Customers, Dealers and Salespeople: Managing Relationships in Over-the-Counter Markets*

Markus Bak-Hansen† David Sloth‡

Job Market Paper

Click here for the latest version

November 19, 2023

Abstract

Why do customers in OTC markets form long-term relationships with dealers? Using a unique data set from a European investment bank containing information on customer trades, the bank's client management system and bank employees, we find that the dealer quotes repeat customers substantially lower bid-ask spreads. In turn, customers are incentivized to abstain from covertly obtain additional quotes, solving a moral hazard problem. We then leverage employee-level data to show that the organizational structure of investment banks is designed such that relationship commitments are enforced internally. Salespeople, a specific category of bank employees, serve as intermediaries between customers and bank traders across multiple asset classes. Our findings suggest that OTC markets should be understood through the lens of repeated games, where cooperation and reputation are important.

*Bak-Hansen is deeply grateful to his advisor, Jean-Edouard Colliard, for continuous support and guidance. We also thank Peter Feldhütter, Thierry Foucault, Terrence Hendershott, Johan Hombert, Augustin Landier, Dmitry Livdan, Stefano Lovo, Elies Lucio (discussant), Daniel Schmidt, Pierre-Olivier Weill, Mao Ye and seminar participants at Berkeley Haas, CSUF and HEC Paris for helpful comments. We are especially indebted to Rasmus Baagøe Jørgensen at Danske Bank who helped us access the trade-level data set. Any views expressed are solely those of the authors and should not be taken to represent those of Danske Bank.

†HEC Paris. Email: markus.bak-hansen@hec.edu.

‡Danske Bank.

1 Introduction

Historically, trading in over-the-counter (OTC) markets involved manually contacting counterparties via phone. Establishing new trading connections was cumbersome, since each party had to conduct bilateral credit checks. Under these conditions it was arguably unsurprising that most customers relied on a relationship dealer for intermediation services. However, in recent decades, these frictions have significantly diminished with the emergence of electronic platforms (Hendershott and Madhavan, 2015) and central counterparty clearing houses[1]. Consequently, customers are no longer constrained to trade with a limited set of counterparties.

Despite these significant changes to the landscape of OTC markets, we document that customers overwhelmingly still opt to concentrate most of their trading with a select few important dealers. The remarkable resilience of dealer-customer relationships in the face of significant regulatory and technological disruption thus suggests a robust preference among customers for maintaining such relationships. In order to understand why relationships play such an important role in OTC markets, this paper will ask two research questions: 1) What is the underlying economic mechanism that can explain customers' preference for relationships? 2) What explains the resilience of customer-dealer relationships?

First, using a hand-collected data set of mandatory MiFID 2 disclosures from European investment firms, we establish that dealer-customer relationships still play a key role in modern electronic OTC markets. We document three stylized facts regarding dealer-customer relationships: 1) Dealer-customer trading is highly concentrated, with a majority (64%) of customers transacting 80% or more of their trading volume with their top 3 dealers. 2) Dealer-customer relationships are highly persistent; conditional on being in the top 5 of a customer's counterparties in a given year, the probability of the dealer appearing again as one of the customer's five most important dealers is 87% (compared to an unconditional

[1] See *Review of OTC derivatives market reforms: Effectiveness and broader effects of the reforms*, Financial Stability Board (2017)

probability of 15%). 3) Customers concentrate their trading with dealers across asset classes. That is, if a dealer has a high share of trading volume with a customer in one asset class, they are also likely to be an important dealer to the same customer in the other asset classes in which this customer is active.

In order to explain the underlying economic phenomena giving rise to these stylized facts, we turn to a proprietary trade-level data set obtained from a large European investment bank. The data set consists of all electronic requests for quotes (RFQ) received from 2018-2022 by the investment bank's fixed income division. Comprising over 1 million RFQs, each observation is a timestamped request from an institutional client, such as an asset manager or a pension fund, for a bid or ask. We observe the anonymous dealer's price quote, whether the RFQ resulted in a trade, and a host of other relevant information for each RFQ: the number of competing dealers, current market prices, and an anonymized customer ID.

Of particular importance, we also observe a customer ranking variable, which the dealer uses to classify customers according to the strength of the dealer-customer trading relationship. Conversations with the dealer indicate that while the rankings are subjective, they are mainly based on the customer's total "engagement" across asset classes. Customers' rankings are time-varying and can take one of four possible values: bronze, silver, gold, and platinum. We will use this customer ranking as a measure of the customer-dealer relationship and show empirically that this ranking is superior in terms of explanatory power relative to alternative relationship measures (in particular, a customer's aggregate trading volume).

Our first key results investigate the link between trade outcomes (bid-ask spreads and quote frequency) and relationship strength (proxied by the customer ranking). We find that customers with a stronger relationship with the dealer receive significantly lower bid-ask spreads and have a higher probability of receiving a quote. Relative to the lowest customer ranking (bronze), the highest ranked customers (platinum) receive 70% lower bid-ask spreads from the dealer and have a 8 pp. higher chance of receiving a quote relative to a bronze customer. Our regression includes trade-level controls (such as trade size) and day, bond and

RFQ platform fixed effects. The results are also robust to including customer fixed effects and relying on within-customer variation in the rankings. The magnitude of our findings is surprising, taking into consideration that previous research (Hendershott and Madhavan, 2015) has shown that RFQ orders tend to be smaller compared to voice trades and are used when the risk of information leakage is low. Furthermore, all the customers we consider are institutional clients who in an electronic RFQ market face relatively low search costs. This suggests that relationship effects in non-RFQ OTC markets, where it is more difficult to obtain quotes and where customers are only connected to a few dealers, are likely to be even larger compared to our estimates.

Having established that customers have a clear financial interest in establishing relationships with dealers in order to obtain more favorable bid-ask spreads, we now ask a more fundamental question: what is the underlying economic mechanism that drives dealers to give relationship customers these substantial price discounts? We provide evidence for a mechanism based on the winner's curse. The essence of the mechanism is the following: due to the winner's curse, dealers rationally bid less aggressively when more dealers participate in a request-for-quote auction. Customers can, however, secretly request quotes from additional dealers, such that the effective number of dealers participating in the auction is not observable. Over time, dealers infer whether customers secretly contact additional dealers by the extent of their mark-to-market losses. However, this requires repeated interactions between the dealer and the customer, i.e., a relationship. Customers with whom the dealer has a good relationship are thus incentivized to contact fewer dealers, since over the long run, they will be rewarded with lower bid-ask spreads and higher response rates. On the other hand, customers with a weak or no relationship do not have the same incentives and thus prefer to contact the maximum number of dealers.

We find strong empirical evidence for this theory. We first establish that the winner's curse is present in over-the-counter markets by showing that the dealers bid less aggressively when many dealers participate in the request-for-quote auction. We then describe how customers in practice can covertly contact additional dealers by sending out multiple RFQs over a short window of time. Although we cannot directly observe RFQs sent to other dealers than the dealer who provided us with our dataset, we provide multiple pieces of evidence that are consistent with weak relationship customers covertly contacting multiple dealers. In particular, we show that customers with a weak relationship with the dealer, relative to customers with strong relationships, 1) have larger dealer networks, 2) more often send requests that do not lead to trades, and 3) inflict the dealer with larger mark-to-market losses.

