%) or go to dealers who do not quote or who quote inferior prices. These dealers respond to other dealers' quotes by improving their inferior quotes. While this price improvement helps clients receive better prices, quote leakage limits dealers' incentives to compete aggressively and offer better quotes in the first place (Godek, 1996; Dutta and Madhavan, 1997).

Our study also relates to the literature on pre-trade transparency in electronic bond platforms. Most electronic trading occurs on request-for-quotation (RFQ) venues, where dealers respond to a client's inquiry with firm quotes. One distinction is that dealer quotes on RFQs are shown only to the inquiring client, while dealer "runs" are broadcast to all potential institutional clients. Hendershott and Madhavan (2015) show that RFQ usage is higher for recently issued, investment-grade, large-issue-size bonds, while O'Hara and Zhou (2021) conclude that electronic trading improves the market for clients and dealers. Some studies (e.g., Harris, 2015; Kozora et al., 2020; Kim and Nguyen, 2021) examine dealer quotation data from corporate bond ATS venues. As O'Hara and Zhou (2021) note, electronic trading remains fairly small and segmented, catering mainly to retail clients and smaller institutional trades, while the traditional OTC dealer market dominates trading in the round lot of $1 million or more. Mattmann (2021) finds that electronic

[4] Cereda et al. (2022) examine the introduction of such a benchmark in the Brazilian stock lending market.

corporate bond quotes reduce trading costs during normal times, but clients received worse prices during COVID-19.

Although the role of quoting in equity markets is well understood, how quotes relate to trades in corporate bonds differs from equities due to several differences in market structure. In the United States, stock quotes are firm and publicly disseminated. In addition, Regulation National Market System (Reg NMS) defines intermarket linkages with best execution rules prohibiting trade-throughs.[5] Corporate bond dealers have no quoting obligations, and what quotes they do disseminate go to only a select list of potential clients. There are no formal market linkages and much weaker best-execution rules. Bessembinder, Spatt, and Venkataraman (2020) note that best execution requirements are not clearly defined in the corporate bond market, potentially reducing the incentives for quote competition. These differences in market structure imply that quotes play a fundamentally different role in bonds than in stocks. Harris (2015) studies quotation data consolidated across several electronic bond trading venues and shows that execution prices are often worse than the best quote, consistent with the lack of best execution. The second difference with equity markets is that clients and competing dealers can exploit quote information from other dealers in their bilateral negotiations. We find evidence of significant asymmetry in how quote quality impacts execution prices. Dealers with the very best quotes offer little improvement over their quotes when executing trades, while dealers with inferior quotes offer significant price improvement. This is consistent with clients using better quotes to negotiate improved prices from their relationship dealers, who may not supply the best quotes.

Finally, our results show that clients benefit from quote competition through lower trading costs and wider market access, which highlights the importance of making bid and ask quotes more widely available. Green, Hollifield, and Schürhoff (2007) predict that fragmentation and lack of transparency create opportunities for dealers to profit from less sophisticated investors.[6] Future research should consider the implications of our results for market design, specifically, whether the wider availability of dealer quotations should arise

[5] In the U.S. equity market, each exchange generally provides a firm quote to the Consolidated Quotation System (CQS), which consolidates and transmits quotes continuously to all participants. The importance of quote competition has been studied extensively in equity markets (Huang and Stoll, 1996; Blume and Goldstein, 1997; Barclay et al., 1999; Cao et al., 2000; Bessembinder, 2003; Boehmer et al., 2005; Stoll and Schenzler, 2006). Consistent with our findings, Barclay et al. (1999) note that "dealers could not obtain this order flow by competing more aggressively using quoted prices […] dealers faced a disincentive to improve the posted quotes, for they would likely fail to attract significant new order flow but would reduce the profits on orders that they (and other dealers) were already receiving."

[6] Consistent with this view, the literature has shown that smaller trades have higher trading costs than larger trades in corporate bonds. See, among others, Schultz (2001, 2017), Bessembinder, Maxwell, and Venkataraman (2006), Edwards, Harris, and Piwowar (2007), Goldstein, Hotchkiss, and Sirri (2007), Friewald, Jankowitsch, and Subrahmanyam (2012), Hendershott, Li, Livdan, and Schürhoff (2020), Bessembinder et al. (2018), and Bao, O'Hara, and Zhou (2018). Trade costs declining in trade size can also arise from fixed costs and relationships.

endogenously in the marketplace or whether a regulator must mandate pre-trade transparency.

The paper is organized as follows. Section I describes the quotes and trades data. Section II explores the determinants of quoting. Section III examines the relationship between quoting and trading. Section IV investigates whether quoting improves clients' execution quality, how quote aggressiveness affects client execution quality, which quotes are firm, and whether quotes lead dealers to improve prices in bilateral negotiations. Section V explores whether quotes substitute for relationships and improve market access. Section VI concludes.

I. Data

A. Quotes and Trades Data

Our analysis covers the period from October 1, 2019, to May 1, 2020. Dealers broadcast indicative bids and offers on lists of bonds to potential institutional clients, typically using Bloomberg's messaging system.[7] Institutions can solicit quotes for a bond through electronic RFQ platforms (e.g., MarketAxess), or by directly contacting dealers via instant messaging or phone. Larger institutions have built a proprietary technology to aggregate the quote information that they receive from many sources. Smaller institutions purchase a similar technology (e.g., ALGOMI Alpha, Neptune) or use Bloomberg to parse quotes for their watch list of bonds. Clients can then complete a bilateral trade by contacting the dealer or by using Bloomberg's functionality.

Our bond quotes come from CliQ, a company seeking to create a centralized, consolidated quote system for U.S. corporate bonds. CliQ collects quotes from participating dealers by requesting inclusion in each dealer's distribution list for runs.[8] CliQ plans on redistributing the quotes to subscribers for a monthly fee, but did not provide quote data to dealers during our sample period. Our study therefore uses CliQ as a data source and does not examine CliQ's role in enhancing quote competition among dealers. This setting allows us to study the relevance of quotes for institutions without any confounding effect from dealers observing each other's quotes on CliQ. Specifically, we use CliQ data as a measure of dealers' quoting interest on a bond day.[9]

[7] Institutions also receive quotes directly for a limited set of bonds through Alternative Trading Systems (ATSs). However, electronic trading of bonds remains a relatively small part of the overall market.

[8] Conversations with market participants suggest that institutional clients undergo a rigorous vetting process focused on potential business benefits to a dealer before being added to the distribution list of runs. Clients receiving runs typically have a trading relationship with the dealers providing quotes.

[9] Dealers' quoting activity in other venues available for advertising interests is likely correlated with CliQ data. Because the unmeasured activity in other venues is still about dealers' quoting interest, it does not affect our qualitative interpretation of the relation between quotes and trades; however, it may impact the quantitative estimates.

The raw quote data contain 8.5 million quotes (bid or ask) on roughly 24,000 bonds. We rely on the Mergent Fixed Income Securities Database (FISD) data to identify known features of corporate bonds, and thus require the bond to be in the FISD.[10] We then apply a series of filters to select bonds with well-defined features relating to the bond type, optionality, offering date, offering size, maturity date, and coupon type. Appendix A details the steps performed to filter the CliQ data on dealer quotes. After filtering, 4,160,948 quotes on 8,077 bonds remain. Since bid-side quotes and ask-side quotes are often quoted at the same time by the same dealer for the same bonds, we can collapse the sides of the quotes and refer to each unique quote by the same dealer on the same bond at a unique timestamp a quote. This yields 2,462,193 run observations (one-sided or two-sided). Each quote is in terms of absolute price or as a spread from the Treasury benchmark yield, and sometimes in both. We convert quotes from spreads to prices when only the spread is available, as explained in Appendix A.

Data on corporate bond transactions are obtained from the supervisory TRACE database, which allow us to link quotes to trades of the same dealer. We apply similar filters in terms of bond characteristics to the transaction data. In addition, because we are mainly interested in comparing the quoting and trading behavior of the same dealer, in our main analysis, we further narrow our trade sample to trades involving at least one CliQ dealer.[11] This yields a sample of 884,030 trades, including client-dealer and interdealer trades.

Our final data on quotes and trades include 9,634 bonds quoted or traded by one of the 35 CliQ dealers over 146 trading days. We maintain two versions of these data, one at the microlevel with each quote and trade as a unique observation, and another version collapsed at the dealer-bond-day level. The latter is a three-dimensional data set, where each observation is identified through unique combinations of dealer-bond-days in the quote and trade data. We first identify dealer-bond pairs. There are 96,108 such pairs (out of 337,190 possible dealer-bond pairs) such that the dealer quotes or trades the bond at least once during the sample period. We then balance the panel along the time dimension by setting the variables that capture trading or quoting activity to zero on days without any quote or trade. This creates a panel that is balanced over time with 14,031,768 observations. Only one-third of quotes have indicative sizes associated with them. For quotes with size, 83% are for over \$1 million, while only 15% of client-dealer trades are for more than \$1 million. Hence, quote size has limited relevance for most trades and is unlikely to be binding

[10] In Section V, we use insurer transaction data to study how quoting affects dealer-client relationships.

[11] For trades between client and dealer, this means the dealer is one of the 35 CliQ dealer firms. For interdealer trades, at least one side must be a CliQ dealer. FINRA Rule 6730(a) requires dealers to report to TRACE transactions in corporate bonds within 15 minutes of the time of execution. Our conversations with market participants suggest that reporting delays greater than 15 minutes are uncommon. We use the trade timestamps from TRACE and quote timestamps from CliQ.

even for the larger trades. We therefore focus on whether a dealer quotes and the quoted price.

During our sample period, CliQ dealers were mid-tier dealers in the corporate bond market. The largest dealers also quote but do not provide their quotes to CliQ.[12] Our results therefore apply to the CliQ dealers. The largest CliQ dealer ranks among the top 10 TRACE dealers by trading volume, while 19 CliQ dealers rank among the top 50 TRACE dealers. The daily market share of all CliQ dealers averages about 25% of the total TRACE (dealer to client) volume, ranging from 15% to 40%. There was no significant change in the daily market share of CliQ dealers in late March 2020.

To measure quoting and trading activity, we define all variables at the transaction level i or aggregated at the dealer-bond-day level for dealer d and bond b on day t. Our main variables of interest are the extensive and intensive margins of trading activity, client execution quality in terms of the transaction cost they pay, and dealers' price improvement over quoted prices. To characterize the extensive margins of quoting and trading activity at the dealer-bond-day level, we construct the quote indicator $HasQuote_{d,b,t}$ and the trade indicator $HasTrade_{d,b,t}$, where $HasQuote_{d,b,t} = 1$ indicates that dealer d quotes bond b on day t, and $HasQuote_{d,b,t} = 0$ otherwise, $HasTrade_{d,b,t} = 1$ if dealer d trades bond b on day t, and $HasTrade_{d,b,t} = 0$ otherwise. We define $HasAskQuote_{d,b,t}$, $HasBidQuote_{d,b,t}$, $HasOnlyAskQuote_{d,b,t}$, $HasOnlyBidQuote_{d,b,t}$, and $HasAskAndBidQuote_{d,b,t}$ when we explore the direction of the quote. To characterize the intensive margins of quoting and trading, we construct the natural log-transformed number of quotes $LogNumQuotes_{d,b,t} = \log(NumQuotes_{d,b,t} + 1)$ and trades $LogNumTrades_{d,b,t} = \log(NumTrades_{d,b,t} + 1)$, where we add one to the number under the log to ensure these measures are well defined when the number of quotes or trades, or both, is zero. In the analysis, we link quoting activity along the extensive margin, $HasQuote_{d,b,t}$, and intensive margin, $LogNumQuotes_{d,b,t}$, to trading activity and client execution quality.

B. Descriptive Statistics about Dealer Quotes and Trades

Each quote contains the time stamp, quoting dealer name, quoted bid or ask price, bond CUSIP number, and, for some quotes, the quantity. The information on quotes is limited to the CliQ dealers. Using the precise timestamp for each quote, we can infer the set of bond quotes sent in the same run message by the dealer to clients. We use all trades by CliQ and non-CliQ dealers from supervisory TRACE and match them to the CliQ data by dealer name and bond CUSIP number. Each trade has a transaction price, a dealer buy-sell indicator, and bond characteristics.

Table I provides descriptive statistics about individual dealer quotes and trades. Results are presented separately for quotes (Panel A), CliQ trades

[12] Large dealers are more likely to have strong relationships with more clients, and thus, increasing the dissemination of their quotes is less valuable, and large dealers are less likely to join

Table I

Descriptive Statistics

The table provides descriptive statistics about individual dealer quotes and trades—number per day, frequency, quality, and intraday timing.

Variable	*N*	Mean	*SD*	5%	25%	50%	75%	95%
Panel A: Quotes by CliQ dealers								
No. dealers quoting per day (on days with quotes)	146	27.03	2.75	22	26	27	29	31
No. dealers quoting per bond-day (conditional on bond quote)	631,435	1.93	1.23	1	1	2	2	4
No. bonds quoted per day (on days with quotes)	146	4,324.90	950.95	2,499	3,781	4,711	5,034	5,387
No. bonds quoted per dealer-day (conditional on dealer quote)	3,946	309.62	412.08	6	41	153	413	1,171
No. bonds quoted per message	179,531	13.71	25.57	1	3	7	16	42
No. messages per dealer-day (conditional on dealer message)	3,946	45.50	81.58	1	5	13.50	40	236
Quoted bid-ask spread if available (winsorized at 0.5% and 99.5%)	1,931,288	0.74	0.65	0.09	0.26	0.56	1.00	2.00
Quote time-of-day (hour)	2,462,193	10.64	3.10	7.25	8.32	9.85	12.57	16.42
Panel B: Trades by CliQ dealers								
No. dealers trading per day (on days with trades)	146	34.13	1.09	32	34	34	35	35
No. dealers trading per bond-day (conditional on bond trade)	413,132	1.64	1.02	1	1	1	2	4
No. bonds traded per day (on days with trades)	146	2,829.67	357.38	2,129	2,725	2,930	3,040	3,182
No. bonds traded per dealer-day (conditional on dealer trade)	4,983	135.73	201.35	2	15	53	164	695
Trade time-of-day (hour)	1,202,957	12.95	2.39	8.97	11.10	13.20	15.00	16.35
Panel C: Quotes and trades at dealer-bond-day level, balanced panel								
$HasQuote_{d,b,t}$	14,031,768	0.09	0.28	0.00	0.00	0.00	0.00	1.00
$HasTrade_{d,b,t}$	14,031,768	0.05	0.21	0.00	0.00	0.00	0.00	0.00
$LogNumQuotes_{d,b,t}$	14,031,768	0.08	0.30	0.00	0.00	0.00	0.00	0.69
$LogNumTrades_{d,b,t}$	14,031,768	0.04	0.21	0.00	0.00	0.00	0.00	0.00

(Panel B), and a balanced panel at the dealer-bond-day level (Panel C). We start with the quote data. On average, 27 dealers quote per day, and two dealers quote per day per bond. The 95$^{\text{th}}$ percentile has 31 dealers quoting per day and four dealers quoting per day per bond. For the 5% most quoted bonds, the number of quoting dealers varies over time between less than five and

CliQ. It is possible that dealers' differences in using CliQ could lead to quantitative differences in the importance of quotes for CliQ versus (larger) non-CliQ dealers.