Each of these three findings corroborates the hypothesis that customers with weak dealer relationships covertly contact additional dealers. First, the fact that these customers have larger dealer networks means that it is less costly for them to request quotes from additional dealers. Secondly, we show that on a given RFQ, the probability that the customer actually trades on one of the quotes provided is lower when the RFQ originates from a customer with a weak relationship. A straightforward explanation for this fact is that the customer is sending out multiple RFQs at the same time, while only intending to trade at the single best price among all the RFQs, causing the remaining RFQs to not result in a trade. Lastly, we directly quantify the cost incurred by the dealer due to the winner's curse. We do this by comparing the pre-trade mid price with the RFQ's 2nd best dealer bid (the 2nd best bid, called the cover price, is made observable to the dealer who provides the best bid). We find that our estimate of the winner's curse is higher when the customer has a weak relationship with the dealer. That is, the dealer incurs larger mark-to-market losses on trades with lowly relationship-ranked customers. Taken together, our findings suggest that there is a cooperative equilibrium between dealers and customers where customers abstain from engaging in exploitative behavior and where dealers reciprocate by responding more often to requests to trade and by quoting tighter bid-ask spreads.

We carefully rule out an alternative explanation based on informed trading. This theory would predict that the customer ranking reflects whether a customer frequently trades on private information. We do not find evidence for an adverse selection channel, since it is not the case empirically that customers with weak relationships trade more frequently based on private information. This is perhaps not surprising, since the majority of our trades are from government and mortgage bond markets where private information should be rare.

Having documented and explained the economic rationale behind relationships, we then turn our focus to the management of relationships between financial institutions. In this section, we leverage the richness of our data set, which includes information on which individual employees at the dealer are involved on a trade-by-trade basis. We first show that traders in one asset class honor relationships customers have built up with traders in other asset classes. For example, a customer who has a good relationship due to his trading with the corporate bond department also receives more favorable pricing when trading government bonds.

We then investigate how the dealer ensures that relationships are internalized, in particular across asset classes traded by different employees. We argue that a particular type of employee, the salesperson, plays a key role in managing customer relationships. We show that highly ranked customers are connected to a higher number of salespeople and that their salespeople are more centrally placed in the organization. We also find evidence that salespeople utilize their own relationship with traders to obtain lower bid-ask spreads for their customers. Lastly, we analyze a special case where the salespersons' monitoring of traders is absent. We show that in these situations, traders exploit relationship customers by charging excessively high prices.

We contribute to the literature on market microstructure and OTC markets by showing that trading relationships can solve a moral hazard problem and thus be beneficial to both customers and dealers. Of course, such relationships would be impossible on a centralized exchange, where trading is non-anonymous and it is not possible to quote different prices for the same asset to different customers. A direct prediction from our results is that in anonymous markets, where dealer-customer relationships cannot be established, customers will covertly request quotes from the maximum amount of dealers. Dealers will rationally expect customers to do so and demand higher bid-ask spreads, making both dealers and customers worse off. The fact that OTC trading relationships can provide incentives that discourage this type of behavior is therefore an argument for why certain asset classes should trade OTC, and not on an exchange. While it is well established that relationship discounts in OTC markets exist (Bernhardt et al., 2004), we are, to the best of our knowledge, the first to show that these discounts can be viewed as an incentive system to discourage hidden actions.

Our paper challenges the current perspective on the role of OTC markets in general and the importance of relationships in these markets. In particular, we argue that researchers should think of these markets through the lens of repeated games, as markets where co-operation and reputation are important. Incidentally this is in line with how traders on these markets describe their activity. This paradigm requires new types of theories, richer data sets, and richer empirical measures. Finally, one may speculate to what extent these mechanisms and observations could also matter for other types of relationships and finance, e.g., between banks and borrowers (households or firms), or relationships on the interbank market.

In recent work, Jurkatis et al. (2022) analyse dealer-customer relationships in U.K. corporate bond markets and also find that customers with strong relationships receive more advantageous bid-ask spreads. They argue that these discounts are a way for the dealer to reward customers for providing liquidity. Since all trades in our sample are customer-initiated, this channel is unlikely to materialize in our context. Di Maggio et al. (2017) show that dealers in the U.S. corporate bond market trade at more favourable prices when transacting with dealers with whom they have strong ties. Afonso et al. (2013) study relationships in the interbank loan market and highlight how relationships may counterbalance idiosyncratic liquidity shocks. Common to Afonso et al. (2013), Di Maggio et al. (2017) and Jurkatis et al. (2022) is that they measure trading relationships by trading volume. We instead use a subjective customer ranking variable and show that this variable affects bid-ask spreads above and beyond a customer's trading volume. Hau et al. (2021) study relationships in the foreign exchange (FX) market and find, as opposed to the previously mentioned studies, that customers with only one relationship dealer suffer very large transaction costs. This may be explained by the fact that FX markets, unlike bond markets, have significant participation from unsophisticated corporate and retail clients.

Hendershott et al. (2020) focus on insurers' dealer networks and show that many insurers trade with just a few select dealers. They argue that if a customer were to expand their dealer network, this would dilute the value of trading relationships. Similar to Allen and Wittwer (2023), who incorporate an implicit value of relationship trading, neither focus on why trading relationships are valuable in the first place. Hendershott and Madhavan (2015) and Riggs et al. (2020) study the trade-off between electronic requests-for-quote and bargaining with a single dealer, while O'Hara and Zhou (2021a) focus on the impact of electronic trading on market liquidity. We contribute to this literature by showing that even in fast electronic markets, institutional relationships play an important role.

A large literature has examined transaction costs in corporate bond markets. An important determinant, transparency, is studied in Bessembinder et al. (2006), Goldstein et al. (2006), Edwards et al. (2007) and Asquith et al. (2013). Our findings highlight that relationships are a key determinant of a customer's transaction costs. Another source of illiquidity is informed trading, which in the context of OTC markets is explored by Lee and Wang (2022), Biais and Green (2019) and Czech and Pinter (2022). Although we do not rule out informed trading per se, we find that it is not the driving factor in the formation of dealer-customer relationships.

A growing literature analyse the choice of number of dealers in a request-for-quote. Wang (2023) and Yueshen and Zou (2023) model the amount of liquidity provision by dealers and show that contacting fewer dealers can counter-intuitively lead to better liquidity. Glode and Opp (2019) show that high dealer concentration can promote dealers' acquisition of expertise. We consider the implications of customers covertly requesting additional quotes and show that this leads to a moral hazard problem.

Kargar et al. (2021), Haddad et al. (2021) and O'Hara and Zhou (2021b) study U.S. corporate bond markets during the Covid-19 pandemic. We complement these papers by analysing European bond markets during this same period and finding that these markets also experienced spikes in volatility.

The remainder of the paper proceeds as follows. Section 2 describes our two data sets. Section 3 uses the first of these data sets to present 3 stylized facts that characterize dealer-customer relationships. We then turn to the trade-level dataset in Section 4 to analyze the link between relationships and trade outcomes. Section 5 builds further by uncovering the role of the winner's curse in dealer-customer relationships. Section 6 investigates how relationships are managed and highlights the importance of the dealer's organizational structure. Section 7 concludes.

2 Data

2.1 RTS28 reports

We hand-collect annual best execution reports from European investment companies from 2017-2021. Since 2017, investment firms have been mandated by MiFiD II (under Regulatory Technical Standard 28) to create these reports and make them publicly available on their websites. A report must cover 22 pre-defined asset classes, with one table per asset class designating the investment firm's 5 most important counterparties in terms of trading volume and number of orders. Table 1 shows an extract from Eaton Vance's 2020 report.[2] As seen in Panel A, most of their trading activity in credit derivatives that year was with Citigroup, who, as per Panel B, was also their preferred dealer for interest rate derivatives.

Since we are focusing on OTC markets, we discard data on 8 of the 22 asset classes that are primarily traded on exchanges (e.g., equities and futures). Our two main variables of interest

[2] Eaton Vance is a US investment company; however, they publish best execution statistics for their European division, Eaton Vance Advisers International Ltd.

will be 1) the $Relationship_{c,d,a,t}$ (measured by trading volume or orders) between customer c and dealer d in asset class a in year t and 2) their *Overall Relationship* which we calculate by summing over the *Relationships* between the customer and dealer in all other asset classes and dividing by $n-1$, i.e., the number of other asset classes that the customer is active in:

$$Overall\ Relationship_{c,d,a,t} = \frac{\sum_{i \neq a} Relationship_{c,d,i,t}}{n-1}$$

Summary statistics are shown for the two key variables and the 14 asset classes in Table 2.

2.2 Request-for-quote data set

Although the RTS28 dataset allows us to describe the broad empirical patterns that characterize OTC market customer-dealer relationships, we need a trade-level data set in order to uncover the underlying mechanisms that lead customers and dealers to form relationships in the first place. To this end, we obtain a proprietary data set from a large European investment bank containing every electronic RFQ received by their fixed income department from January 2018 to October 2022. RFQs are transmitted through electronic platforms such as Tradeweb, Bloomberg, MarketAxess, and Bondvision. The data set covers 6 asset classes (corporate, government, mortgage, supranational, and inflation-linked bonds and interest rate swaps) and eight currencies. Each observation contains an anonymized customer, trader, and salesperson ID. We also obtain end-of-day prices from Bloomberg and merge these data with the RFQ data set by ISIN code.

An RFQ is initiated by a customer who chooses which dealers to acquire a quote from. Dealers can choose whether to respond or not to the RFQ, and if they supply a quote, the customer has around 1-2 minutes to decide whether to trade at the best price or pass. RFQs can thus be viewed as a first-price auction, and each observation in our data set corresponds to an auction. A sample observation is shown in Table 3, where a customer requested a bid for 15 million of a German government bond. 5 dealers participated in the auction, and our dealer showed a bid of 101.96. The mid-price at the time of the trade was 102.04, yielding a bid-ask spread of around 8 basis points.[3] The customer decided to sell to the dealer at 101.96, implying that the 4 other dealers showed worse bids. In fact, whenever our dealer wins the auction, we also observe the second-best bid or ask from the competing dealers (called the cover price), which in this case was 101.92. Summary statistics are shown in Table 4.

2.3 Bid-ask spreads

Bid-ask spreads will play an important role in our analysis, in part due to their close connection to transaction costs and dealer's hedging costs, and more broadly as a measure of frictions in the market. For price-quoted assets, we calculate the bid-ask spread as:

$$Spread = \frac{QuotedPrice - MidPrice}{MidPrice} \cdot D$$

Where D equals 1 for ask RFQs and -1 for bid RFQs. $MidPrice$ is the reference mid-price for the asset at the time of the RFQ. Reference prices are sourced from Bloomberg CBBT. For observations where there is no Bloomberg reference price (around 5% of all observations) and where an interdealer mid-price is available, we instead use the mid-price from the interdealer market.[4] Around 9% of the bonds in our sample are quoted in yield, in which case we calculate the bid-ask spread as:

$$Spread = \frac{(MidYield - QuotedYield) * Dv01}{MidPrice} \cdot D$$

Where $Dv01$ is the bond's duration.[5] In the remainder of the paper, whenever we define a price-based measure, we calculate a similar version for yield-quoted bonds using the yield and $Dv01$.

[3]From here on forward, we denote basis points as bps.

[4]Interdealer prices are only available for government bonds and are sourced from electronic interdealer markets such as EBM, BrokerTec, and MTS.

[5]Duration is the sensitivity of the bond's price to a change in its yield, i.e., $Dv01 = -\frac{dP(i)}{di}.$, where P is the bond's price and i is the corresponding yield.

2.4 Relationship measure

To distinguish between customers with a weak trading relationship with the dealer and customers with a strong relationship, we use a variable that denotes the ranking of each customer. These rankings are decided by the dealers' salespeople and reflect the overall business relationship between the customer and the dealer's market operations and post-trade services (e.g., repo, collateral services, securities lending). Note that the ranking takes into account business done with asset classes not included in our data set (e.g., foreign exchange and equities). There are four customer tiers: Bronze, Silver, Gold and Platinum. Table 5 provides summary statistics for each customer tier. We see that Platinum customers pay an average spread of 6.4 bps and have an 84.5% chance of receiving a quote, while Bronze customers pay a 21.4 bps spread and only have a 43.2% chance of receiving a quote. Surprisingly, Bronze customers trade more often than Platinum customers (153 trades per quarter vs 132), although their average trade size is smaller. Finally, customers with strong relationships solicit fewer bidders on average. In our regression analysis, we convert the rankings into an integer between 0 and 3 (i.e., Bronze = 0, Silver = 1, Gold = 2 and Platinum = 3).

3 Three stylized facts about dealer-customer relationships

In this section we document the importance of dealer-customer relationships in a post-MiFID 2 world (i.e., after 2018). We present three stylized facts that illustrate the close links between customers and dealers.

3.1 Concentration of customers' trading with a few select dealers

We first document that most customers rely on just a few dealers for most of their trading. On average, the customers represented in our data set transacted 92% (87%) of their volume (orders) with their 5 most important dealers (note that we do not observe data on dealers that are below the top 5 in terms of trading volume or number of orders). If we focus on the top 3 most important dealers, we find that they represent 73% (78%) of customers' volume (orders).

This stylized fact is striking when we consider that our dataset only covers institutional clients who presumably have access to a wide array of dealers. In total, our data covers 100 unique OTC dealers. Yet the vast majority of customers pick a few important dealers and concentrate most of their trading with those dealers.

3.2 Dealer-customer relationships are persistent

We next look at whether ties between dealers and customers are persistent. In other words, if a dealer is responsible for a large share of a customer's trading volume in a given year, is it then likely that the relationship will continue in the next year? We test this by computing a dummy variable $R_{c,d,a,t}$. $R_{c,d,a,t}$ equals 1 if customer c traded with dealer d in asset class a in year t. The unconditional mean of R is 5%, meaning that the probability of a random customer and a random dealer in our sample trading together in a given year is only 5%. However, if we restrict our sample to observations where the dealer and the customer had ties in the previous year, we arrive at a conditional mean of 87% (formally, $E[R_{c,d,a,t} \,|\, R_{c,d,a,t-1} = 1] \approx 0.87$). It is thus clear dealer-customer relationships are highly persistent, since the probability of a recurrent connection between a dealer and a customer is much higher than the unconditional probability.