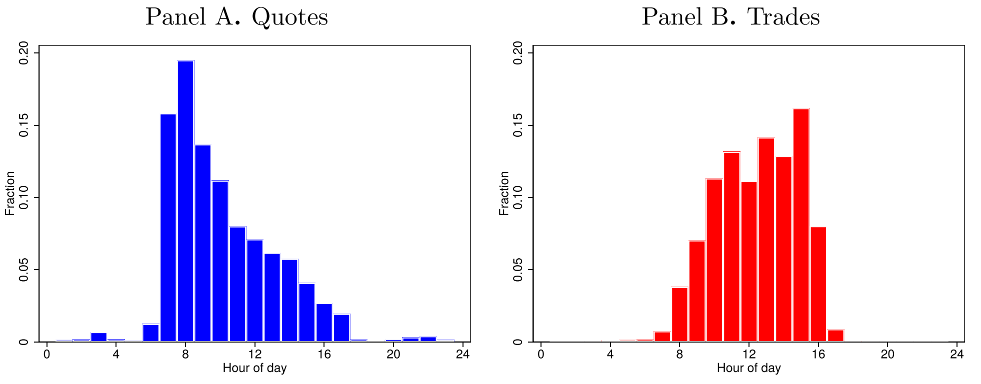

Figure 1. Distribution of quotes and trades during the day. The figure documents the distribution of trades and quotes during the day. We pool all dealer bond days and plot the fraction of the quotes (Panel A) and trades (Panel B) that arrive during a given hour. (Color figure can be viewed at wileyonlinelibrary.com)

more than 15. About 30% of the quotes are one-sided. One-sided bid quotes are less frequent than one-sided ask quotes. As shown in Table I, a median message contains seven bonds, but this number varies substantially across dealers and days. At the 5% and 95% tails, a message provides quotes on one and 42 bonds, respectively. Dealers send out many of these lists of quotes throughout the day. The messaging frequency varies substantially across dealers and days. A median dealer sends out 13.5 such messages a day. At the 5% and 95% tails, dealers send out one and 236 such messages a day, respectively.

On a typical day, 4,325 bonds are quoted on CliQ and 310 bonds per dealer. At the 95$^{\text{th}}$ percentile, 5,387 bonds are quoted on CliQ per day, and 1,171 bonds are quoted per day per dealer. The quoted bid-ask spread is winsorized at 0.5% and 99.5%. Its average (median) value is 74bps (56bps), and it can be as high as 2%, at the 95$^{\text{th}}$ percentile. Panel B of Table I reports descriptive statistics for CliQ dealer trades. On average, 34 CliQ dealers trade per day. An average of 1.64 CliQ dealers trade a given bond per day.

Panel C of Table I details descriptive statistics for quotes and trades for the pooled data in a dealer-bond-day balanced panel. The average value of $HasQuote_{d,b,t}$ ($HasTrade_{d,b,t}$) is the unconditional probability of a quote(trade) for a given dealer-bond-day, which equals 9% for quotes and 5% for trades.

Figure 1 documents the intraday distribution of quotes (Panel A) and trades (Panel B). As can be seen both quoting and trading activity are slow in the early morning. Quoting activity then spikes up to 17% at 7 AM, right before trading picks up. The peak of quoting activity is at 8 AM, when nearly 20% of daily quotes arrive, after which quoting activity gradually declines. Quoting occurs on average between 10 AM and 11 AM, while trading tends to occur in the afternoon, with a mean at about 1 PM. Only around 3% of daily quotes arrive at 3 PM, when the fraction of daily trades jumps to its highest value of 17%, before declining dramatically after 4 PM. Quoting activity hits its lowest simultaneously with the lowest for trading activity at 6 PM. Together, these results suggest a lead-lag intraday relation between quotes, which lead, and trades, which lag. The next section provides insights about the determinants of quoting activity across bonds and over time.

II. Determinants of Quoting

A. Why Do Dealers Quote?

To set the stage for our analysis of dealer quotes, trading activity, and client execution quality, we consider three overlapping motives that influence dealers' incentives to quote bid and ask prices:

Advertising: Dealers use quotes to signal their willingness to trade, effectively acting as market makers. By reducing clients' search frictions, quoting helps direct order flow to dealers who actively participate in the market (Robert and Stahl, 1993; Duffie et al., 2005; Chen and Zhong, 2017; Hugonnier et al., 2020; Weill, 2020). Offering competitive quotes allows dealers to attract trading volume, often at the expense of competitors.

Inventory Management: Dealers quote bid and ask prices to manage their inventory risk. By adjusting quotes based on inventory levels and funding conditions, they can control exposure to specific bonds (Stoll, 1978; Ho and Stoll, 1983). Dealers may also strategically quote in response to the inventories of connected dealers, either exploiting imbalances (Brunnermeier and Pedersen, 2005) or supporting their counterparties (Colliard et al., 2021).

Market Access and Relationships: Quoting facilitates broader market access, allowing clients to trade without relying solely on preexisting dealer relationships. Smaller dealers, in particular, benefit from quoting, as it enables them to compete with larger, more established market participants (Hendershott et al., 2020). By fostering competition, quoting expands market reach and reduces reliance on relationship-based trading.

These motives are not mutually exclusive—quoting can simultaneously serve multiple economic functions in the corporate bond market, benefiting both investors and dealers. To empirically assess the relevance of these quoting channels, we begin by analyzing the determinants of dealers' quoting activity while controlling for dealer and day fixed effects. In Section V, we further explore the role of market access in quoting behavior and its implications for competition in the bond market.

B. Determinants of Quoting

Table II presents the determinants of dealers' decision to supply a quote, or to supply a one-sided (only bid price or only ask price) quote, in the corporate bond market. The dependent variables are $\textit{HasQuote}_{d,b,t}$, a dummy variable indicating whether a dealer has quoted a price for a particular bond and date, $\textit{HasAskQuote}_{d,b,t}$ and $\textit{HasAskQuote}_{d,b,t}$ (one-sided), dummy variables indicating whether a dealer has quoted an ask price (and no bid price) for a particular

Table II

Determinants of Quoting

The table reports results on the determinants of dealers' decisions to quote at the ask or bid, ask only, and bid only, where $h = 20$ days. Estimates are obtained from panel regressions with dealer and day fixed effects. All coefficients are scaled by 100. Standard errors are double-clustered at the dealer and bond levels. Significance levels: *** 1%, ** 5%, * 10%.

Dependent Variable:	$HasQuote_{d,b,t}$	$HasAskQuote_{d,b,t}$		$HasBidQuote_{d,b,t}$	
		All	One-Sided Ask	All	One-Sided Bid
	(1)	(2)	(3)	(4)	(5)
$Dealertype_{d,b}$:					
Lead underwriter	2.688**	2.618**	0.069	2.631**	0.082
	(1.081)	(1.023)	(0.062)	(1.079)	(0.106)
Underwriter	1.451	1.458	−0.068	1.533	0.007
	(1.009)	(1.069)	(0.073)	(1.008)	(0.089)
$Inventorymanagement_{d,b,t-1-h,t-1}$:					
Signed inventory change	0.179**	0.220**	0.126***	0.050	−0.044
	(0.077)	(0.092)	(0.042)	(0.065)	(0.027)
Connected inventory change	−0.185	−0.190	−0.029*	−0.157	0.004
	(0.260)	(0.249)	(0.016)	(0.260)	(0.014)
No inventory change	−3.185***	−2.654***	−0.951**	−2.230**	−0.527**
	(1.105)	(0.944)	(0.355)	(0.857)	(0.252)
$Bondtype_{b,t-1}$:					
Rating (1 = AAA, 2 = AA+,...)	−0.617***	−0.537***	−0.061	−0.546***	−0.069***
	(0.163)	(0.150)	(0.038)	(0.154)	(0.022)
Log years to mature	1.249*	1.392*	−0.123	1.424**	−0.092
	(0.671)	(0.686)	(0.119)	(0.660)	(0.066)
Log age of bond	0.807***	0.744***	0.049	0.753***	0.058*
	(0.204)	(0.196)	(0.037)	(0.195)	(0.030)
Log no. institutional investors	−0.148	−0.190	−0.155	−0.010	0.025
	(0.572)	(0.525)	(0.145)	(0.547)	(0.080)
Log size of issuance	0.812**	0.823**	0.251*	0.562*	−0.010
	(0.318)	(0.305)	(0.131)	(0.285)	(0.037)

(Continued)

Table II—*Continued*

Dependent Variable:	$HasQuote_{d,b,t}$	$HasAskQuote_{d,b,t}$		$HasBidQuote_{d,b,t}$	
		All	One-Sided Ask	All	One-Sided Bid
	(1)	(2)	(3)	(4)	(5)
MTN	0.364	0.242	0.180	0.189	0.127
	(0.684)	(0.621)	(0.166)	(0.666)	(0.124)
Rule 144a bond	0.976	0.898	−0.114	1.071*	0.059
	(0.640)	(0.579)	(0.136)	(0.585)	(0.114)
Private placement	0.584	0.818	−0.230	0.832	−0.216**
	(1.282)	(1.315)	(0.186)	(1.272)	(0.104)
$Informationevent_{b,t,t+h}$:					
Rating change in next 5 days	−0.733	−0.737	−0.059	−0.676	0.002
	(0.532)	(0.515)	(0.078)	(0.524)	(0.068)
Fixed effects	Dealer, Date	Dealer, Date	Dealer, Date	Dealer, Date	Dealer, Date
R^2	0.129	0.130	0.029	0.131	0.012
N	14,031,768	14,031,768	14,031,768	14,031,768	14,031,768

bond and date, and $HasBidQuote_{d,b,t}$ and $HasBidQuote_{d,b,t}$ (one-sided), dummy variables indicating whether a dealer has quoted a bid price (and no ask price) for a particular bond and date. We estimate the likelihood of a dealer quoting a price, and of a dealer quoting a price at either the bid or ask, based on the following panel linear probability specification with standard errors double-clustered at the dealer and bond levels:

$$\begin{aligned} HasQuote_{d,b,t} = \alpha_d + \alpha_t + \beta_1 \times Dealer\ type_{d,b} + \\ +\beta_2 \times Inventory\ management_{d,b,t-1-h,t-1} + \beta_3 \times Bond\ type_{b,t-1} + \\ +\beta_4 \times Information\ event_{b,t,t+h} + \epsilon_{d,b,t}. \end{aligned} \tag{1}$$

The explanatory variables are split into four categories: $Dealer\ type_{d,b}$ at the dealer-bond level, $Inventory\ management_{d,b,t-1-h,t-1}$ at the dealer-bond-day level, $Bond\ type_{b,t-1}$ at the bond-day level, and $Information\ event_{b,t,t+h}$ at the bond-day level. We also control for the lagged dependent variable in alternate specifications reported in Internet Appendix I.[13]

According to the advertising channel, quotes reflect the dealer's interest in trading a bond. We identify active dealers as those with specialized expertise in the bond, such as the lead underwriter or any syndicate member in the bond's issuance process. We conjecture that dealers with more prominent roles during bond issuance are more familiar with the bond and, therefore, should be active in providing liquidity by quoting. A lead bond underwriter or "book runner" typically receives a larger allocation of the bond issue than other underwriters. Lead bond underwriters thus play a more prominent role as marketmakers in the secondary market (Bessembinder et al., 2022).[14]

Table II reports the β coefficients from specification (1) for the dependent variables $HasQuote_{d,b,t}$ in column (1), $HasAskQuote_{d,b,t}$ in column (2), $HasAskQuote_{d,b,t}$ (one-sided) in column (3), $HasBidQuote_{d,b,t}$ in column (4), and $HasBidQuote_{d,b,t}$ (one-sided) in column (5), providing insights into the factors influencing dealers' quoting behavior in the corporate bond market. Lead underwriters exhibit 2.688pps, 2.618pps, and 2.631pps higher likelihood of quoting as compared to underwriters ($\beta_1 = 2.688$, 2.618, 2.631) in columns (1), (2), and (4), respectively,[15] suggesting that dealers with more prominent roles in bond issuance, and thus more familiar with the bond, are more active in providing liquidity by quoting at both the ask and bid.

The inventory management channel implies that quoting behavior is shaped by inventory levels and risk exposure. If dealers quote to adjust inventories, then bid-ask activity should vary with dealers' inventory changes in the

[13] The Internet Appendix is available in the online version of this article on *The Journal of Finance* website.

[14] Using dealers' market share in a given bond seems like a natural proxy for identifying active dealers, but it is endogenous to quoting. We collect dealer-type explanatory variables at the dealer-bond level.

[15] All coefficients are scaled by 100 in Table II.

bond and with bond characteristics, including maturity and credit rating. Dealers holding more extreme inventories or facing higher risk may increase quoting activity to manage their positions. To capture dealers' inventory management, we include variables that reflect inventory changes in the bond at the dealer level and among other dealers within the same trading network (Li and Schürhoff, 2019). At the dealer-bond level, we compute the average daily inventory change, $x_{d,b,t-1} = \frac{1}{h}\sum_{\tau=t-1-h}^{t-1} \Delta Inventory_{d,b,\tau}$, over the past $h = 20$ days in that bond (results for $h = 5, 10$ are similar). The variable $Signedinventorychange_{d,b,t-1-h,t-1} = sgn(x_{d,b,t-1}) \cdot \ln(|x_{d,b,t-1}| + 1)$ is the signed log of the dealer's absolute inventory change based on customer and interdealer trades. In addition, to capture activity we construct the dealer-bond-level indicator $Noinventorychange_{d,b,t-1-h,t-1}$ that is equal to one if the dealer's bond inventory remained unchanged over the past h days in that bond and zero otherwise.

Standard models of dynamic inventory management, for example, Amihud and Mendelson (1980) and Avellaneda and Stoikov (2008), assume that market makers quote on both the bid and ask sides and focus on the prices of these quotes. All else equal, in these models dealers' quoted prices move in the opposite direction to the change in their inventory, that is, as dealers buy (sell), their quoted prices decrease (increase). In line with the intuition from these models the coefficient on $Noinventorychange_{d,b,t-1-h,t-1}$ is negative ($\beta_1 = -3.185$, -2.654, and -2.230 in columns (1), (2), and (4)) and statistically significant in all specifications, consistent with dealers quoting more on both sides of the market when their inventory has changed in either direction. Economically, dealers are, respectively, 3.2pps, 2.7pps, and 2.2pps less likely to quote bonds without inventory changes over the past 20 days.

When shorting is constrained, dealers may be more aggressive in quoting on the ask side (when they have excess inventory) than on the bid side (when they are low on inventory). The regression coefficient on the signed inventory change, $\beta_2 = 0.179$ in column (1), is positive and significant at the 5% level, indicating that dealers quote more after experiencing inventory increases. Economically, doubling the bond's inventory over the past 20 days increases the likelihood of that bond being quoted by 0.2pps.

If more interest in selling after increasing inventory translates into a higher likelihood of an ask quote and a lower likelihood of a bid quote, then the coefficient on the inventory change variable should change sign between $HasAskQuote_{d,b,t}$ (columns (2) and (3)) and $HasBidQuote_{d,b,t}$ (columns (4) and (5)). Both quoting variables are related to whether a dealer's inventory has changed. However, while we find asymmetric effects in the magnitudes of the coefficients, $\beta_2 = 0.220$ (0.126) in column (2)((3)) versus $\beta_2 = 0.050$ (-0.044) in column (4) ((5)), the coefficient is positive on $HasAskQuote_{d,b,t}$ and statistically significant at the 5% (1%) level, but it is not statistically significant on $HasBidQuote_{d,b,t}$. Therefore, our results are consistent with dealers wanting to quote relatively more to sell than to buy after their inventory increases, but not so much so that their quoting to buy increases after their inventory decreases, implying that new or extended theoretical models that incorporate dealer decisions to quote are needed to fully capture these results.