3.3 Cross-market concentration of trading relationships

Lastly, we look at concentration of dealer-customer relationships across asset classes. In particular, we test whether having a relationship in a given asset is associated with a higher likelihood of the same customer and dealer having a relationship in other asset classes. Formally, we run the following regression:

$$Relationship_{c,d,a,t} = \gamma_0 + \gamma_1 Overall\ Relationship_{c,d,a,t} + \alpha_{d,m} + \varepsilon_{c,d,a,t}$$

where c refers to a customer, d to a dealer, a to an asset class and t to a year. Table 6 reports the regression results. We find estimates of γ_1 in the range of 27% - 40%, indicating a strong correlation between the relationship intensity between a given dealer and customer across asset classes. The regression results imply that a customer who is already trading a lot of interest rate derivatives with a specific dealer will, on average, also use this dealer to trade e.g., corporate bonds. We include Dealer x Asset Class fixed effects to account for two possible sources of unobserved heterogeneity: 1) certain large dealers have a strong market position in many asset classes, which might lead us to find a positive estimate of γ_1, even if no true association exists and 2) there might be some smaller specialist dealers who only operate in specific asset classes, biasing $\hat{\gamma_1}$ downwards. In specifications (2) and (4) in Table 6 where fixed effects are included, our estimate of γ_1 actually increases, indicating that effect 2) is a larger source of unobserved heterogeneity.

4 Customer relationships and trade outcomes

In this section we turn to the trade-level RFQ data set to understand the effect that relationships have on trade outcomes. We first provide direct evidence of multi-period optimization on part of the dealer. We then look at the association between relationship strength (proxied by the customer ranking) and bid-ask spreads and the probability of receiving a quote.

4.1 Do quotes reflect multi-period optimization?

If trading relationships are to facilitate cooperation between the dealer and the customer, where the customer avoids certain behaviors that raise hedging costs for the dealer and where the dealer reciprocates by quoting a lower bid-ask spread, it must be that both parties are forward looking. If for example the dealer optimized with respect to every single trade, he would not reciprocate vis-a-vis the customer and would quote the same price regardless of the bilateral relationship. This is the case in Duffie et al. (2005) where quotes are independent of the trading history, thus ruling out behavior which is not optimal on a one-period basis.

To test whether quotes can be explained by one-period maximization, we first consider a subset of trades where we can directly estimate the optimal one-period price of a monopolist facing inelastic demand. This subset concerns trades where no competing bidders were solicited (i.e., where the customer only requested a quote from our dealer). For these trades, we compute the one-period monopolist price as the best available bid or ask in the market (depending on whether the trade request is a buy or sell). The best available market price is generated by comparing all available dealer quotes and quotes on interdealer markets and selecting the best bid and ask for the asset at the time of the trade. This process is carried out by the dealer on a real-time basis, but in our sample we only observe the resulting best prices, not the entire range of market quotes.

For each RFQ, we calculate the discount relative to the monopolist price as:

$$MonopolistDiscount = \frac{OnePeriodPrice - QuotedPrice}{MidPrice} \cdot D$$

Where the $OnePeriodPrice$ is equal to the current best market price. For example, assume that the dealer shows an ask quote of 100.10 and that the best available ask in the market is 100.20, with the mid-price at 100. In this case, we would calculate the monopolist discount as $\frac{100.20-100.10}{100} = 10$ bps. We report the average monopolist discount in Table 7. All relationship levels receive discounts relative to the one period optimal price, except for Silver customers. Gold and platinum customers receive sizable discounts of 6.10 and 8.77 bps (compared to the sample average bid-ask spread of 14.2 bps). Surprisingly, the lowest ranked customers also receive a discount relative to the one-period. This may reflect that while such customers are ranked low, they are still repeat customers and it is therefore still possible that a level of cooperation exists for such customers. Based on the above evidence, we conclude that the dealer's quotes reflect multi-period optimization, which opens up for dealer-customer trading relationships.

4.2 Relationships and bid-ask spreads

We now test whether relationship customers receive more competitive bid-ask spreads. In order to estimate this effect we run the following regression:

$$\begin{aligned}
Spread_{a,c,i,t,p} = &\gamma_0 + \gamma_1 Relationship_{t,c} + \gamma_2 Relationship_{t,c} \cdot VIX_t \\
&+ \gamma_3 PastVolume_{t,c} + \beta \mathbf{X} \\
&+ \alpha_i + \omega_p + \phi_{a,t} + \theta_c + \varepsilon_{a,c,i,t,p}
\end{aligned}$$

Where $Spread_{a,c,i,t,p}$ is the bid-ask spread on a RFQ for bond i sent by customer c at time t through platform p in asset class-currency a. *Relationship* is the customer ranking converted to an integer between 0 and 3 (0 corresponds to the lowest ranking, 3 to the highest), VIX is the daily closing level of the VIX index minus 25 (its sample mean value), $PastVolume$ is the customer's (normalised) aggregate trading volume in the asset class in the previous quarter and $\mathbf{X}$ is a vector of trade-level controls. The trade-level controls are $Size$, the trade notional, $NumofBidders$, the number of competing dealers included in the RFQ and $Maturity$, the time until maturity of the bond or derivative. Since average trade volume varies widely across asset classes (the mean trade size in EUR-denominated government bonds is 6.6 million, while requests for USD corporate bonds' have an average notional of only 300k), we use $log(size)$. Together with asset-class fixed effects, this allows us to interpret the estimate of the $Size$ coefficient as a relative change in trade size compared to the average trade size in that asset class. We also apply a $log(x)$ transformation to $Maturity$ and the count variable $NumofBidders$. We motivate using $log(Maturity)$ by the fact that a 1-day decrease in the time to maturity should have a larger effect for a bond with say 180 days to maturity than if the bond had 30 years to maturity. We similarly expect a larger impact of going from 1 to 2 dealers than from 20 to 21.

In the full specification, we include ISIN (α_i), Date $\times$ Asset Class $\times$ Currency ($\phi_{a,t}$), Platform (ω_p), and Customer (θ_c) fixed effects. ISIN FEs control for different levels of liquidity among different bonds, while Date $\times$ Asset Class $\times$ Currency FEs absorb asset-class specific changes in liquidity over time. We interact asset classes with the currency to differentiate between trading in e.g., EUR-denominated government bonds and US Treasuries. Platform refers to whether the RFQ was sent through e.g., Bloomberg, Tradeweb or MarketAxess, and accounts for differences in spreads due to the platform-specific costs and rules. Customer FEs absorb unobserved heterogeneity among customers and allow us to exploit the within-customer variation in customer rankings.

Table 8 reports the results. On average, highly valued customers pay between 1-2.5 bps lower spreads for each increase in relationship level. The difference increases with volatility. Note that the highest relationship customers have a *Relationship* value equal to 3. This implies that when volatility is very high (e.g., $VIX = 80$), their quoted bid-ask spreads are 6.9-12.9 bps lower compared to the lowest ranked customers. This difference is economically very large, considering that the mean quoted spread is 14.2 bps. Similar to Di Maggio et al. (2017) and Jurkatis et al. (2022), we find a negative association between bid-ask spreads and past trading volume. $PastVolume$ is normalised, so the results imply that a 1-std deviation in a customer's aggregate trading volume results in a 0.4-0.9 bps reduction in bid-ask spreads. Based on this evidence, we conclude that the customer rankings measure cooperation above and beyond a quantity price discount. We also note that an upgrade or downgrade in a customer's ranking has a larger impact than a 1-std change in aggregate trading volume. Lastly, note that coefficient on $Size$ is negative (but not statistically significant) in specifications 1, 2, 4 and 5, but when controlling for customer fixed effects the coefficient becomes positive (statistically significant at the 1% level). This is in line with the results reported in Pinter et al. (2022), which show that trades in OTC markets generally exhibit a size discount, but when controlling for customer IDs, a size penalty emerges.

4.3 Probability of receiving a quote

We now turn to the probability of receiving a quote on a particular request. We previously presented evidence that customers with strong relationships receive more frequent quotes. To test this formally, we run the following linear probability model:

$$
\begin{aligned}
Quoted_{a,c,i,t,p} = &\gamma_0 + \gamma_1 Relationship_{t,c} + \gamma_2 Relationship_{t,c} \cdot VIX_t \\
&+ \gamma_3 PastVolume_{t,c} + \beta \mathbf{X} \\
&+ \alpha_i + \omega_p + \phi_{a,t} + \theta_c + \varepsilon_{a,c,i,t,p}
\end{aligned}
$$

Where *Quoted* is a dummy variable which indicates for a given RFQ whether the dealer showed a quote or not. We refer to section 4.2 for a detailed description of the other regression variables and fixed effects.

Table 9 reports the results. Cross-sectionally, an upgrade in the customer ranking translates into a 2.3-2.8 percentage point higher chance of receiving a quote. This effect is even more pronounced when market volatility is high, where the highest ranked customers have a 3.6-11.6 higher percentage point probability of receiving a quote (relative to the average quote probability of 61.6%). Although we find strong evidence for a cross-sectional association between customer ranking and quote frequency, the effect disappears when including customer FEs, as in specification 3. That is, within customers we find no correlation between customer ranking and the quote frequency. Lastly, the probability of receiving a quote decreases when the trade size is small or when the number of bidders is large. This is consistent with the dealer facing a fixed cost to participating in an auction, such that it only transmits a quote when the potential profit is large (when the trade size is large) or if the probability of winning the auction is high (there are few other bidders).

5 Relationships and the winner's curse

The previous section documented that the dealer provided more competitive and frequent quotes to customers with a high relationship ranking. In this section, we attempt to understand what is different about highly ranked customers that induces the dealer to reward them. In other words, what do the customers bring to the table?

We test two theories: a winner's curse theory and an adverse selection theory. In the winner's curse theory, the dealer widens the bid-ask spread when competing against other dealers to compensate for winner's curse. The customer will, all else equal, prefer to collect as many quotes as possible to ensure that they trade at the best possible price. In more general terms, this theory describes a situation where the customer can engage in hidden actions that lower their transaction costs but increase the dealer's costs. Based on the dealer's ex-post mark-to-market loss, he can over time infer how many quotes the customer is receiving. Customers that contact few dealers for quotes are ranked highly and awarded with tighter spreads, incentivising them to continue with this behavior.

Under the adverse selection theory, certain customers trade based on private information, while other customers are uninformed. Over time, the dealer learns the customer's type and quotes lower spreads to high-ranked (uninformed) customers. We present evidence that supports the winner's curse theory, while we reject the adverse selection theory.

We will test the winner's curse theory by investigating whether customers are truthful when reporting the number of other dealers they are contacting. The adverse selection theory can be tested by analyzing whether customers with weak relationships have a higher likelihood of informed trading.

5.1 Do customers with weak relationships have larger dealer networks?

We first test whether customers with weak relationships systematically contact more dealers, which would indicate that they have larger dealer networks. This fact would also make it more likely that they covertly contact additional dealers, since their large network would facilitate such contact. Formally, we run the following regression:

$$
\begin{aligned}
NumOfDealers_{a,c,i,t,p} = {} & \gamma_0 + \gamma_1 Relationship_{t,c} + \\
& + \gamma_2 Spread_{a,c,i,t,p} + \beta \mathbf{X} \\
& + \alpha_i + \omega_p + \phi_{a,t} + \theta_c + \varepsilon_{a,c,i,t,p}
\end{aligned}
$$

Where $NumOfDealers$ equals the number of dealers contacted on the RFQ. We refer to section 4.2 for a detailed description of the other regression variables and fixed effects. Table 10 reports the results. Lower-ranked customers contact 14% more dealers per RFQ, showing that customers with weak relationships tend to have larger dealer networks.

5.2 Do customers obtain more quotes than indicated?

Although we do not observe RFQs sent to other dealers, we can infer it from the frequency with which a customer trades. The intuition here is that a customer who solicits bids from 5 dealers, but only trades with one of the 5 dealers 30% of the time is likely soliciting more additional bids than a customer who trades 90% of the time. We analyse the probability of not trading by running the following linear probability model:

$$
\begin{aligned}
NoTrade_{a,c,i,t,p} = {} & \gamma_0 + \gamma_1 Relationship_{t,c} + \\
& + \gamma_2 Spread_{a,c,i,t,p} + \beta \mathbf{X} \\
& + \alpha_i + \omega_p + \phi_{a,t} + \theta_c + \varepsilon_{a,c,i,t,p}
\end{aligned}
$$

Where $NoTrade$ is a dummy variable that equals 1 if the RFQ did not result in the customer trading with any dealer. We include the $Spread$, the dealer's quoted bid-ask spread, since we naturally would expect this variable to influence the customer's decision to trade.

We refer to section 4.2 for a detailed description of the other regression variables and fixed effects. Table 11 reports the results. An upgrade in customer tier is associated with a 4.4-0.8% percentage point lower probability of not trading (which is sizeable, considering that on average 47.2% of all RFQs do not result in a trade).

5.3 Measuring the winner's curse problem

We now turn to measuring the magnitude of the winner's curse. We proxy for the winner's curse by measuring on a trade-by-trade basis the difference between our dealer's and other dealers' valuation. Specifically, we calculate the cover spread as the difference between the best price (i.e., the traded price) and the 2nd best price (the cover price):

$$CoverSpread = \frac{CoverPrice - TradedPrice}{MidPrice} \cdot D$$

Note that the cover spread is defined such that it is (weakly) greater than 0. We will then test whether traders from customers with a stronger relationship exhibit lower cover spreads. The rationale behind the test is as follows: envision an auction with 10 bidders. We compare two scenarios. In the first scenario, there is a single auction (equivalent to 1 RFQ with 10 dealers). In the next scenario, the seller conducts two auctions simultaneously, the first with 2 bidders and the second with 8 bidders (with the intention to sell to only 1 bidder in total). In our setup, this corresponds to 1 RFQ with 2 dealers, and concurrently, the customer conducts a second RFQ with 8 dealers covertly. Assume that our dealer is part of the "small" RFQ with just 2 dealers.