To check if the dealer's decision to quote is made in isolation, versus based on the inventory of other dealers in the network, we compute the inventory change by connected dealers, $Connectedinventorychange_{d,b,t-1-h,t-1}$, as the aggregate change in inventory across all connected dealers, using the same approach as for the dealer's own inventory change. If other dealers acquire a large position, then the dealer may quote more aggressively in a predatory sense (Brunnermeier and Pedersen, 2005) or less aggressively in an inventory risk-sharing sense (Colliard et al., 2021). We identify connected dealers within the trading network using all interdealer trading over the nine months before our quote data starts, from January 2019 to September 2019.[16] When we test whether dealers quote strategically in response to connected dealers' inventory changes, we find the opposite signs on *Connectedinventorychange* compared to *Inventorychange*, which suggests that dealers' selling decisions substitute for one another. However, the negative effect is statistically significant only for ask quotes, potentially due to a lack of power.

We also collect bond characteristics such as bond rating, years to maturity, age of bond in years, size of issuance, and the number of institutional investors holding the bond at the bond-day level. We additionally include indicators for types of bonds such as Medium-Term Notes (MTN), Rule 144a Bonds, and Private Placement. If quoting helps dealers capitalize on private information before it becomes obsolete (e.g., due to upcoming rating changes in the bond), we expect bid-ask activity to anticipate such events. Among bond characteristics (β_3 coefficients), better bond ratings and longer time-to-maturity are associated with an increased likelihood of quoting, although bid quotes are affected more than ask quotes by bond ratings. Older bonds and bonds with larger issues also increase the propensity to quote. Private placements exhibit a lower probability of bid quoting, indicating potential differences in liquidity provision for these bonds.

To control for private information events, we include an indicator for the period before a rating change in the next $h = 5$ days at the bond-day level. Ownership patterns and private information events, such as anticipated rating changes, do not significantly influence dealers' quoting decisions, suggesting that exploiting private information about bond fundamentals is not a major channel for quoting. Section I of the Internet Appendix explores alternative specifications, including (1) with saturated dealer-bond, dealer-day, and bond-day fixed effects and an alternative setup with the lagged dependent variable estimated using the Arellano-Bond Generalized Method of Moments (GMM) estimator. Overall, the results show that dealer characteristics, bond attributes, and changes in dealers' inventories shape dealers' quoting behavior. We next examine the relationship between quoting and trading.

[16] We thank a referee for these suggestions. The procedure to identify the interdealer trading resembles the approach in Li and Schürhoff (2019) and Dick-Nielsen, Poulsen, and Rehman (2023).

III. Quoting and Trading

Dealer quotes are indicative and as such nonbinding, and they could have no impact or a significant impact on trading activity. In this section we explore the relationship between quoting activity and the extensive (trade probability) and intensive (log number of trades) margins of trading activity at the individual dealer level, daily, and intraday. To study the market-wide impact of quoting, we use a shift-share instrument that exploits the granular dealer-bond-day structure of our data, linking dealer-level quote supply and bond-level trading.

A. Hypotheses

The hypotheses we test in this section are based on the observation that corporate bond trading is decentralized and pre-trade transparency about the best available quotes is limited. We start with the hypothesis that by advertising bid and ask prices, dealers reduce search and matching frictions for investors (e.g., Duffie et al., 2005), thus attracting order flow and lowering trading costs. Additionally, quotes may enhance market access for lesser connected investors, benefiting smaller, lesser connected dealers and helping clients trade with the dealers quoting better prices irrespective of prior relationships (e.g., Duffie et al., 2017; Hendershott et al., 2020). Consequently, quoting should improve the trade probability, increase trading at the individual dealer level, and increase overall trading volume.

The alternative to an increase in volume is that quoting is a zero-sum game whereby dealers quote to steal clients from each other, thus redistributing order flow between dealers who quote and those who do not. Dealers may try to exploit the information they possess and gain from trading with investors, thus potentially diminishing trust and confidence in the market and reducing trading volume. We therefore investigate whether quoting increases trading at the individual dealer-day and aggregate bond-day levels.

Producing quotes is costly for dealers, and clients may use them to improve the prices they obtain from the quoting dealer or other dealers, resulting in quote competition among dealers. Under quote competition, dealers have incentives to post better quality quotes, and clients have incentives to search for better quotes. If the competition is perfect, trades should always be consummated at the best quotes. If the best quotes often fail to attract order flow, and trades frequently occur at prices worse than the best quotes, then quote competition is imperfect. This occurs if corporate bond dealers disseminate indicative quotes to institutional customers but provide only limited access to quotes to less sophisticated participants, such as retail investors, who may not see the best available prices. Thus, a dealer offering a good quote might get passed over for order flow that goes to competitors offering inferior quotes. This would discourage better quotes from being offered in the first place (Godek, 1996). Dutta and Madhavan (1997) provide a formal model of how better quotes that fail to attract order flow lessen quote competition. Following this reasoning, we next examine the degree of quoting competition, whether quoting improves clients' execution quality, how quote aggressiveness affects execution quality, which quotes are firm, and whether quotes lead dealers to improve prices in bilateral negotiations.

B. Dealer-Level Quoting and Trading

To examine the relation between quoting and trading at the most granular dealer-bond-day level, we start with a univariate analysis within the CliQ dealers. We calculate the daily trade probability by a dealer, conditional on that dealer having versus not having a quote, using a balanced panel of 14,031,768 dealer-bond-day observations. Since quotes are sent only to institutional clients, we refine the analysis by splitting all trades into institutional and retail trades using the large (i.e., ≥\$100K), and small (i.e., <\$100K) trade sizes as proxies.[17] The hypothesis is that quoting increases institutional order flow but not retail order flow. Retail-sized trades can thus be viewed as a control group. In addition, we examine the effect of the default risk on quoting and trading by splitting the sample into investment-grade and high-yield bonds.

Panel A of Table III documents dealer-bond-day-level results. Trading is more likely on days with quoting activity, 6.7%, than on days without quoting activity, 4.6%, although the difference of 2.1pps is statistically significant only at the 10% level. The split by trade size reveals that large trades are more likely to occur on days with quoting activity, 4.6%, than on days without quoting, 2.2%, with the difference of 2.4pps statistically significant at the 1% level. By contrast, having a quote does not change the likelihood of trading for small trades. Finally, both investment-grade (IG) and high-yield (HY) bonds are more likely to be traded on days with quoting activity, 6.5% (10.8%), than on days without quoting activity, 4.3% (5.8%), with the difference of 2.1pps (4.9pps) significant at the 10% level. The impact of having a quote on the trade probability is greater for HY than IG bonds, although the former are less likely to be quoted than the latter, perhaps because HY bonds are harder to price and trade less than IG bonds.

Additionally, Panel A of Table III shows that the trade-quote relationship is stronger for client-dealer trades than for interdealer trades. This is consistent with dealers not observing each other's quotes. In Panel B, we rerun the exercise from Panel A at the intraday frequency for morning quotes and afternoon trades. Afternoon trading is more likely on days with morning quoting activity, 4.6%, than on days without morning quoting activity, 3.2%, with the difference of 1.4pps once again statistically significant only at the 10% level. Along the trade-size dimension, only afternoon large trades benefit from morning quotes, with the likelihood of trading 1.5pps greater, significant at the 1% level, on days with morning quotes. As in the daily sample, both IG and HY bonds are

[17] We select this trade size threshold to account for order splitting by institutions. Our conclusions are similar when the threshold for identifying large trades is trade size $\geq \$1 million$. The higher threshold makes it more likely that the client is an institution. For our insurance company sample in Section V, the trade size classification is imperfect as the mean insurer trade size is about \$1,000,000, the median is roughly \$200,000, and the 25th percentile is \$50,000.

Table III
Individual Quoting and Trading Activity

The table reports results on the relationship between individual dealers' quoting and trading. We aggregate quotes and trades by each CliQ dealer at the bond-day level. Standard errors are triple-clustered at the dealer, bond, and day levels. Significance levels: *** 1%, ** 5%, * 10%.

Panel A: Probability of trade by dealer d in bond b on day t

Variable	N	All dealer-bond-days	$HasQuote_{d,b,t} = 0$	$HasQuote_{d,b,t} = 1$	Δ (1–0)
$HasTrade_{d,b,t}$	14,031,768	4.8%	4.6%	6.7%	2.1pps*
Trade size ≥$100K		2.4%	2.2%	4.6%	2.4pps***
Trade size <$100K		2.8%	2.8%	2.8%	0.0pps
Client trade		2.5%	2.4%	3.6%	1.2pps*
Interdealer trade		3.3%	3.3%	4.2%	0.9pps
$HasTrade_{d,b,t}$, split by:					
IG rated	11,286,354	4.5%	4.3%	6.5%	2.1pps*
HY rated	2,745,414	5.9%	5.8%	10.8%	4.9pps*

Panel B: Probability of afternoon trade by dealer d in bond b on day t

Variable	N	All Dealer-bond-days	$HasQuote^{AM}_{d,b,t} = 0$	$HasQuote^{AM}_{d,b,t} = 1$	Δ (1–0)
$HasTrade^{PM}_{d,b,t}$	14,031,768	3.3%	3.2%	4.6%	1.4pps*
Trade size ≥$100K		1.6%	1.5%	3.0%	1.5pps***
Trade size <$100K		1.9%	1.9%	2.0%	0.1pps
$HasTrade^{PM}_{d,b,t}$, split by:					
IG rated	11,286,354	3.1%	3.0%	4.5%	1.5pps*
HY rated	2,745,414	4.0%	4.0%	6.9%	2.9pps

more likely to be traded in the afternoon on days with morning quotes, 4.5% (6.9%), than on days without morning quotes, 3.0% (4.0%).

Overall, the results are consistent with the hypothesis that quoting facilitates trading by individual dealers. Importantly, the effect derives from institution-sized trades, consistent with the observation that quotes are sent only to institutional clients, and retail investors having at best indirect access to quoting information via their brokers. We next use multivariate analysis to understand the link between quoting and trading at the dealers' extensive (trade probability) and intensive (log number of trades) margins.

We start by estimating a linear probability model for how the occurrence of trades depends on quote provision. The dependent variable of interest is the indicator $HasTrade_{d,b,t}$, and the explanatory variable of interest is the indicator $HasQuote_{d,b,t}$. Alternatively, we use $LogNumQuotes_{d,b,t}$ as the explanatory variable to capture quoting intensity.[18] Quote competition at the dealer level is best identified by looking at the dealer quoting and trading in a specific bond relative to other dealers. This requires controlling for unobserved factors that jointly cause dealers to quote more bonds and lead to higher volume across all dealers. To control for all time-invariant unobserved heterogeneity in the

[18] The distribution of the number of quotes is right-skewed.

demand and supply of a given bond, we use dealer-bond fixed effects, $\alpha_{d\times b}$ (Paravisini et al., 2015). We also include a full set of dealer-day fixed effects, $\alpha_{d\times t}$, and bond-day fixed effects, $\alpha_{b\times t}$, that control for dealer- and bond-specific evolution in the overall demand and supply of bonds during the sample period. This leads to the following empirical specification with saturated fixed effects:

$$HasTrade_{d,b,t} = \alpha_{d\times b} + \alpha_{d\times t} + \alpha_{b\times t} + \beta \times \begin{Bmatrix} HasQuote_{d,b,t} \\ LogNumQuotes_{d,b,t} \end{Bmatrix} + \\ + \gamma \times HasTrade_{d,b,t-1} + \epsilon_{d,b,t}. \tag{2}$$

Standard errors are triple-clustered at the dealer, bond, and day levels.

Table IV, Panel A, illustrates how an individual dealer's quoting activity relates to trading activity along the extensive margin. Columns (1) through (4) report results for four variants of specification (2), which share the same fixed effects but use the indicator $HasQuote_{d,b,t}$ or $LogNumQuotes_{d,b,t}$ alone in columns (1) and (2) and with the lagged dependent variable $HasTrade_{d,b,t-1}$ to account for persistence due to inventory effects or knowledge of customer demand in columns (3) and (4). The regression coefficient on $HasQuote_{d,b,t}$, β, captures the difference in trade probability when the same dealer is quoting in the same bond.

Column (1) of Panel A shows that the estimate of β is 0.048, which is statistically significant at the 1% level. This estimate is 2.3 times as high as its univariate counterpart from Table III, 0.021. This is because, unlike the change in the unconditional trade probability reported in Table III, β captures the change in the trade probability conditional on saturated fixed effects. The estimate of β in column (3), with the lagged trade indicator included in specification (2), is 0.043 (statistically significant at the 1% level). Economically, these estimates imply that when dealer d quotes in bond b on day t, dealer d's trade probability in the same bond on the same day is 4.8pps (4.3pps) higher.

When $LogNumQuotes_{d,b,t}$ is the explanatory variable instead of $HasQuote_{d,b,t}$, the estimate of β is 0.060 (0.053) in column (2) ((4)), significant at the 1% level. Note that according to Panel C of Table I, most of the variation in $LogNumQuotes_{d,b,t}$ is a change from $\log(0+1)=0$ to $\log(1+1)=0.69$. Therefore, economically, these estimates imply that having a quote versus not having a quote increases the trade probability by 4.1pps (3.7pps).

We next examine the intensive trading margin through the relation between quoting and the number of trades by the quoting dealer. The dependent variable of interest is $LogNumTrades_{d,b,t}$, which is defined as the natural logarithm of the number of trades plus one by dealer d in bond b on day t given that the dealer trades. Similar to specification (2), our baseline specifications for the intensive trading margin are panel regressions with saturated dealer-bond, dealer-day, and bond-day fixed effects. Standard errors are triple-clustered at the dealer, bond, and day levels. Once again, in the last two specifications we include the lagged dependent variable as an additional control to account for inventory management and persistence in customer trading behavior.

Table IV

Dealer's Quoting Activity and Order Flow

The table reports results on the determinants of dealer trades. In Panel A, the dependent variable equals one if dealer d trades bond b on day t, and zero otherwise. In Panel B, the dependent variable equals the natural logarithm of the number of trades plus one by dealer d in bond b on day t. Estimates are obtained from panel regressions with saturated dealer-bond, dealer-day, and bond-day fixed effects. The number of observations before (after) dropping singleton observations is 14,031,768 (13,935,660). Standard errors are triple-clustered at the dealer, bond, and day levels. Significance levels: *** 1%, ** 5%, * 10%.

Panel A: Dealer's trading activity, extensive margin

Dependent Variable	$HasTrade_{d,b,t}$ (1)	$HasTrade_{d,b,t}$ (2)	$HasTrade_{d,b,t}$ (3)	$HasTrade_{d,b,t}$ (4)
$HasQuote_{d,b,t}$	0.048***		0.043***	
	(0.008)		(0.007)	
$LogNumQuotes_{d,b,t}$		0.060***		0.053***
		(0.008)		(0.007)
$HasTrade_{d,b,t-1}$			0.146***	0.145***
			(0.008)	(0.007)
Fixed effects	Saturated	Saturated	Saturated	Saturated
R^2	0.256	0.257	0.272	0.273
N	14,031,768	14,031,768	13,935,660	13,935,660

Panel B: Dealer's trading activity, intensive margin

Dependent variable:	$LogNumTrades_{d,b,t}$ (1)	$LogNumTrades_{d,b,t}$ (2)	$LogNumTrades_{d,b,t}$ (3)	$LogNumTrades_{d,b,t}$ (4)
$HasQuote_{d,b,t}$	0.044***		0.038***	
	(0.008)		(0.007)	
$LogNumQuotes_{d,b,t}$		0.055***		0.048***
		(0.008)		(0.007)
$LogNumTrades_{d,b,t-1}$			0.174***	0.172***
			(0.011)	(0.011)
Fixed effects	Saturated	Saturated	Saturated	Saturated
R^2	0.277	0.278	0.299	0.300
N	14,031,768	14,031,768	13,935,660	13,935,660

Panel B of Table IV has the same layout as Panel A and shows that quoting relates to the dealer's trading activity along the intensive margin. Column (1) of Panel B shows that the estimate of $\beta = 0.044$ is statistically significant at the 1% level. Economically, this result implies that a dealer's number of trades increases by 4.4% when the dealer quotes the bond on the same day. The estimate of $\beta = 0.038$ in column (3), with the lagged trade indicator included in specification (2), suggests that the increase in the number of trades is 3.8%. When $LogNumQuotes_{d,b,t}$ is used as the explanatory variable instead of $HasQuote_{d,b,t}$, its regression coefficient is 0.055 (0.048) in column (2) ((4)), statistically significant at the 1% level. Once again, since most of the variation in $LogNumQuotes_{d,b,t}$ is a change from not having a quote to having a single quote, economically these coefficients imply that having a quote translates into the number of trades by the same dealer being 3.8% (3.3%) higher.