We then calculate the cover spread as the difference between the traded price (the best bid) and the 2nd best bid. Remember that the 2nd best bid is computed within a single RFQ. In the second scenario, if our dealer in the "small" RFQ wins the trade, the 2nd best price is simply the other dealer's price, and the other 8 bids are not considered. Therefore, when our dealer wins the RFQ, the spread is consistently smaller in the first scenario than in the second scenario. Intuitively, in the second scenario, we discard 8 bids, and the 2nd price is now just 1 random price among the 9 other dealers.

In conclusion, while holding the effective number of bidders constant, the cover spread increases as the seller divides auctions/runs covert RFQs. To test whether we empirically observe any differences in cover spread between customers with varying relationships, we run the following regression:

$$
\begin{aligned}
CoverSpread_{a,c,i,t,p} = & \gamma_0 + \gamma_1 Relationship_{t,c} + \beta \mathbf{X} \\
& + \alpha_i + \omega_p + \phi_{a,t} + \theta_c + \varepsilon_{a,c,i,t,p}
\end{aligned}
$$

Table 12 reports the results. A stronger relationship is associated with a 0.8 bps reduction in cover spreads for each relationship level (the average cover spread is 8.2 bps). The coefficient is not significant when including customer fixed effects, although note that the sample in this regression is much smaller, since we only observe the cover price when the customer trades with our dealer. Combined with the fact that there is limited time variation in the relationship measure, the effective variation in specification (3) is small.

A different explanation for the above results might be that low relationship customers' demand is more elastic. This however seems difficult to reconcile with our findings that the same customers are shown much higher quoted spreads. Alternatively, low relationship customers might have a lower innate need to trade. One could imagine that high relationship customers mainly trade in order to hedge, while low relationship customers trade to speculate. If this is the case, low relationship customers solicit quotes to gain information or simply to see if a dealer quotes an abnormally advantageous price. If the latter were true, this could also be considered as a moral hazard problem. Dealers would prefer that customers only request quotes when they have an actual desire to trade, but it may be profitable for customers to continually ask for quotes until a dealer makes a mistake and shows a too good price.

5.4 Do customers trade on information?

We now turn to the adverse selection theory. Specifically, we analyse how informative customers' trades are, to see whether weak relationship customers trade based on private information more often than customers with a strong relationship. This would be in line with Lee and Wang (2022), where dealers (imperfectly) price discriminate customers based on whether they have private information. We measure a trade's informativeness as the mark-to-market loss from the dealer's side:[6]

$$DealerLoss_{i,t} = \frac{\Delta MidPrice_{i,t+1}}{MidPrice_{i,t}} \cdot D$$

Equivalently, $DealerLoss$ can be interpreted as customer's 1-day return on a trade (marked to the end-of-day reference price on the following day) if the bid-ask spread had been 0. To test whether customers with weaker relationships trade more often on information, we run the following regression:

$$\begin{aligned} DealerLoss_{a,c,i,t,p} = &\gamma_0 + \gamma_1 Relationship_{t,c} + \gamma_2 NoTrade + \beta \mathbf{X} \\ &+ \alpha_i + \omega_p + \phi_{a,t} + \theta_c + \varepsilon_{a,c,i,t,p} \end{aligned}$$

Table 13 reports the results. We do not find any relation between customer ranking and the informativeness of trades. On average, the dealer loss relative to the next day mid-price is only 0.9 bps, i.e., just 6% of the quoted spread. Interestingly, the dummy variable $NoTrade$ is highly significant. The interpretation of the coefficient is that RFQs that do not result in a trade on average would have cost the dealer a loss of 2 bps.

One possible explanation for our non-result could be that we lack statistical power, since one-day price changes are very noisy. Under this alternative hypothesis, even if certain customers actually do trade on information, our sample would not be sufficiently large to

[6]When calculating this measure, we convert all bond prices to dirty prices.

detect the association. To show that our result is likely not due to a lack of statistical power, we construct a less noisy measure of trade informativeness, *Adj. DealerLoss*. The idea is to exploit the fact that bond prices are highly correlated with prices on liquid government bond futures. For example, consider a mortgage bond issued by Jyske Bank maturing in 2032, shown together with the German Bund future in Figure 1. Clearly, the prices of the two assets are highly correlated. If we assume that customers do not have private information about future price changes in government bond futures[7], we can thus focus on the variation in bond prices which is orthogonal to variation in futures prices. Intuitively, if one decomposes the yield on the mortgage bond into a risk-free rate and a spread, we assume that customers may be informed about changes in the spread, but not about changes in the risk-free rate.

Using data on 6 highly liquid exchange-traded government bond futures,[8] we employ a machine learning (ML) model to predict bond prices using changes in futures prices and features such as currency, issuer, asset class and time to maturity as the input to the model. To give an example of the model's out-of-sample performance, we train the model only using data prior to 2022 and find that it on average can explain 90% of total variation in 42 German government bonds' price changes in 2022. We refer to Appendix A for further details on the construction of *Adj. DealerLoss*.

We now compute the adjusted mark-to-market dealer loss, subtracting the price change predicted by futures prices:

$$Adj.\ DealerLoss_{i,t} = \frac{\Delta MidPrice_{i,t+1} - \Delta Mid\hat{P}rice_{i,t+1}}{MidPrice_{i,t}} \cdot D$$

Where $\Delta Mid\hat{P}rice_{i,t+1}$ is a (non-linear) function of changes in futures prices. We then re-estimate the regression of trade informativeness on customer relationships:

[7]Equivalently, we could assume that if customers did have such private information, they would simply trade in the futures market, where transaction costs are substantially lower than in the OTC market

[8]The futures are traded on the exchange Eurex and consist of 4 German government bond futures (Schatz, Bobl, Bund and Buxl), 1 French future (OAT) and an Italian future (BTP). Their bid-ask spread is typically around 0.5-1 bps.

$$
\begin{aligned}
Adj.\ DealerLoss_{a,c,i,t,p} = & \gamma_0 + \gamma_1 Relationship_{t,c} + \gamma_2 NoTrade + \beta \mathbf{X} \\
& + \alpha_i + \omega_p + \phi_{a,t} + \theta_c + \varepsilon_{a,c,i,t,p}
\end{aligned}
$$

Table 13 reports the results. We still find no statistical significant relation between customer rankings and trades' informativeness. In conclusion, we reject the adverse selection theory which stated that the relationship discount can be explained by highly rated customers trades' being less informative.

6 Does the dealer's organisational structure impact customer relationships?

In today's financial markets, large financial institutions are often active in multiple asset classes across different currencies. Since intermediation in OTC markets is concentrated among a select group of global investment banks, customers are likely to encounter the same dealers in different markets. Imagine a Japanese pension fund looking to invest in U.S. corporate bonds and at same time hedging the USDJPY currency risk. It is likely that the pension fund can find a dealer active in both of these OTC markets, thus establishing a trading relationship with the same dealer in multiple asset classes. A natural question is therefore whether dealer-customer relationships are defined narrowly within each asset class or whether trading history across all asset classes can affect trade outcomes? Put differently: are there spill-over effects from trading in one asset class to trading in other asset classes? To answer this question, we exploit the multi asset-class nature of our request-for-quote data set, which covers trades in corporate, mortgage, government, supranational and inflation-linked bonds as well as interest rate derivatives in five different currencies. In our sample, the median customer is active in two asset classes across two currencies and the top 5% most active customers (who account for 62% of all trade requests) are active in 5 out of 6 asset classes and 4 out of 5 currencies.

6.1 Do relationships carry over when trading new asset classes?

To test whether trading relationships extend across asset classes, we zoom in on customers when they trade a new asset class for the first time and test whether they are treated differently than repeat customers. Specifically, we define a dummy variable $NewClient$ which is equal to 1 if the customer did not send any RFQs in the given asset class in the previous quarter (we exclude observations from a customer's first quarter of trading). We then run the regression on bid-ask spreads from section 4.2, now including an interaction between $NewClient$ and $Relationship$:

$$\begin{aligned}Spread_{a,c,i,t,p} = &\gamma_0 + \gamma_1 Relationship_{t,c} + \gamma_2 Relationship_{t,c} \cdot NewClient_{t,a,c}\\ &+ \gamma_3 NewClient_{t,a,c} + \beta\mathbf{X}\\ &+ \alpha_i + \omega_p + \phi_{a,t} + \theta_c + \varepsilon_{a,c,i,t,p}\end{aligned}$$

We refer to section 4.2 for a detailed description of the other regression variables and fixed effects. Table 14 reports the results. If indeed relationships are narrowly defined within each asset class, a customer ranking built up through trading in other asset classes should have no effect on the bid-ask spread when trading in a new asset class, and we should thus expect $\gamma_2 > 0$. On the other hand, $\gamma_2 = 0$ would show that when a customer trades an asset class for the first time, his reputation from trading in other asset classes is taken into account, allowing him to benefit from his customer ranking. In fact, we see that $\hat{\gamma}_2$ is not statistically different from 0 in all specifications, which indicates that the dealer fully accounts for the reputation that a customer may have built up in other asset classes. Note that the coefficient on $NewClient$ is positive which shows that new customers on average do pay higher bid-ask spreads. By comparing γ_1 and γ_3, we can see that this penalty (2.2-2.6 bps) is smaller than the discount offered to the highest rated customers (2.4-6 bps). That is, a customer can avoid paying a higher bid-ask spread when trading a new asset class by achieving a sufficiently strong relationship via trading in other asset classes.

While the previous section emphasised the institutional links between participants in OTC markets, we now turn to the frictions caused by the traders and salespeople employed at the dealer. Note that unlike in equity markets where trading and pricing is mainly determined by algorithms, decision-making in OTC markets is mostly done by human traders. Which trader handles a specific trade request may therefore play a large role in the pricing of an OTC asset.

6.2 Does reputation pricing vary across traders?

We first investigate the effect of sending a trade request to a non-specialist trader. Traders in OTC markets tend to be highly specialized; for example, one trader in our sample only trades short-end interest-rate derivatives in Swedish Kroner. In practice, the customer cannot choose or even observe which trader the RFQ is routed to. The dealer's IT system will attempt to send the RFQ to the specialist trader for the bond and if this trader is not available, will route it to a different trader, who is available. Figure 2 shows requests to trade a German government bond during September 2022. Trader 11 usually prices these requests, however during two days in late September, this trader recorded zero trades and Trader 32 priced all requests for the German government bond.

For each asset, we categorize traders in three groups: 1) the specialist trader, defined as the trader who handled the majority of requests for the bond, 2) a $NonSpecialist$ trader is someone who while not a specialist mainly trades assets in the same asset class as the specialist trader and lastly 3) an $OutsideTrader$: someone who is neither a specialist, nor an expert in the particular asset class. To test whether trader routing influences relationship, we estimate the following regression:

$$
\begin{aligned}
Spread_{a,c,i,t,p} = {} & \gamma_0 + \gamma_1 Relationship_{t,c} + \beta \mathbf{X} \\
& + \gamma_2 NonSpecialist_{t,i,a} + \gamma_3 NonSpecialist \cdot Relationship_{t,c} \\
& + \gamma_4 OutsideTrader_{t,i,a} + \gamma_5 OutsideTrader \cdot Relationship_{t,c} \\
& + \alpha_i + \omega_p + \phi_{a,t} + \theta_c + \varepsilon_{a,c,i,t,p}
\end{aligned}
$$

We refer to section 4.2 for a detailed description of the other regression variables and fixed effects. Table 15 presents the results. In all specifications, we find $\hat{\gamma}_2 > 0$ and $\hat{\gamma}_3$ which is statistically insignificant from 0. This means that when an RFQ is routed to a trader specialized in the asset class, but not in the particular bond, the bid-ask spread is around 1 bp wider, but the relationship discount is unchanged (relative to the pricing of the usual specialist trader). On other hand, we find $\hat{\gamma}_5 > 0$, meaning that an outside trader does not offer a similar relationship discount, almost halving the usual discount of 1-2 bps per customer ranking.

These results provide strong evidence of agency issues within the bank. As traders are compensated based on their group's (i.e., asset class') financial performance, an outside trader is not directly affected by the loss in relationship between a client and an asset class, he is not specialized in. The outside trader is therefore incentivised to play the one-period optimal response (i.e., offer a less favorable price). The non-specialist trader, on the other hand, is incentivised to honor the relationship discount, but he may lack the sufficient expertise vis-a-vis the particular bond, which explains the added spread when such a trader prices the RFQ.

6.3 Role of salespeople

Working alongside traders, virtually all large investment banks have employees called "salespeople". Anecdotally, the job of these individuals is to serve as a conduit between customers and traders. In practice, each portfolio manager at a customer will be connected to one salesperson (since a customer can employ several portfolio managers, a firm can be connected to multiple salespeople). The salesperson is then responsible for managing the long-term relationship and connecting the customer to traders in different asset classes. We plot the network structure of the 5 most important salespeople in Figure 3. The figure shows how customers are connected to salespeople, who then in turn connects the customers to traders in order to obtain quotes. Notice that each of the 5 salespeople is connected to traders in the different asset classes, that is the salespeople do not specialize in a specific asset class. As documented earlier, customers trade multiple asset classes and it is therefore important that they are connected to salespeople who are involved with a diverse set of assets.

To investigate if customers with strong relationships have ties to more well-connected salespeople, we calculate the degree centrality for each salesperson based on the total network between customers, salespeople and traders. Then for each customer, we compute the average centrality of each of the salespeople it is connected to. We document two findings: 1) highly ranked customers are connected to more salespeople and 2) their salespeople have a higher degree centrality. This indicates that salespeople do in fact play a role in facilitating long term relationships.