These results show that bonds with quotes trade more than bonds without quotes on the same day by the quoting dealer, even after controlling for past trading. The magnitude of the difference is both economically and statistically significant. To see if the daily quoting and trading relation is purely contemporaneous, in Section II of the Internet Appendix we investigate the lead-lag intraday relation between quotes and trades. Table IA.II reports the results and shows that quotes are more prevalent in the morning than in the afternoon and tend to facilitate afternoon trades by the same dealer in the same bond along both the extensive and intensive margins even after controlling for trade persistence. Next, we use a shift-share instrument to investigate whether quoting increases market-wide trading volume.

C. Do Quotes Increase Trading or Redistribute Order Flow across Dealers?

To explore the net effect of quoting on trading, we analyze whether CliQ dealer market share, trading volume, and aggregate trading volume all rise when CliQ dealers provide quotes. Higher volume across these metrics suggests that quoting by CliQ dealers creates a positive externality, boosting overall market activity, while lower volume implies the opposite.

We define the market-wide quoting activity by all CliQ dealers in bond b on day t as

$$\begin{aligned} QuoteSupply_{b,t}^{ext} &= \textstyle\sum_d \mathrm{w}_{d,b,t} HasQuote_{d,b,t}, \\ QuoteSupply_{b,t}^{int} &= \textstyle\sum_d \mathrm{w}_{d,b,t} NumQuotes_{d,b,t}, \end{aligned} \tag{3}$$

where $\mathrm{w}_{d,b,t}$ defined in (B2) captures the importance of a CliQ dealer's quotes and $HasQuote_{d,b,t}$ and $NumQuotes_{d,b,t}$ captures the extensive and intensive margins of dealer d's bond-specific quoting activity, respectively. Table V, Panel A, summarizes the bond-day level quote supply variables. We find that average $QuoteSupply_{b,t}^{ext/int}$ is 0.07 (0.19) with a standard deviation of 0.19 (0.74).

To investigate daily trading at the bond level, we construct for bond b on day t the number of institutional trades with CliQ dealers, $CliQDealerTrades_{b,t}$, and the total number of institutional trades, $TotalTrades_{b,t} = CliQDealerTrades_{b,t} + non\text{-}CliQDealerTrades_{b,t}$, where $non\text{-}CliQDealerTrades_{b,t}$ is the number of institutional trades with non-CliQ dealers in bond b on date t.[19] We define the market share of CliQ dealers

[19] Both of these variables are not restricted to bonds quoted or traded by CliQ dealers, that is, $CliQDealerTrades_{b,t} = 0$ if CliQ dealers do not trade bond b on date t, thus adding 17 bonds for a total of 1,406,564 bond-day observations.

Table V

Bond-Level Quote Supply and Trading Activity

The table reports results on the relationship between CliQ dealers' aggregate quote supply and trading activity by CliQ dealers and non-CliQ dealers. We focus on institutional-sized trades between dealers and clients, and in falsification tests, we focus on retail-sized trades. We split trades by CliQ dealers versus non-CliQ dealers and collapse all trades at the bond-day level. In columns (1) and (2), we use $QuoteSupply_{b,t}^{ext/int}$ as the explanatory variable in the OLS specification (4). In columns (3) and (4), we use the dealer's share of institutional-sized trades from (B2) as our measure of dealers' importance and the dealer's aggregate daily change in quotes from (B3) as quote supply in bond b on day t to construct our instrument and report the IV second-stage coefficient estimates on the predicted $\widehat{QuoteSupply}_{b,t}^{ext/int}$. Estimates are obtained from panel regressions with bond and day fixed effects. Standard errors are double-clustered at the bond and day levels. Significance levels: *** 1%, ** 5%, * 10%.

Panel A: Quotes and trades at bond-day level, balanced panel

Variable	N	Mean	SD	5%	25%	50%	75%	95%
$QuoteSupply_{b,t}^{ext}$	1,406,564	0.07	0.19	0.00	0.00	0.00	0.00	0.50
$QuoteSupply_{b,t}^{int}$	1,406,564	0.19	0.74	0.00	0.00	0.00	0.00	1.04
$CliQShare_{b,t}$	530,817	0.20	0.34	0.00	0.00	0.00	0.33	1.00
$\log(CliQDealerTrades_{b,t}+1)$	1,406,564	0.11	0.32	0.00	0.00	0.00	0.00	0.69
$\log(TotalTrades_{b,t}+1)$	1,406,564	0.42	0.62	0.00	0.00	0.00	0.69	1.61

Panel B: Impact of dealer quotes on CliQ dealer trading and total trading

	OLS		2SLS	
	(1)	(2)	(3)	(4)
	Dependent variable: $CliQShare_{b,t}$			
$QuoteSupply_{b,t}^{ext}$	0.151***		0.107**	
	(0.004)		(0.050)	
$QuoteSupply_{b,t}^{int}$		0.031***		0.015*
		(0.001)		(0.008)
Fixed effects	Bond, Date	Bond, Date	Bond, Date	Bond, Date
R^2	0.099	0.097	0.007	0.004
N	530,576	530,576	530,576	530,576
	Dependent variable: $\log(CliQDealerTrades_{b,t}+1)$			
$QuoteSupply_{b,t}^{ext}$	0.150***		0.107*	
	(0.004)		(0.062)	
$QuoteSupply_{b,t}^{int}$		0.042***		0.029**
		(0.002)		(0.013)
Fixed effects	Bond, Date	Bond, Date	Bond, Date	Bond, Date
R^2	0.180	0.181	0.007	0.008
N	1,406,564	1,406,564	1,406,564	1,406,564

(*Continued*)

Table V—*Continued*

Dependent variable: $\log(TotalTrades_{b,t}+1)$				
$QuoteSupply^{ext}_{b,t}$	0.201***		0.244*	
	(0.010)		(0.145)	
$QuoteSupply^{int}_{b,t}$		0.051***		0.075**
		(0.003)		(0.030)
Fixed effects	Bond, Date	Bond, Date	Bond, Date	Bond, Date
R^2	0.425	0.425	0.005	0.004
N	1,406,564	1,406,564	1,406,564	1,406,564

as $CliQShare_{b,t} = \frac{CliQDealerTrades_{b,t}}{TotalTrades_{b,t}}$ when $TotalTrades_{b,t}$ is positive.[20] Table V, Panel A, summarizes the bond-day-level trading variables. The average CliQ share is 20%, with a standard deviation of 34%. The average log number of institutional CliQ trades is 0.11 (SD = 0.32) and hence much lower than the average log number of total institutional trades, 0.42 (SD = 0.62).

Our specification to examine the relationship between quote supply and trading is a bond-day regression with bond, α_b, and day, α_t, fixed effects to control for variation explained by bond characteristics and market conditions,

$$\left\{\begin{matrix} CliQShare_{b,t} \\ \log(CliQDealerTrades_{b,t}+1) \\ \log(TotalTrades_{b,t}+1) \end{matrix}\right\} = \alpha_b + \alpha_t + \beta \times QuoteSupply^{ext/int}_{b,t} + \epsilon_{b,t}. \quad (4)$$

To explain bond-level trading activity through $QuoteSupply^{ext/int}_{b,t}$, we must address the issue of endogeneity that arises from unobserved common shocks affecting both a bond's trading volume and dealers' quoting incentives. These shocks can lead to simultaneous determination via the weights w and the aggregate quoting across all dealers. This issue can result from reverse causality, where dealers, having information about clients' trading interests, adjust their quotes accordingly, or from dealers who quote more actively in bonds they wish to trade. To mitigate this endogeneity at the dealer-bond-day level, we use the daily change in each dealer's quoting across all bonds as a shock to quote supply, $q^{ext}_{d,t} = \frac{1}{B}\sum_{b=1}^{B}(HasQuote_{d,b,t} - HasQuote_{d,b,t-1})$. To leverage the cross-section of bonds, we incorporate the lagged weights $\mathrm{w}_{d,b,t-l}$, reflecting the past institutional share of trading by each dealer in each bond, as these weights indicate the relative importance of dealers in specific bonds. This method follows the frameworks of Goldsmith-Pinkham, Sorkin, and Swift (2020) and Borusyak, Hull, and Jaravel (2022, 2024), constructing shift-share instruments $QuoteSupply^{ext/int,IV}_{b,t}$ given in (B4) as weighted averages of market-wide shocks to quoting rates ("shift"), with weights based on past institutional trading activity ("shares"). This approach measures the bond-specific

[20] Since $CliQShare_{b,t}$ is undefined when there is no trade, the number of observations is reduced to 530,576.

effect of dealer quoting without relying on contemporaneous dealer-bond-day information, thus avoiding simultaneity concerns. Appendix B details our instrument construction and the necessary exclusion restrictions.

Table V, Panel B, presents the OLS (columns (1) and (2)) and shift-share 2SLS (columns (3) to (4)) results from specification (4) for the market share of trades by CliQ dealers, trades by CliQ dealers, and all trades. The β coefficient is significantly positive in all specifications, suggesting that quoting increases CliQ dealers' market share and trading volume. Panel B demonstrates that the CliQ market share of trades is higher when they quote the bond. Economically, a 1-SD (0.19) increase in $QuoteSupply^{ext}_{b,t}$ results in an additional 2.9pps (2.0pps) (OLS (IV)) CliQ dealers' market share on the given bond-day. Similarly, a 1-SD (0.74) increase in $QuoteSupply^{int}_{b,t}$ results in an additional 2.3pps (1.1pps) (OLS (IV)) CliQ dealers' market share. This evidence is consistent with clients shifting trading to CliQ dealers when they quote and/or CliQ dealers' quotes attracting clients to trade who would not have traded otherwise. Consistent with the CliQ dealers' market share results, bond-level trading activity by all CliQ dealers combined is larger when the bond is quoted and when the quote supply is larger. Economically, a 1-SD increase in $QuoteSupply^{ext}_{b,t}$ results in a 2.9% (2.0%) (OLS (IV)) increase in CliQ dealer trading activity. In addition, a 1-SD increase in $QuoteSupply^{int}_{b,t}$ results in a 3.1% (2.1%) (OLS (IV)) increase in the number of trades by CliQ dealers on the given bond-day.

Panel B of Table V reports that the total number of trades increases more than the CliQ dealer number of trades when the bond is quoted on that day. The coefficients on the extensive and intensive margins of quote supply equal 0.201 (0.244) and 0.051 (0.075) (OLS (IV)), respectively, and are statistically significant at the 10% (5%) level. Economically, a 1-SD increase in $QuoteSupply^{ext}_{b,t}$ increases the total number of trades on the bond-day by 3.9% (4.7%). Similarly, a 1-SD increase in $QuoteSupply^{int}_{b,t}$ increases the total number of trades on the bond-day by 3.8% (5.5%). These numbers are larger than the corresponding increase in CliQ dealer trades, suggesting that quoting stimulates trading by CliQ and non-CliQ dealers.[21]

In summary, consistent across specifications, more active quoting by CliQ dealers leads to a higher share of trades by CliQ dealers, more trading by CliQ dealers, and higher aggregate trading activity. Thus, quote competition is not a "zero-sum game" between dealers whereby one dealer wins order flow at the expense of another, but rather overall trading activity benefits from dealers' quoting activity, which is important for investor welfare.[22]

[21] Even though the regression coefficients on $QuoteSupply^{ext}_{b,t}$ are greater for total trades (0.201 (0.244) for OLS (IV)) than for CliQ trades (0.150 (0.107) for OLS (IV)), the CliQ share of trades increases with $QuoteSupply^{ext/int}_{b,t}$. This is because these regressions have different baselines. After all, there are more trades overall than CliQ trades (see Panel A of Table V). For instance, using the mean values for baselines, we can write the expression for the CliQ trade share as $CliQShare_{b,t} = (e^{0.11+0.15*QuoteSupply^{ext}_{b,t}} - 1)/(e^{0.42+0.20*QuoteSupply^{ext}_{b,t}} - 1)$ in the OLS case, and it increases in $QuoteSupply^{ext}_{b,t} \in [0, 1]$.

[22] Table B.I documents first-stage IV results for the relationship between CliQ dealers' quote supply and trading activity. We perform underidentification tests using the Anderson LM statistic

IV. Quoting and Client Execution Costs

The previous section establishes that quoting matters for trading both at the individual dealer level and market-wide. In this section we investigate whether quoting improves clients' execution quality, how quote aggressiveness affects client execution quality, which quotes are firm, and whether quotes lead dealers to improve prices in bilateral negotiations.

A. Measuring Client Execution Quality

To examine the relationship between quotes and trade prices, we explore the link between quoting, quote quality, and client execution quality. We define client execution quality in terms of the transaction cost incurred by the client during trade $i = 1, \ldots, N_{d,b,t}$ with dealer d in bond b on date t. To compute client execution quality, we compare the trade price $Price_{d,b,t,i}$ to a reference price at the time of the trade, denoted by $BenchPrice_{b,t,i}$

$$ClientExecutionQuality_{d,b,t,i} = \begin{cases} Price_{d,b,t,i} - BenchPrice_{b,t,i}, & \text{for dealer buy trades,} \\ BenchPrice_{b,t,i} - Price_{d,b,t,i}, & \text{for dealer sell trades.} \end{cases} \tag{5}$$

We use two alternative proxies for the reference price $BenchPrice_{b,t,i}$. In our base case, we define $BenchPrice_{b,t,i}$ as the Bank of America Merrill Lynch (BAML) end-of-day quote on the same bond the day before the transaction. Alternatively, following Hendershott and Madhavan (2015), we define $BenchPrice_{b,t,i}$ as the price on the last interdealer trade before the transaction and require the last interdealer trade to be no more than three calendar days before the trade.[23]

and weak identification tests based on the Cragg-Donald Wald F-statistic and Stock-Yogo critical values. All IV regressions yield significant results for both tests, indicating the validity of the approach. Table B.II presents two falsification tests that we construct as proposed by Borusyak, Hull, and Jaravel (2024) and Danieli et al. (2024). In pre-trend tests, we replace the dependent variable by its 20-day lag to check if the quote supply is correlated with past trading activity, which would violate the exclusion restriction and confound the 2SLS estimates. In placebo tests, we replace the dependent variable with bond-level trading that is not expected to be causally affected by quoting. Because quotes are sent to institutional clients, we choose bond-level trading in small sizes, defined as those with a par value less than $100K. Across all panels, the results are economically and statistically insignificant when we lag the dependent variable. The placebo tests are also economically and statistically insignificant. Overall, the identification and falsification tests support the validity of our instrument.

[23] Hendershott, Li, Livdan, and Schürhoff (2020) provide a detailed description of BAML quotes. Because BAML end-of-day quotes are available only for the bid side, we add 15bps (equal to half of the sample average effective spread) to the benchmark level to make the bid- and ask-sides comparable. When the dealer has multiple trades in a bond, the interdealer benchmark may vary over the day. While we use a benchmark price specific to the transaction, our notation suppresses this for ease of notation. The requirement for a benchmark price drops the number of trades with execution quality defined from 884,030 trades to 417,512 and 452,235, respectively.

Client execution quality, as defined in expression (5), is essentially the negative of trading costs. A higher number indicates lower transaction costs and, therefore, better client execution quality. While two alternate benchmarks are used to construct $ClientExecutionQuality_{d,b,t,i}$, for ease of exposition we report results only for the benchmark based on the BAML end-of-day quote; Table IA.V in the Internet Appendix reports results for the alternate benchmark.

Table VI, Panel A, provides descriptive statistics for $ClientExecutionQuality_{d,b,t,i}$. The average (median) client execution quality is −37bps (−15bps) when using the BAML quote as a benchmark, and it is −29bps (−8bps) when using the interdealer benchmark. The standard deviation of 1.75% implies a large dispersion in execution quality. Smaller trades receive, on average, worse execution quality than larger trades, −54bps versus −24bps, respectively. The execution quality for IG bonds is slightly better on average than the execution quality for speculative-grade bonds, −36bps versus −40bps, respectively. Overall, consistent with prior literature (e.g., Edwards et al., 2007), execution quality exhibits significant heterogeneity across different trade sizes and bond credit ratings.

B. Impact of Dealer Quotes on Execution Quality

We proceed by using multivariate analysis to link execution quality to quoting using the following specification at the trade level (trades are indexed $i = 1, \ldots, N_{d,b,t}$ with dealer d in bond b on date t), with saturated dealer-bond, dealer-day, and bond-day fixed effects:

$$\begin{aligned} ClientExecutionQuality_{d,b,t,i} &= \alpha_{d\times b} + \alpha_{d\times t} + \alpha_{b\times t} + \\ &+ \beta \times \begin{Bmatrix} HasQuote_{d,b,t} \\ LogNumQuotes_{d,b,t} \end{Bmatrix} + \epsilon_{d,b,t,i}. \end{aligned} \tag{6}$$

In specification (6), the coefficient β captures the degree to which a dealer's quotes relate to the prices at which the dealer executes a trade.

Panel B of Table VI presents results from specification (6) on how a dealer's quoting relates to client execution quality. Results are reported for three specifications. In column (1), the coefficient $\beta = 0.069$ is positive and statistically significant at the 5% level, suggesting that clients obtain about 7bps better executions when they trade with a dealer posting quotes. Columns (2) and (3) show that more quotes do not incrementally improve execution quality. Overall, the presence of a quote improves client execution quality by 7bps to 9bps in this base specification. Given average half-spreads of 37bps, this is a significant improvement.

We next examine, analogously to Table V, the relationship between CliQ dealers' quote supply and bond-level client execution quality. We define bond-level client execution quality as the average across all institution-sized trades

Table VI

Client Execution Quality and Dealer Quotes

Panel A reports descriptive statistics on client execution quality. Panel B documents the relationship between CliQ dealers' quotes and trade-level client execution quality. Estimates are obtained from panel regressions with saturated dealer-bond, dealer-day, and bond-day fixed effects. Standard errors are triple-clustered at the dealer, bond, and day levels. Panel C documents the relationship between CliQ dealers' quote supply and bond-level client execution quality. We split trades by CliQ dealers versus non-CliQ dealers and collapse all trades at the bond-day level. Estimates are obtained from 2SLS and OLS regressions with bond and day fixed effects. Standard errors are double-clustered at the bond and day levels. Significance levels: *** 1%, ** 5%, * 10%.

Panel A: Descriptive statistics on $ClientExecutionQuality_{d,b,t,i}$

Variable	N	Mean	SD	5%	25%	50%	75%	95%
$ClientExecutionQuality_{d,b,t,i}$ ($):								
BAML benchmark	417,512	−0.37	1.75	−2.87	−0.64	−0.15	0.13	1.43
Interdealer benchmark	452,235	−0.29	1.18	−2.00	−0.46	−0.08	0.03	0.81
$ClientExecutionQuality_{d,b,t,i}$, split by:								
Trade size ≥$100K	233,106	−0.24	1.79	−2.72	−0.53	−0.12	0.19	1.81
Trade size <$100K	184,406	−0.54	1.67	−3.02	−0.81	−0.19	0.07	0.85
IG rated	303,876	−0.36	1.69	−2.71	−0.55	−0.13	0.12	1.16
HY rated	113,636	−0.40	1.88	−3.18	−0.88	−0.22	0.16	2.09

Panel B: Impact of dealer quotes on trade-level client execution quality

	Dependent variable: $ClientExecutionQuality_{d,b,t,i}$		
	(1)	(2)	(3)
$HasQuote_{d,b,t}$	0.069**		0.089*
	(0.029)		(0.045)
$LogNumQuotes_{d,b,t}$		0.035	−0.020
		(0.024)	(0.036)
Fixed effects	Saturated	Saturated	Saturated
R^2	0.489	0.489	0.489
N	417,512	417,512	417,512

Panel C: Impact of dealer quotes on bond-level client execution quality

	Dependent variable: $BondExecutionQuality_{b,t}$			
	OLS		2SLS	
	(1)	(2)	(3)	(4)
$QuoteSupply^{ext}_{b,t}$	0.066***		0.794**	
	(0.024)		(0.386)	
$QuoteSupply^{int}_{b,t}$		0.008**		0.101**
		(0.003)		(0.044)
Fixed effects	Bond, Date	Bond, Date	Bond, Date	Bond, Date
R^2	0.103	0.103	−0.009	−0.004
N	154,528	154,528	154,528	154,528

across the CliQ dealers,

$$BondExecutionQuality_{b,t} = \frac{1}{\sum_{d=1}^{D} N_{d,b,t}} \sum_{d=1}^{D} \sum_{i=1}^{N_{d,b,t}} ClientExecutionQuality_{d,b,t,i}, \tag{7}$$

where D is the number of CliQ dealers and $N_{d,b,t}$ is the number of institution-sized trades by dealer d in bond b on day t.[24]

Table VI, Panel C, reports OLS and 2SLS results for (7) as the dependent variable and has the same layout as Table V. The key findings from Panel C are that $QuoteSupply^{ext}_{b,t}$, representing quote supply along the extensive margin, improves bond-level execution quality in both OLS and IV estimations. Bond-level execution quality improves when the bond is quoted and increases further when quote supply is larger. A 1-SD (0.19) increase in extensive quote supply lowers trading costs by 15.1bps. Similarly, $QuoteSupply^{int}_{b,t}$, representing quote supply along the intensive margin, improves bond-level execution quality in both OLS and IV estimations. A 1-SD (0.74) increase in intensive quote supply lowers trading costs by 7.5bps.[25] For comparison, the OLS economic magnitudes are smaller at 1.3bps (0.6bps) along the extensive (intensive) margin, suggesting they are attenuated relative to the IV estimates.

Overall, the findings suggest that CliQ dealers' quote supply positively influences bond-level execution quality, highlighting the importance of quote competition in enhancing execution quality in the corporate bond market.

C. Quote Quality and Client Execution Quality

We expect that not only the presence of a quote but also the quality or aggressiveness of a quote matters for client execution quality. To capture the quality of a dealer's quoted prices relative to other dealers in bond b on day t, we compare the dealer's ask and bid quotes to their respective benchmarks, $BenchAskQuote_{b,t}$ and $BenchBidQuote_{b,t}$. The benchmark quotes are obtained by aggregating the quotes of all dealers in bond b on day t. We use two alternative benchmarks in the empirical implementation: the average dealer ask or bid quotes (our baseline quote quality measure) and the best offer (BO) or best bid (BB).

[24] We split trades by CliQ dealers versus non-CliQ dealers and aggregate all trades at the bond-day level. We use the same shift-share IV design as in Appendix B to address endogeneity, with the lagged share of institutional-sized trades as shares and the dealer's aggregate quotes serving as a shifter. The regression includes bond and day fixed effects to control for time and bond-specific characteristics. Standard errors are double-clustered at the bond and day levels. The regressions yield significant results for the underidentification LM-test and weak identification F-test, indicating the validity of the IV approach (see Table B.I, Panel B).

[25] For these computations, we use the unconditional standard deviation from Table V, Panel A, and not the selected one based on a trade occurring. Results are similar if we use the standard deviation of quote supply restricted to the sample of trades.

With these benchmark quotes at hand, we define the bid and ask quote quality of dealer d in bond b on day t as

$$QuoteQuality_{d,b,t} = \begin{cases} BidQuoteQuality_{d,b,t} = BidQuote_{d,b,t} - BenchBidQuote_{b,t}, \\ AskQuoteQuality_{d,b,t} = BenchAskQuote_{b,t} - AskQuote_{d,b,t}, \end{cases} \tag{8}$$

where $BidQuote_{d,b,t}$ and $AskQuote_{d,b,t}$ are the dealer d quotes to buy and sell, respectively. By construction, $QuoteQuality_{d,b,t}$ is a measure of the price aggressiveness of dealer d's quotes relative to the respective benchmark quotes across all CliQ dealers. A positive $QuoteQuality_{d,b,t}$ means that the dealer d's quote is at a better price than the benchmark quote in bond b on day t. When we examine how quote quality relates to order flow, we average $BidQuoteQuality_{d,b,t}$ and $AskQuoteQuality_{d,b,t}$ from the same dealer on the same day. When the dealer provides multiple quotes on the same day, we average across quotes on the same side of the market. When one side is missing, we use the side that is not missing. We set $QuoteQuality_{d,b,t}$ to zero when $BenchBidQuote_{b,t}$/$BenchAskQuote_{b,t}$ are undefined or when the dealer does not provide a quote on a bond day.

Table VII, Panel A, shows basic descriptive statistics for $QuoteQuality_{d,b,t}$ across all quotes in our sample. The average and median quote quality are 1bps and 0bps (standard deviation 15bps) when using the average quote as a benchmark, and -14bps and 0bps, compared to a standard deviation of 28bps, when using the best quote as a benchmark.

We link execution quality to quote quality at the trade level using panel regressions with saturated dealer-bond, dealer-day, and bond-day fixed effects:

$$ClientExecutionQuality_{d,b,t,i} = \alpha_{d\times b} + \alpha_{d\times t} + \alpha_{b\times t} + \beta \times QuoteQuality_{d,b,t} + \\ + \delta \times HasQuote_{d,b,t} + \epsilon_{d,b,t,i}, \tag{9}$$

for all client trades $i = 1, \dots, N_{d,b,t}$ with dealer d in bond b on date t. In specification (9), the coefficients β measure the sensitivity of prices at which the dealer executes a trade to the dealer's quote quality.[26] If $\beta = 0$, then client execution quality is unrelated to quote quality and quotes are not meaningful for prices, and hence all of the execution quality comes from price improvement. The hypothesis $H_0 : \beta = 0$ thus tests whether quotes affect client execution quality. If $\beta = 1$, then quotes are firm, and all of the execution quality comes from quote quality. The hypothesis $H_0 : \beta = 1$ thus tests whether quotes are firm. If $\beta > 1$, dealers indicate trade interest with good quotes and offer even

[26] Section III of the Internet Appendix uses a similar specification to confirm that both the aggressiveness of quotes and trade size are also related to the propensity to trade. The findings suggest that dealers use quotes to compete for order flow and advertise their willingness to trade. Dealers with better quotes trade more along the extensive and intensive margin at the dealer-bond-day level. The relation of quote *quantity* and *quality* to order flow is concentrated primarily in large trades. For small trades, having a quote is associated with a higher trade probability, and a higher quoting frequency is associated with a greater trading activity; however, for small trades, quote quality is related to neither trade probability nor trading intensity.

Table VII

Client Execution Quality and Quote Quality

The table reports results on the relationship between client execution quality and quote quality. Panel A is restricted to the sample in which client execution quality is not missing and there is at least a quote. Estimates are obtained from panel regressions with saturated dealer-bond, dealer-day, and bond-day fixed effects. Standard errors are triple-clustered at the dealer, bond, and day levels. Significance levels: *** 1%, ** 5%, * 10%.

Panel A: Descriptive statistics on $QuoteQuality_{d,b,t}$

Variable	N	Mean	SD	5%	25%	50%	75%	95%
$QuoteQuality_{d,b,t}$ ($):								
BenchQuote = Average quote	49,727	0.01	0.15	−0.21	0.00	0.00	0.02	0.29
BenchQuote = Best quote	49,727	−0.14	0.28	−0.81	−0.14	0.00	0.00	0.00

Panel B: Impact of dealer's quote quality on client execution quality

	Dependent variable: $ClientExecutionQuality_{d,b,t,i}$			
Sample:	All days (1)	$HasQuote_{d,b,t}$=1 (2)	All days (3)	$HasQuote_{d,b,t}$=1 (4)
$QuoteQuality_{d,b,t}$	0.838***	1.102***		
	(0.180)	(0.216)		
$QuoteQuality^{+}_{d,b,t}$			1.202***	1.389***
			(0.199)	(0.166)
$QuoteQuality^{-}_{d,b,t}$			0.385	0.730
			(0.349)	(0.627)
$HasQuote_{d,b,t}$	0.066**		0.037	
	(0.030)		(0.030)	
Fixed effects	Saturated	Saturated	Saturated	Saturated
R^2	0.489	0.418	0.489	0.418
N	417,512	49,727	417,512	49,727

better prices via negotiation. If $\beta \in (0, 1)$, dealers also indicate trade interest with good quotes, but not all quote quality is passed through to execution quality.

Panel B of Table VII documents results from specification (9) on how a dealer's quote quality relates to client execution quality. Results are reported both for the pooled sample (columns (1) and (3)) and conditional on quoting (columns (2) and (4)). In column (1) ((2)), the coefficient $\beta = 0.838$ (1.102) is positive and significant, suggesting that clients obtain better executions when they trade with a dealer posting better quotes. The results further show that 84% to 110% of quote quality is passed through to execution quality. Finally, the coefficient $\delta = 0.066$ (column (1)) suggests that the presence of a quote increases client execution quality by 4bps to 7bps.

Good quotes are firm, bad quotes get improved: Dealers posting bad quotes can improve the quoted prices during bilateral negotiations with their clients. We therefore split $QuoteQuality_{d,b,t}$ defined in (8) into its positive,

$QuoteQuality^{+}_{d,b,t}$, and negative, $QuoteQuality^{-}_{d,b,t}$, parts:

$$QuoteQuality_{d,b,t} = QuoteQuality^{+}_{d,b,t} \times \mathbb{1}\{QuoteQuality_{d,b,t} \geq 0\} + \\ + QuoteQuality^{-}_{d,b,t} \times \mathbb{1}\{QuoteQuality_{d,b,t} < 0\},$$

where $\mathbb{1}\{\cdot\}$ is the indicator function, and $QuoteQuality^{+/-}_{d,b,t}$ captures quotes that are better or worse than the benchmark quote. We use the following specification to estimate how good versus bad quote quality relates to execution quality:

$$ClientExecutionQuality_{d,b,t,i} = \alpha_{d\times b} + \alpha_{d\times t} + \alpha_{b\times t} + \beta^{+} \times QuoteQuality^{+}_{d,b,t} + \\ + \beta^{-} \times QuoteQuality^{-}_{d,b,t} + \delta \times HasQuote_{d,b,t} + \epsilon_{d,b,t,i}. \tag{10}$$

In specification (10), similar to specification (9), the regression coefficients β^{+} and β^{-} measure the sensitivity of prices at which the dealer executes a trade to the dealer's quote quality. The hypothesis $H_0 : \beta^{+} = \beta^{-} = 0$ tests for whether quotes affect client execution quality, while the hypothesis $H_0 : \beta^{+} = \beta^{-} = 1$ tests for whether quotes are firm. Asymmetry between β^{+} and β^{-} indicates that dealers respond differently to good and bad quotes. For positive quote quality, $\beta^{+} > 1$ implies that dealers indicate trade interest with good quotes and offer even better prices via negotiation. The case $\beta^{+} \in (0, 1)$ implies that dealers also indicate trade interest with good quotes, but not all quote quality is passed through to execution quality. For negative quote quality, $\beta^{-} < 0$ implies that quotes are not entirely firm and dealers improve execution quality via price improvement in bilateral negotiations. In this case, price improvement compensates more than one-to-one for bad quotes. In the limit when $\beta^{-} = 0$, client execution quality is determined entirely by good quotes. The case $\beta^{-} > 0$ would mean that investors trade with dealers despite their poor quote quality, and price improvement only partially offsets dealers' bad quotes.

The results in Table VII point to a striking difference between the effect of high- and low-quality quotes on execution quality. For pooled trades (conditional on quoting), the statistically significant coefficient $\beta^{+} = 1.202$ (1.389) means that a 1-SD increase in quote quality (15bps) results in an 18bps improvement in execution quality. The statistically insignificant coefficient $\beta^{-} = 0.385$ (0.730) indicates that inferior quotes do not affect execution quality, as dealers partially compensate for bad quotes via price improvement. Finally, the coefficient $\delta = 0.037$ on $HasQuote_{d,b,t}$ means that the average execution quality is 4bps higher on bond days when dealer d quotes bond b versus days when not quoting that bond, although this coefficient is not statistically significant.

Table IA.IV explores the importance of trade size using specification (9) split by trade size. The results suggest that, even for institutional clients who trade in large sizes, quotes are meaningful but not firm. For clients trading in small sizes, the pass-through is not statistically significant. Table IA.V provides robustness checks by examining alternative specifications for client execution quality and dealer quote quality. The findings are in line with our base specification.

Overall, we find that quotes matter for trade execution quality, and the competition between dealers on quotes improves trade outcomes for investors. The aggressiveness of quotes by the transacting dealer translates into better prices for large trades. However, quote quality does not translate into better execution quality for small trades, presumably because investors in small trade sizes do not access high-quality quotes.

D. Imperfect Quote Competition

To better understand the firmness of dealer quotes and the conditions under which they are not firm, we examine the relationship between trade prices and the best quoted prices, dealers' price improvements, and the role of quote presence and quality in trade execution.

Trade-throughs: Table VIII, Panel A, reports the frequency of trade-through trades executed at prices worse than the best dealer quote from the past hour.[27] Consistent with our earlier findings on trade size, quotes play a larger role in large trades, which are significantly less likely to execute at inferior prices. The best quoting dealer executes trades at worse prices than the best quote 17% of the time, compared to roughly 31% (33%) for other CliQ (non-CliQ) dealers. Trade-throughs are more frequent for small trades: the best-quoting dealer (other CliQ dealers) executes at worse prices 16% (25%) of the time for large trades and 23% (40%) for small trades.

Overall, trade prices frequently deviate from the best quote, and transactions often involve dealers who do not provide the best quote. While Table VIII, Panel A, highlights the imperfections in quote competition, it also shows that better quotes lead to better trade prices, which helps explain why dealers posting superior quotes attract more order flow. However, our findings suggest that this mechanism operates imperfectly, with best-quoting dealers not always executing trades at the best price.

Price improvement over inferior quotes: Quoted prices differ from traded prices. Here we analyze whether dealers trade at better or worse prices than their own quotes. Dealer quotes can affect client execution quality for at least three reasons. First, dealers compete for order flow by updating their quotes over the benchmark price. Second, dealers attract order flow by posting more aggressive quotes than their peers, as captured by quote quality. And third, dealers can improve bilaterally negotiated prices to the extent that quotes are not entirely firm.

To check if and when clients can negotiate better prices than dealers' quotes, we construct a price improvement measure that captures the improvement in the trade price over the last available quote. We first match each trade to

[27] The trade-through rates we report are lower than in Harris (2015), where trade-through rates are 43% when defined based on all bids and offers that are reported to be standing.

Table VIII

Trade-Throughs and Price Improvement over Quote

The table reports results on trade-throughs and the price improvement over the dealer's quote defined in (11) at the dealer-bond-day level. Panel A reports the fraction of trades that occur at a price worse than the best dealer quote that is less than one hour old. Fractions are calculated by small (< \$100K) and large (≥ \$100K) trade sizes for the best-quoting dealer, CliQ dealers who are not quoting or quoting at an inferior price, and non-CliQ dealers. In Panels B and C, we use the last quote provided by the dealer as the relevant dealer quote. Trades not preceded by a quote from the same dealer in the same bond on the same day are eliminated since we cannot compute price improvement. For Panel C, we further restrict the sample to cases in which the trading dealer has at least a quote and at least one other dealer provides a quote.

Panel A: Trade occurs at price worse than best quote

Sample:	Best Quote Dealer	CliQ Dealer, Not Best Quote	Non-CliQ Dealer
$Trade-through_{d,b,t,i}$ (%/100)	0.17	0.31	0.33
Trade size ≥ \$100K	0.16	0.25	0.26
Trade size < \$100K	0.23	0.40	0.39

Panel B: Descriptive statistics on $PriceImprovement_{d,b,t,i}$

Variable	N	Mean	SD	5%	25%	50%	75%	95%
$PriceImprovement_{d,b,t,i}$ (\$)	40,844	0.07	0.75	−0.75	−0.04	0.03	0.19	0.89
Trade size ≥\$100K	31,567	0.12	0.71	−0.45	−0.02	0.04	0.21	0.95
Trade size < \$100K	9,277	−0.11	0.83	−1.63	−0.12	0.00	0.12	0.74
$PriceImprovement_{d,b,t,i}$ split by:								
IG rated	37,516	0.07	0.74	−0.72	−0.04	0.03	0.18	0.88
HY rated	3,328	0.08	0.75	−1.09	−0.03	0.05	0.25	1.03

Panel C: $PriceImprovement_{d,b,t,i}$ split by quote quality

Quartile of $QuoteQuality_{d,b,t}$	N	Mean	SD	5%	25%	50%	75%	95%
Low	8,230	0.18	0.87	−0.81	−0.02	0.09	0.34	1.27
2	6,277	0.04	0.60	−0.44	−0.03	0.02	0.11	0.52
3	8,012	0.05	0.36	−0.20	−0.02	0.02	0.10	0.43
High	8,654	−0.01	0.83	−1.29	−0.12	0.02	0.21	0.86

the last quote before the trade by the same dealer on the same day for the same bond on the same side of the trade. We require that either $BidQuote_{d,b,t,i}$ or $AskQuote_{d,b,t,i}$ arrives before the trade. Roughly 8% of all trades can be matched to such a quote. For each quote-trade pair i (here, quote-trade pairs are indexed by $i = 1, \ldots, N_{d,b,t}$, with dealer d in bond b on date t), we follow Petersen and Fialkowski (1994) and define $PriceImprovement_{d,b,t,i}$ based on whether it is a dealer sell or buy:

$$PriceImprovement_{d,b,t,i} = \begin{cases} Price_{d,b,t,i} - BidQuote_{d,b,t,i}, & \text{for dealer buy trades,} \\ AskQuote_{d,b,t,i} - Price_{d,b,t,i}, & \text{for dealer sell trades.} \end{cases} \tag{11}$$

Price improvement is one potential reason why dealers' quotes are not entirely firm. A positive $PriceImprovement_{d,b,t,i}$ would mean the client executed at a price better than the last available quote.

Panel B of Table VIII reports price improvement overall and by trade size, credit rating, and quote quality. The sample average (median) price improvement across all trades is 7bps (3bps), with a standard deviation of 75bps. The price improvement is economically significant compared to the average execution quality of −37bps. For some trades, the price improvement can be as high (low) as 89bps (−75bps). Most of the price improvement occurs for large trades. The average (median) price improvement for large trades is 12bps (4bps), with a standard deviation of 71bps, while for small trades it is −11bps (0bps), with a standard deviation of 83bps. This is not surprising since retail investors, who are mostly responsible for small trades, are unlikely to receive quotes. By contrast, institutions are more likely to receive quotes and thus also benefit from quote competition in the form of price improvement. IG and HY bonds have similar price improvements. The average (median) price improvement for IG bonds is 7bps (3bps), with a standard deviation of 74bps, while for HY bonds it is 8bps (5bps), with a standard deviation of 75bps.

Panel C of Table VIII splits $PriceImprovement_{d,b,t,i}$ into quartiles by *QuoteQuality*.[28] The univariate sort on the transacting dealer's quote quality shows that better quality quotes are associated with less improvement of the transaction price over the quoted price. This holds at the mean, median, and right tail. Dealers thus improve their negotiated prices when they offer poor-quality quotes (18bps (9bps) at the mean (median) for quartile 1). In contrast, dealers with the most attractive quotes provide little to no price improvement (−1bps (2bps) at the mean (median) for quartile 4).

Overall, price improvement is particularly high for large trades and when a dealer's quote quality is low. These results further support our findings from the previous section. Dealers with good quotes improve transaction prices over their quotes less than dealers with bad quotes. This is consistent with the coefficient β^+ in specification (9) being greater than one and statistically significant, and the coefficient β^- in the same specification being insignificant. In the next section, we investigate whether quoting improves clients' access to markets by altering their relations with bond dealers.

V. Do Quotes Substitute for Relationships and Improve Market Access?

Insurance companies often maintain long-term relationships with a small number of bond dealers, and these client-dealer relationships significantly impact execution quality (e.g., Hendershott et al., 2020). The access-to-market channel of quoting discussed in Section II suggests that dealer quotes can partially substitute for these relationships. Dealer quotes provide transparent pricing information, allowing investors to compare prices without relying

[28] The unequal number of observations in each quartile is due to overdispersion at zero.

Table IX

Quoting and Trading with (Non)Relationship Dealers

Panel A reports ex ante quote rates across relationship and nonrelationship CliQ dealers. For each insurer trade, all possible counterparties (relationship and nonrelationship dealers) are considered. Panel B reports quote rates depending on whether insurers choose to trade with relationship or nonrelationship CliQ dealers. The sample consists of all trades between insurers and CliQ dealers. Relationship dealers are defined as those in the top half of counterparties of a given insurer from January 1, 2018, to September 30, 2019.

Panel A: Ex ante quote rates (across all possible dealer counterparties for each insurer trade)

Variable	Total	Quote Rate
Relationship dealers ($RDQuote_{c,b,t}$)	1,375,309	4.4%
Nonrelationship dealers ($NRDQuote_{c,b,t}$)	1,054,520	3.6%

Panel B: Trades and quote rates (across all insurer trades)

Sample:	Total	Quoted	Not Quoted	Quote Rate
All trades	107,523	11,797	95,726	11.0%
Relationship dealers ($RDTrade_{c,d,b,t,i}$)	94,448	9,041	85,407	9.6%
Nonrelationship dealers ($NRDTrade_{c,d,b,t,i}$)	13,075	2,756	10,319	21.1%

solely on established relationships. This transparency reduces the necessity of relationships for obtaining pricing information. Additionally, quotes allow investors broader market access, allowing them to trade with any dealer offering competitive prices, thus reducing dependence on specific relationships.[29]

A. Quoting by Relationship and Nonrelationship Dealers

To explore the access-to-market channel of quotes, we collect additional data on insurance company transactions in corporate bonds with dealers to test whether dealer quotes complement or substitute for client relationships and improve market access for investors with or without strong dealer relationships. These time-stamped transactions are part of the Refinitiv eMaxx bond holdings data. Notably, the data report both holdings and trades. For each trade, we collect the data that reveal the identities of both counterparties in each eMaxx trade. We filter the data to exclude all trades on bonds that never appeared in our CliQ sample. The sample for analyzing client-dealer relationships includes all trades between insurer clients and CliQ dealers. Table IX, Panel A, shows 107,523 insurer trades with CliQ dealers in our sample period.

[29] From the dealers' perspective, quote competition incentivizes dealers to offer better prices and enhance their services to attract trading volume and new clients. This competition benefits dealers by increasing activity and benefits investors by delivering better execution prices and tighter bid-ask spreads, reducing the need for relationships to secure favorable terms. However, while dealer quotes can partially substitute for certain aspects of relationships, these relationships still play a significant role in the corporate bond market.

For each insurer client c, we classify dealers into two categories based on their trading activity with the insurer from January 1, 2018, to September 30, 2019. We define a dealer d as a relationship dealer for insurer c if d is among the top 50% of counterparties ranked by the number of trades executed with insurer c during the specified period. All other dealers not classified as relationship dealers for insurer c are considered nonrelationship dealers. For insurer c, relationship dealers are denoted by RD_c and nonrelationship dealers by NRD_c.

We measure the quoting activity of relationship dealers and nonrelationship dealers through the average quoting activity of relationship and nonrelationship dealers in bond b on day t, $RDQuote_{c,b,t}$ and $NRDQuote_{c,b,t}$, respectively. Table IX, Panel A, provides summary statistics showing that relationship dealers quote on average 4.4% of the time while nonrelationship dealers quote on average 3.6% of the time. It is not surprising that these ex ante quote rates are similar since dealers quote to all clients, and a relationship dealer to some insurers may be a nonrelationship dealer to others.

Table IX, Panel B, relates trades to dealers' quote activity. A total of 11,797 (11.0%) trades have a quote by the transacting dealer, more than double the unconditional quote rate. For each trade $i = 1, \ldots, N_{c,d,b,t}$, where an insurer client c trades bond b with CliQ dealer d on date t, we define the indicator variable

$$NRDTrade_{c,d,b,t,i} = \begin{cases} 1, & \text{if } d \in NRD_c, \\ 0, & \text{if } d \in RD_c. \end{cases} \tag{12}$$

This indicator equals one if the trade occurs between the insurer client c and a nonrelationship CliQ dealer d and zero if the trade occurs with a relationship CliQ dealer. The variable $RDTrade_{c,d,b,t,i} = 1 - NRDTrade_{c,d,b,t,i}$ captures trades with relationship dealers. Of 107,523 trades in our sample, 87.8% (94,448 trades) are with relationship dealers, and 12.2% (13,075 trades) are with nonrelationship dealers. Nonrelationship dealers handle 23% of trades when they quote, as opposed to 11% when they do not quote. For relationship dealers, the quote rate is 9.6%. By contrast, nonrelationship dealers quote in 21.1% of all transactions, which is more than four times the unconditional quoting rate. These relations are consistent with nonrelationship dealers attracting trades by quoting more. Next, we perform multivariate analysis.

B. Quote Competition and Client-Dealer Matching

To estimate how the overall quoting environment, including activity by both NRDs and RDs, influences insurers' trading decisions, we perform a logit regression for the probability of trading with a nonrelationship CliQ dealer (1) as opposed to a relationship CliQ dealer (0),

$$\begin{aligned}\Pr(NRDTrade_{c,d,b,t,i}) = F(&\alpha + \beta_{\text{NRD}} \times NRDQuote_{c,b,t} + \beta_{\text{RD}} \times RDQuote_{c,b,t} + \\ &+ \beta_{\text{NRD}\times\text{RD}} \times NRDQuote_{c,b,t} \times RDQuote_{c,b,t} + \gamma' \mathbf{X}_{c,b,t,i}),\end{aligned} \tag{13}$$

Table X

Quoting and Client-Dealer Matching

The table reports logit regression results for the probability of trading with a nonrelationship CliQ dealer (1) as opposed to a relationship CliQ dealer (0). The sample consists of all trades between insurers and CliQ dealers. Relationship dealers are defined as those in the top half of counterparties of the same insurer from January 1, 2018 to September 30, 2019. Standard errors are clustered at the insurer level. Significance levels: *** 1%, ** 5%, * 10%.

Dependent Variable:	Pr($NRDTrade_{c,d,b,t,i}$)		Pr($FirstNRDTrade_{c,d,b,t,i}$)	
	(1)	(2)	(3)	(4)
$NRDQuote_{c,b,t}$	4.417***	5.126***	3.824***	4.129***
	(0.623)	(0.766)	(0.506)	(0.612)
$RDQuote_{c,b,t}$	−1.517***	−0.789	−0.815	−0.488
	(0.589)	(0.498)	(0.761)	(0.682)
$NRDQuote_{c,b,t} \times RDQuote_{c,b,t}$		−9.083***		−4.478*
		(2.889)		(2.687)
Controls	Yes	Yes	Yes	Yes
Pseudo R^2	0.053	0.054	0.067	0.067
N	107,523	107,523	107,523	107,523

where F is a logistic function. In specification (13), β_{NRD} (β_{RD}) measures how the average quoting activity of NRDs (RDs) influences the likelihood of trading with an NRD, while $\beta_{\text{NRD}\times\text{RD}}$ captures the interaction between NRD and RD quoting activity, indicating whether their effects are complementary ($\beta_{\text{NRD}\times\text{RD}} > 0$) or substitutive ($\beta_{\text{NRD}\times\text{RD}} < 0$). Aggregating quoting activity across dealers in (13) reduces noise from individual dealers but is not counterparty-specific, which we explore below in specification (C1).

We focus on two outcomes, $NRDTrade_{c,d,b,t,i}$ from (12) and $FirstNRDTrade_{c,d,b,t,i}$, defined as the first trade between the client and the dealer since at least before January 1, 2018. Zooming in on the first trade between the client and the dealer allows us to understand the importance of quoting for matching with a new counterparty. As controls $\mathbf{X}_{c,b,t,i}$, we include the insurer's number of relationship dealers (in logs), the log size of the trade, the bond's rating, log maturity, log age, log size of issuance to capture pertinent bond features, and the level of the VIX index to capture market conditions.

Table X summarizes the results for all trades (columns (1) and (2)) and first trades (columns (3) and (4)) with NRD excluding (columns (1) and (3)) and including (columns (2) and (4)) the interaction term $NRDQuote_{c,b,t} \times RDQuote_{c,b,t}$ in specification (13). The coefficient estimates support the view that dealer quotes substitute for relationships by attracting new clients. For all trades with NRDs, $\beta_{\text{NRD}} = 4.417$ is significantly positive while $\beta_{\text{RD}} = -1.517$ is significantly negative. For first trades with NRD, $\beta_{\text{NRD}} = 3.824$ is significantly positive, but $\beta_{\text{RD}} = -0.815$, while negative, is not statistically significant. The interaction term captures whether quotes from NRDs and RDs reinforce or offset each other. For both the first and all trades with NRD, β_{NRD} is significantly positive, while β_{RD} is negative but statistically insignificant once we consider the interaction. The negative coefficients $\beta_{\text{NRD}\times\text{RD}} = -9.083$ (-4.478) in column (2) ((4)) highlight the importance of quote competition for client-dealer matching decisions.[30] Smaller magnitudes of coefficients β_{NRD} when the client trades with NRDs for the first time indicate that the substitutive effect of dealer quotes is less pronounced during initial client-NRD interactions, suggesting that relationship-specific factors may play a more critical role in attracting and retaining clients once trading relationships are established.

C. Do Quotes Substitute for Client-Dealer Relationships?

Specification (13) explores the relative impact of NRD and RD quoting activity, where quoting is captured by the variables $NRDQuote_{c,b,t}$ and $RDQuote_{c,b,t}$, respectively. While specification (13) does not isolate the impact of a particular counterparty dealer's quoting behavior, showing how quotes from individual NRDs versus RDs affect trade probabilities is important for checking if quotes substitute for client-dealer relationships, which we do next.[31]

To test the relationship channel, we perform two sets of analysis with results reported in Appendix C: logit regressions using specification (C1) for the probability of trading with a nonrelationship CliQ dealer (1) as opposed to a relationship CliQ dealer (0), and multinomial regressions using specification (C2) with the following classification: Insurers can trade with their relationship dealer or a nonrelationship dealer irrespective of whether the (non)relationship dealer is in CliQ.

Table C.I presents the results and provides evidence in support of the view that dealer quotes substitute for relationships. In the logit model, quoting more than doubles the baseline probability of trading with the nonrelationship dealer. In the multinomial model, quoting increases the likelihood of insurers trading with nonrelationship CliQ dealers relative to the other dealer choices, that is, relationship CliQ dealers, relationship non-CliQ dealers, and nonrelationship non-CliQ dealers.

VI. Conclusion

Pre-trade transparency in opaque OTC markets remains largely unexplored. Using unique data from CliQ, which aggregates quotes from participating dealers by requesting inclusion on their distribution lists for runs, we analyze the

[30] When we repeat the logit regressions for the bid and ask sides separately for all trades with NRD, we consistently find positive coefficients $\beta_{\text{NRD}} = 4.504$ (6.148) and negative coefficients $\beta_{\text{NRD}\times\text{RD}} = -6.393$ (-18.672) for the ask (bid) side.

[31] Focusing on the counterparty dealer's quote ignores how quotes from other dealers (both NRDs and RDs) influence the trade decision. It also assumes that the impact of a quote is independent of other dealers' quoting behavior. Note also that $HasQuote_{d,b,t}$ is counterparty specific and therefore could have a spuriously positive (negative) relation with $NRDTrade_{c,d,b,t,i}$ if the ex ante quote rate of RDs were lower (higher) than NRDs. However, as shown in Table IX, Panel A, the ex ante quote rates are similar.

role of indicative quotes in corporate bond trading. Our findings show that at the dealer level, providing more and better quotes is associated with a higher likelihood of trading, increased order flow, and improved client execution quality. At the bond level, a greater supply of quotes enhances trading volume and reduces trading costs. Dealers use quotes both to manage inventories and to attract orders from nonrelationship clients. As a result, quotes serve as substitutes for client-dealer relationships, broadening dealers' market reach and improving investors' market access in opaque OTC markets.

These findings offer insights into the state of the corporate bond market. Dealers are incentivized to post high-quality quotes, while clients have strong incentives to search across dealers for the best price, with both effects being economically significant. Although quotes are indicative, quote competition is important but imperfect, as the best quote often fails to attract order flow, and trade-throughs occur frequently. Inventory management and relationship frictions influence dealers' quoting decisions. These dynamics suggest several directions for theoretical modeling of quote competition in OTC markets, particularly as electronic trading platforms expand and enable greater quote dissemination. First, search models can incorporate how quotes guide investors toward dealers offering better prices, leading to greater gains from trade. Second, even when clients do not trade with the dealer posting the best quotes, they can benefit from improved pricing in bilateral negotiations with their relationship dealers. Third, clients may leverage quote information to balance the advantages of established relationships with the potential benefits of transacting with nonrelationship dealers. Fourth, cross-dealer effects, such as price matching, introduce additional competitive forces that merit further theoretical exploration.

Indicative quotes in this study are generally not accessible to retail investors and smaller institutions. As a result, we cannot directly estimate the impact of broader quote dissemination on participants with limited access to dealer quotes. However, the restricted availability of quote data may explain why small trades receive worse execution than large trades. One potential way to level the playing field is to facilitate bond trading on consolidated and transparent exchanges, akin to the transformation of the Nasdaq market in the mid-1990s, combined with best-execution requirements ensuring that orders are routed to dealers posting superior quotes or executed at the best available price (Abudy and Wohl, 2018; Biais and Green, 2019). Another possibility is to develop a centralized system for aggregating and disseminating dealer and electronic platform quotes to enhance market-wide transparency.[32] However, numerous challenges arise when considering the centralization of bond trading and mandated quote disclosures, which warrant further investigation.

[32] Bloomfield and O'Hara (1999) and Madhavan, Porter, and Weaver (2005) find that mandated pre-trade transparency can reduce liquidity. Unlike executed trades, which are clearly defined, regulators would need to establish a precise definition of quotes subject to mandatory disclosure (O'Hara, 2010).

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Appendix A: Data Filters and Yield Spread-Price Conversion

The following table presents the steps to filter the CliQ data on dealer quotes. Quotes on the bid side and the ask side are treated as separate quotes.

Step	No. Quotes	No. Bonds
Original (Oct 1, 2019–May 1, 2020)	8,546,249	24,441
In FISD	6,526,786	13,477
Keep bond type "CDEB", "CZ", "CPIK", "CCOV", "CLOC", "UCID", "CMTN", "CMTZ", "EBON", "EMTN"	6,045,106	12,102
Not exchangeable, preferred or convertible	6,042,870	12,091
Drop government type or foreign	4,584,077	9,678
Drop if missing offering date, maturity, offering amt or offering amt <\$100K	4,583,478	9,670
Drop floating rate	4,312,326	8,764
Drop maturity < 1/1/2021 or maturity > 12/31/2070 or payment-in-kind type coupon	4,229,643	8,113
Drop if price = spread	4,187,757	8,101
Drop bond trading holiday	4,183,125	8,101
Drop non-unique observation at the timestamp, firm, CUSIP, and quote side	4,170,931	8,101
Keep semi-annual interest payment or zero coupon	4,160,948	8,077

To measure the quality of the quotes, we need to ensure that all quotes are in the price. Many investment-grade bonds are quoted as yield spreads to the benchmark yields. When the bond is quoted in yield-spread space and a price quote is missing, we infer the price from the quoted yield spread. A key step is to identify and match the corresponding benchmark yield (not provided in the data). The steps are:

(1) Match the bonds to benchmark securities based on tenor (2, 3, 5, 10, 30 years). We follow market convention in terms of the cutoffs of maturity dates for each tenor bucket.
(2) Get intraday benchmark Treasury yields at five-minute intervals from Bloomberg.
(3) Match the bond spread to its benchmark yield based on the quote timestamp and the tenor.
(4) Calculate yields by adding the quoted spread and the benchmark yields.
(5) Convert yields to prices.
(6) For callable bonds, treat the quoted yields as yield to worst.

Appendix B: Shift-Share Construction of Bond-Level Quoting

We construct a shift-share instrument (Bartik, 1991) for dealers' quoting activity at the bond level, $QuoteSupply_{b,t}$, to eliminate variation across bonds over time due to endogenous changes in a dealer's activity level (e.g., due to changes in balance sheet capacity), organizational structure of the dealer, and endogenous bond-specific trends, (e.g., dealer-bond-specific quoting shocks such as inventory management or private information). We proceed in three steps.

Step 1: With $HasQuote_{d,b,t}$ and $NumQuotes_{d,b,t}$ being the extensive and intensive margins of dealer d's bond-specific quoting activity, respectively, we define quote supply in bond b on day t as

$$\begin{aligned} QuoteSupply_{b,t}^{ext} &= \textstyle\sum_d \mathrm{w}_{d,b,t} HasQuote_{d,b,t}, \\ QuoteSupply_{b,t}^{int} &= \textstyle\sum_d \mathrm{w}_{d,b,t} NumQuotes_{d,b,t}, \end{aligned} \tag{B1}$$

with dealers' importance weights $\mathrm{w}_{d,b,t}$, $\sum_d \mathrm{w}_{d,b,t} = 1$. The weights capture the exposure to shocks in quoting activity, motivated by the fact that dealers send quotes to their institutional clients. We use as weights dealer d's bond-specific activity share, defined as the dealer's share of trading in institutional sizes as a fraction of the dealer's total trading over the past 20 (the results are robust to using 10) days,

$$\mathrm{w}_{d,b,t} = \frac{\sum_{l=0}^{19} (\text{NumTrades with size} \geq \$100\text{K})_{d,b,t-l}}{\sum_{\mathbf{d}} \sum_{l=0}^{19} (\text{NumTrades with size} \geq \$100\text{K})_{\mathbf{d},b,t-l}}. \tag{B2}$$

This choice of shock exposure is based on the observation that dealers' institutional market shares $\mathrm{w}_{d,b,t}$ are relevant for their incentive to quote (Goldsmith-Pinkham et al., 2020).

Step 2: Following Goldsmith-Pinkham, Sorkin, and Swift (2020) and Borusyak, Hull, and Jaravel (2022, 2024), we create a dealer-level quote supply shock that captures the extensive and intensive margins of dealer d's total quoting activity on day t by aggregating the daily changes in $HasQuote_{d,b,t}$ and $NumQuotes_{d,b,t}$, respectively, over all bonds $b = 1, \ldots, B$,

$$\begin{aligned} q_{d,t}^{ext} &= \tfrac{1}{B} \textstyle\sum_{b=1}^{B} (HasQuote_{d,b,t} - HasQuote_{d,b,t-1}), \\ q_{d,t}^{int} &= \tfrac{1}{B} \textstyle\sum_{b=1}^{B} (NumQuotes_{d,b,t} - NumQuotes_{d,b,t-1}). \end{aligned} \tag{B3}$$

Expressions (B3) yield the dealer-bond-day decompositions $HasQuote_{d,b,t} = q_{d,t}^{ext} + \varepsilon_{d,b,t}^{ext}$ and $NumQuotes_{d,b,t} = q_{d,t}^{int} + \varepsilon_{d,b,t}^{int}$ which isolate the dealer's daily quoting activity from the dealers' incentives to quote a specific bond that day.

Step 3: The quote supply across all dealers in bond b on the day t is the share-weighted average of quoting activity across dealers at the bond-day level. Hence, we can instrument $QuoteSupply_{b,t}^{ext/int}$ by

$$\begin{aligned} QuoteSupply_{b,t}^{ext,IV} &= \textstyle\sum_d \mathrm{w}_{d,b,t-1} q_{d,t}^{ext}, \\ QuoteSupply_{b,t}^{int,IV} &= \textstyle\sum_d \mathrm{w}_{d,b,t-1} q_{d,t}^{int}, \end{aligned} \tag{B4}$$

where $\mathrm{w}_{d,b,t-1}$ are the lagged predetermined activity shares from (B2) and $q^{ext}_{d,t}$ and $q^{int}_{d,t}$ are the market-wide dealer-specific quoting rates from (B3), which replace the dealer-bond-specific quoting rates $HasQuote_{d,b,t}$ and $NumQuotes_{d,b,t}$.

We now have a standard 2SLS setup where the first stage is a regression of quote supply on the controls and the shift-share instrument

$$QuoteSupply^{ext/int}_{b,t} = \alpha_b + \alpha_t + \gamma \times QuoteSupply^{ext/int,IV}_{b,t} + \eta_{b,t}. \tag{B5}$$

The predicted quote supply in a bond is then a weighted average of the market-wide quoting shocks of each dealer (the "shift"), with weights depending on the past distribution of trading activity (the "shares").

The exclusion restriction here is that the dealer-level quote supply shock on the day t, $q_{d,t}$ from (B3) is uncorrelated with the compound error $\epsilon_{d,t} \equiv \frac{1}{\sum_b \mathrm{w}_{b,d,t-1}} \sum_b \mathrm{w}_{b,d,t-1}\epsilon_{b,t}$ which is the share-weighted average across bonds in the unexplained component of bond-level trading activity on day t from specification (4) and, in particular, the error term of the bond most exposed to that shock. By construction, endogenous changes in the activity shares and endogenous bond-specific trends do not cause variation in $QuoteSupply^{ext/int}_{b,t}$ across bonds and over time.

Identification and falsification tests: Table B.I reports the first-stage estimates for the relationship between CliQ dealers' quote supply and trading activity (Panel A) and client execution quality (Panel B). All underidentification and weak identification tests reject the null.

Table B.II reports results for two falsification tests that support the validity of the IV design.

1. Pre-trend test: We replace the dependent variable at time t, $y_{b,t}$, by its value in a prior period, $y_{b,t-L}$, and we rerun the IV. For the lag L we use 20 days. The results, reported in columns (1) and (2) of Table B.II, show that *QuoteSupply* is insignificant in explaining past bond-level trading.

2. Placebo test: We replace the dependent variable at time t, $y_{b,t}$, by a contemporaneous placebo outcome that we do not expect to be causally affected by the treatment. This is, analogous to the trade-sized splits, the amount of retail-sized trading in the bond on the same day, as proxied by trades with a par value less than \$100K. Table B.II reports the results in columns (3) and (4). The results show that *QuoteSupply* is economically immaterial in explaining retail-sized trading at the bond level.

Appendix C: Quoting and Client-Dealer Matching

To test the relationship channel, we perform a logit regression for the probability of trading with a nonrelationship CliQ dealer (1) as opposed to a relationship CliQ dealer (0),

$$\Pr(NRDTrade_{c,d,b,t,i}) = F(\alpha + \beta \times HasQuote_{d,b,t} + \delta \times QuoteQuality_{d,b,t} + \gamma' \mathbf{X}_{c,b,t,i}), \tag{C1}$$

Table B.I
Quote Supply IV First-Stage

The table reports the first-stage estimates for the relationship between bond-level quote supply and trading activity (Panel A) and bond-level quote supply and client execution quality (Panel B). Standard errors are double-clustered at the bond and day levels. Significance levels: *** 1%, ** 5%, * 10%.

Panel A: Bond-level trading activity		
Dependent variable:	$QuoteSupply^{ext}_{b,t}$ (1)	$QuoteSupply^{int}_{b,t}$ (2)
$QuoteSupply^{ext,IV}_{b,t}$	0.434***	
	(0.101)	
$QuoteSupply^{int,IV}_{b,t}$		0.972***
		(0.222)
Fixed effects	Bond, Date	Bond, Date
N	1,406,564	1,406,564
Underidentification LM-test	14.27 ($p = 0.00$)	14.62 ($p = 0.00$)
Weak identification F-test	18.56 ($p = 0.00$)	19.24 ($p = 0.00$)

Panel B: Bond-level client execution quality		
Dependent variable:	$QuoteSupply^{ext}_{b,t}$ (1)	$QuoteSupply^{int}_{b,t}$ (2)
$QuoteSupply^{ext,IV}_{b,t}$	0.361***	
	(0.084)	
$QuoteSupply^{int,IV}_{b,t}$		1.305***
		(0.295)
Fixed effects	Bond, Date	Bond, Date
N	154,528	154,528
Underidentification LM-test	13.94 ($p = 0.00$)	14.59 ($p = 0.00$)
Weak identification F-test	18.45 ($p = 0.00$)	19.63 ($p = 0.00$)

with the same controls $\mathbf{X}_{c,b,t,i}$ as in specification (13).[33] We define $HasQuote_{d,b,t}$ and $QuoteQuality_{d,b,t}$ as in Section I to capture the availability of a quote from a specific counterparty matched with each insurer trade. In specification (C1), the coefficient β is the difference in quote sensitivity between nonrelationship and relationship dealers. It tells us how much the likelihood of trading with an NRD relative to an RD is affected by the presence of a quote. In alternate specifications, we use

[33] In a random utility model for insurer trades with relationship versus nonrelationship dealers, $U_{(N)RD} = \alpha_{(N)RD} + \beta_{(N)RD} \times HasQuote_{d,b,t} + \delta_{(N)RD} \times QuoteQuality_{d,b,t} + \gamma'_{(N)RD}\mathbf{X}_{c,b,t,i} + \epsilon_{(N)RD}$ are the respective utilities for the client. Suppose the client chooses the dealer with the highest utility. The probability of trading with a nonrelationship dealer as opposed to a relationship dealer is given by the difference in their utilities, $\Pr(NRDTrade_{c,d,b,t,i}) = \Pr(U_{NRD} > U_{RD})$, which yields (C1) with $\beta = \beta_{NRD} - \beta_{RD}$, $\delta = \delta_{NRD} - \delta_{RD}$, $\gamma = \gamma_{NRD} - \gamma_{RD}$ if $\epsilon_{(N)RD}$ are iid Gumbel errors. The case $\beta > 0$ implies that having a quote increases the probability of trading with an NRD more than an RD.

Table B.II

Falsification Tests

The table reports results on falsification tests for the relationship between CliQ dealers' quote supply and trading activity by CliQ dealers and non-CliQ dealers. We split trades by CliQ dealers versus non-CliQ dealers and collapse all trades at the bond-day level. We perform two types of falsification tests, pre-trend tests in which we replace the dependent variable by its 20-day lag, and placebo tests in which we replace the dependent variable by bond-level trading in retail sizes, defined as those with par value less than \$100K. We report the IV second-stage coefficients. Estimates are obtained from panel regressions with bond and day fixed effects. Standard errors are double-clustered at the bond and day levels. Significance levels: *** 1%, ** 5%, * 10%.

	Pre-Trend Tests		Placebo Tests	
	Dep. Var Lagged 20 Days		Trade Size $<$ \$100K	
Panel A: Impact of dealer quotes on bond-level CliQ dealer market share				
Dependent variable:	$CliQShare_{b,t-20}$		$CliQShare_{b,t}$	
	(1)	(2)	(3)	(4)
$QuoteSupply^{ext}_{b,t}$	0.057		0.019	
	(0.087)		(0.026)	
$QuoteSupply^{int}_{b,t}$		0.003		0.005
		(0.017)		(0.005)
Fixed effects	Bond, Date	Bond, Date	Bond, Date	Bond, Date
R^2	−0.001	0.000	0.000	0.000
N	450,148	450,148	556,733	556,733
Panel B: Impact of dealer quotes on bond-level execution quality				
Dependent variable:	$BondExecutionQuality_{b,t-20}$		$BondExecutionQuality_{b,t}$	
	(1)	(2)	(3)	(4)
$QuoteSupply^{ext}_{b,t}$	0.236		0.111	
	(0.493)		(0.325)	
$QuoteSupply^{int}_{b,t}$		0.073		−0.005
		(0.077)		(0.044)
Fixed effects	Bond, Date	Bond, Date	Bond, Date	Bond, Date
R^2	−0.001	−0.002	−0.000	0.000
N	42,870	42,870	117,325	117,325

$HasOnlyAskQuote_{d,b,t}$, $HasOnlyBidQuote_{d,b,t}$, $HasAskAndBidQuote_{d,b,t}$, and respectively, $AskQuoteQuality_{d,b,t}$ and $BidQuoteQuality_{d,b,t}$.

Panel A of Table C.I presents the results and provides evidence in support of the view that dealer quotes substitute for relationships. In Panel A, the significant coefficient $\beta = 0.830$ in column (1) indicates a strong effect of dealer quoting behavior on insurers' trading decisions, controlling for insurer, trade, bond, and market characteristics $\mathbf{X}_{i,b,t}$. Since $e^{0.830}$-1 $= 1.29$ or 129%, quoting more than doubles the baseline probability of trading with the nonrelationship dealer. Since the ex-ante quote rate of relationship dealers (5%) is larger than

Table C.I

Quoting Alters Client-Dealer Matching

Panel A documents logit regression results for the probability of trading with a nonrelationship CliQ dealer (1) as opposed to a relationship CliQ dealer (0). The sample consists of all trades between insurers and CliQ dealers. Relationship dealers are defined as those in the top half of counterparties of the same insurer from January 1, 2018 to September 30, 2019. Panel B documents estimates from a multinomial logit model for insurers' trade choices. We consider four possibilities with CliQ relationship dealers being the baseline: relationship CliQ dealer ($Y = 0$), nonrelationship CliQ dealer ($Y = 1$), nonrelationship non-CliQ dealer ($Y = 2$), and relationship non-CliQ dealer ($Y = 3$). We only report coefficients for the relevant category, nonrelationship CliQ dealer, $Y = 1$. The sample includes all trades between insurers and dealers during the sample period when we have CliQ quote information for the subset of bonds in our CliQ sample. Standard errors are clustered at the insurer level. Significance levels: *** 1%, ** 5%, * 10%.

Dependent Variable:	$\Pr(NRDTrade_{c,d,b,t,i})$		$\Pr(Buy\,fromNRD_{c,d,b,t,i})$		$\Pr(SelltoNRD_{c,d,b,t,i})$	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Logit model for insurers' trade choices						
$HasQuote_{d,b,t}$	0.830***	0.807***				
	(0.125)	(0.124)				
$QuoteQuality_{d,b,t}$		1.196***				
		(0.405)				
$HasOnlyAsk_{d,b,t}$			1.159***	1.161***	0.585***	0.583***
			(0.192)	(0.192)	(0.221)	(0.221)
$HasOnlyBid_{d,b,t}$			1.045***	1.034***	0.962***	0.965***
			(0.292)	(0.297)	(0.301)	(0.302)
$HasAskandBid_{d,b,t}$			0.789***	0.744***	0.555***	0.555***
			(0.172)	(0.172)	(0.152)	(0.152)
$AskQuoteQuality_{d,b,t}$				0.572***		0.250**
				(0.194)		(0.114)
$BidQuoteQuality_{d,b,t}$				0.581**		−0.056
				(0.289)		(0.396)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.045	0.045	0.055	0.056	0.038	0.038
N	107,523	107,523	84,163	84,163	23,360	23,360
Panel B: Multinomial logit model for insurers' trade choices						
$HasQuote_{d,b,t}$	2.399***	2.374***				
	(0.108)	(0.107)				
$QuoteQuality_{d,b,t}$		1.317***				
		(0.419)				
$HasOnlyAsk_{d,b,t}$			2.685***	2.686***	2.111***	2.110***
			(0.185)	(0.184)	(0.232)	(0.232)
$HasOnlyBid_{d,b,t}$			2.618***	2.605***	2.615***	2.616***
			(0.278)	(0.283)	(0.284)	(0.285)
$HasAskandBid_{d,b,t}$			2.359***	2.309***	2.179***	2.180***
			(0.145)	(0.146)	(0.149)	(0.150)
$AskQuoteQuality_{d,b,t}$				0.645***		0.226**
				(0.209)		(0.115)
$BidQuoteQuality_{d,b,t}$				0.632**		−0.076

(*Continued*)

Table C.I—*Continued*

Panel B: Multinomial logit model for insurers' trade choices

				(0.308)		(0.398)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.047	0.047	0.258	0.258	0.792	0.792
N	472,267	472,267	372,499	372,499	99,768	99,768

that of nonrelationship dealers (4%), the counterparty-specific impact of quoting on trading is unlikely to be spurious. Column (2) adds the nonrelationship CliQ dealer's quote quality and confirms that more aggressive quotes increase the switching probability even further. A 1-SD increase in *QuoteQuality* improves the baseline probability by 16.8% ($e^{1.196*0.13}$-1 = 0.168). These results suggest that dealer quoting increases the likelihood of trading with nonrelationship dealers compared to relationship dealers.

To capture the effect of CliQ dealers' quotes on insurers' buy and sell choices, respectively, in columns (3) to (6) we replace *HasQuote* with all three possibilities: *HasOnlyAsk*, which equals one if the dealer provides an ask quote only, and zero otherwise, *HasOnlyBid*, which equals one if the dealer supplies a bid quote only and zero otherwise, and *HasAskAndBid*, which equals one if the dealer supplies both an ask and bid quote and zero otherwise. When we split into buy (columns (3) and (4)) and sell (columns (5) and (6)) trades, ask quotes are more important than bid quotes in enticing insurers to buy from nonrelationship CliQ dealers. The converse holds for insurer sales to nonrelationship CliQ dealers, as one would expect. Overall, these findings suggest that dealer quotes substitute for relationships in facilitating bond trades.

A concern with the analysis in Table X and Panel A of Table C.I may be that it focuses exclusively on insurers' choice among CliQ dealers while ignoring non-CliQ dealers, which may attenuate the quotes' effect on switching. To overcome this potential issue, we expand insurers' choice set and study insurers' trade choices more broadly across all dealers. We introduce the following classification: insurers can trade with their relationship dealer or a nonrelationship dealer, irrespective of whether the (non)relationship dealer is in CliQ. To model insurer c's trade choice $Y_{c,d,b,t,i}$ in bond b on date t in trade i, we consider four possibilities with CliQ relationship dealers being the baseline: relationship CliQ dealer ($Y = 0$), nonrelationship CliQ dealer ($Y = 1$), nonrelationship non-CliQ dealer ($Y = 2$), and relationship non-CliQ dealer ($Y = 3$).

In this multinomial choice model of insurer-dealer matching, we estimate a set of coefficients, $(\alpha_d, \beta_d, \delta_d)$, $d = 1, 2, 3$, corresponding to each outcome relative to the baseline,

$$\Pr(\mathit{Trade\ with}\ Y_{c,d,b,t,i} = d) = \frac{e^{\alpha_d + \beta_d \times \mathbb{1}_{d=1} \times \mathit{HasQuote}_{d,b,t} + \delta_d' \mathbf{X}_{c,b,t,i}}}{1 + \sum_{\mathbf{d}=1,2,3} e^{\alpha_{\mathbf{d}} + \beta_{\mathbf{d}} \times \mathbb{1}_{\mathbf{d}=1} \times \mathit{HasQuote}_{\mathbf{d},b,t} + \delta_{\mathbf{d}}' \mathbf{X}_{c,b,t,i}}}, d = 1, 2, 3. \tag{C2}$$

We estimate (C2) using multinomial logit and report the coefficients for $d = 1$ in Table C.I and omit the coefficients for $d = 2, 3$. As controls $\mathbf{X}_{c,b,t,i}$, we use the same factors influencing insurers' trade choices as in Panel A, including insurer, trade, bond, and market characteristics at the time of the trade. Since $\Pr(\mathit{TradewithY}_{c,d,b,t,i} = 0) = 1/(1 + \sum_{\mathbf{d}=1,2,3} e^{\alpha_{\mathbf{d}} + \beta_{\mathbf{d}} \times \mathbb{1}_{\mathbf{d}=1} \times \mathit{HasQuote}_{\mathbf{d},b,t} + \delta'_{\mathbf{d}} \mathbf{X}_{c,b,t,i}})$, the relative probability of $Y_{c,d,b,t,i} = d$ to the base outcome is the relative risk,

$$\frac{\Pr(\mathit{Trade\ with\ } Y_{c,d,b,t,i} = d)}{\Pr(\mathit{Trade\ with\ } Y_{c,d,b,t,i} = 0)} = e^{\alpha_d + \beta_d \times \mathbb{1}_{d=1} \times \mathit{HasQuote}_{d,b,t} + \delta'_d \mathbf{X}_{c,b,t,i}}. \tag{C3}$$

Panel B of Table C.I summarizes the multinomial logit estimates examining insurers' dealer choices. Column (1) shows the effect of dealer quoting behavior on insurers' choice of counterparties. The coefficient on *HasQuote* is statistically significant and positive, indicating that dealer quoting increases the likelihood of insurers trading with nonrelationship CliQ dealers compared to relationship CliQ dealers, relationship non-CliQ dealers, and nonrelationship non-CliQ dealers.

We repeat the estimation in columns (3) to (6) of Table C.I separately for insurer buys from dealers (columns (3) and (4)) and insurer sells to dealers (columns (5) and (6)). Once again, when we split into buy and sell trades, the results are similar, and having ask or bid quotes matters similarly for switching to a nonrelationship CliQ dealer.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.