6.4 Salespeople trader relationships

How do investment banks ensure that customers with strong relationships receive advantageous bid-ask spreads, even when trading asset classes where they perhaps have a weak relationship with the particular traders? We here investigate whether relationships between salespeople and traders can play a role. The idea here is that while the customer may have little trading history with certain traders, the salesperson can use the relationship with the trader that he has obtained through all his other customers' trading. To measure this sales-trader relationship, we compute the quarterly trading volume between each trader and sales ID in our sample:

$$SalesTraderRelationship_{trader,s,q} = \sum TradeVolume_{trader,s,q-1}$$

Where $TradeVolume_{trader,s,q-1}$ is the trade notional on any trade involving salesperson s and trader t during quarter $q-1$. Put differently, we measure the relationship by summing the size of all trades in the previous quarter between the specific trader and salesperson. To see whether this relationship impacts a customer's bid-ask spread, we run the following regression:

$$\begin{aligned} Spread_{a,c,i,t,p} = & \gamma_0 + \gamma_1 Relationship_{t,c} \\ & + \gamma_2 SalesTraderRelationship_{t,a} + \beta \mathbf{X} \\ & + \alpha_i + \omega_p + \phi_{a,t} + \theta_c + \varepsilon_{a,c,i,t,p} \end{aligned}$$

The results are shown in Table 16. We find that customers who are connected to salespeople with strong relationships to the specific trader receive even low bid-ask spreads. $SalesTraderRelationship$ is standardized, meaning that we can interpret the estimate as follows: a 1 std increase in the sales-trader relationship leads to a reduction of bid-ask spreads of around 0.4-0.7 bps.

7 Conclusion

We show that trading relationships play a key role even in fast electronic RFQ markets. For customers with close trading relationships, the dealer deviates significantly from the one-period optimal response and rewards such customers with more advantageous bid-ask spreads and more frequent quotes. Furthermore, during times of market stress the same customers are insulated from sudden drops in market liquidity. The strength of the dealer-customer relationship can best be explained by the propensity of customers to engage in a hidden action. The rankings thus work as an incentive system: if the customer behaves well, their ranking increases and they enjoy more competitive and frequent quotes.

We also show that the scope of OTC relationships extends across asset classes and that customers prefer to trade with the same dealer across different asset classes. Finally, we provide evidence that investment banks' organisational structure are designed to ensure that traders offer discounts to highly valued customers. Our findings raise questions for future research in OTC markets, since data limitations usually force empirical researchers to focus on a single market (Czech and Pinter (2022) and Pinter et al. (2022) being notable exceptions). For example, previous studies have shown that trading costs generally decrease in a customer's number of relationship dealers (Hendershott et al., 2020) and yet on average, customers only contact few dealers (Riggs et al., 2020). However, this seemingly irrational behavior might be driven by the desire to solidify trading relationships with certain dealers in order to to lower trading costs in other less liquid asset classes.

A fruitful avenue for future research would be to investigate the link between concentration among dealers and customers and trading relationships. In recent years, high frequency trading companies have begun competing with established OTC dealers in certain markets (Risk.net, 2017), while the customer side has arguably seen increased concentration due to consolidation in the asset management industry[9] and the continued growth of global giants like Blackrock and Amundi. It could therefore be interesting to understand how existing trading relationships are affected by these changes and to see whether the new crop of market makers establish the same bilateral links despite lacking a presence across multiple OTC markets.

All in all, we paint a picture of OTC markets where asset classes are intertwined and where reputation matters greatly. Customers' optimal response may be to build close trading relationships with just a few select dealers. This may explain why investment banks tend to be global and active in all major asset classes, thus allowing a customer to access all

[9]2021 set a historical record for M&A deals in the asset management industry (Financial Times, 2021).

markets through their favorite intermediary. Our findings also have implications for policy-makers. Consider for example a (hypothetical) proposal to ban off-exchange OTC trading of equities. Such a proposal might aim to move trading to centralized exchanges, where competition among intermediaries is higher, presumably allowing investors to trade at more favourable prices. An unintended side effect of such a ban would however be a weakening of trading relationships between OTC dealers and their customers. This might have particularly strong effects on asset classes that are infrequently traded, such as inflation-linked bonds and corporate bonds which experienced large increases in quoted spreads during the 2020 Covid crisis. A customer with fewer dealer relationships from equity trading would then face higher bid-ask spreads on average in other less liquid OTC markets and would not benefit from the insurance-like protection that dealers offer to their best clients.

Table 1. Best Execution report, example

A. Eaton Vance, Credit derivatives counterparties, 2020

Dealer	% of volume	% of orders
Citigroup	67.92	49.59
Barclays	9.90	9.43
Bank of America	7.67	9.02
Citibank NA	6.70	17.62
Goldman Sachs	6.40	8.61

B. Eaton Vance, Interest rate derivatives counterparties, 2020

Dealer	% of volume	% of orders
Citigroup	75.16	84.29
Goldman Sachs	17.69	8.23
JP Morgan	3.51	2.24
Bank of America	1.80	1.25
BNP Paribas	1.70	2.99

Table 2. Summary Statistics: Best Execution reports

	mean	median	10th pct	90th pct	std	no. obs
Relationship*	16.68%	11.21%	4.27%	35.62%	17.32%	1,496
Relationship$^+$	14.78%	9.33%	1.35%	33.74%	17.17%	1,496
Overall Relationship*	6.38%	3.29%	0.00%	16.11%	9.18%	1,496
Overall Relationship$^+$	5.87%	2.38%	0.00%	15.73%	9.29%	1,496

	obs	dealers	customers	top dealer*	top dealer$^+$	HHI*	HHI$^+$
Bonds	194	41	12	JPM	JPM	0.09	0.06
CFD	83	15	7	JPM	JPM	0.26	0.25
Commod derivs	66	18	6	Citi	Citi	0.39	0.39
Convertible bonds	26	10	2	Jefferies	Jefferies	0.12	0.13
Credit derivs	196	17	16	JPM	JPM	0.30	0.23
Credit options	20	7	2	JPM	Barc	0.34	0.35
EQ derivs	45	12	6	MS	JPM	0.33	0.29
FX derivs	256	42	19	JPM	JPM	0.29	0.30
FX derivs (linear)	56	16	5	Banque Lux	BNP	0.43	0.38
Fixed income	98	20	9	GS	GS	0.10	0.09
IR derivs	102	22	8	JPM	JPM	0.33	0.29
IR derivs (linear)	155	26	11	GS	JPM	0.26	0.21
Money market	126	35	11	BNY	BNY	0.31	0.25
Repo	73	21	6	Barc	Barc	0.31	0.28
Total	1,496	100	24	JPM	JPM	0.26	0.24

* = based on volume, $^+$ = based on orders

Table 3. RFQ observation, example

Bond	DE0001102507
BondDescription	German Bund, DBR 0 08/15/30
Currency	EUR
Date	Apr 25 2022, 11:37:02
Customer ID	Cust39
CustomerRanking	Silver
CustomerRequest	RequestForBid
Size	15,000,000
NumofBanks	5
Quoted	Yes
DealerQuote	101.96
ReferenceMid	102.04
InterdealerMid	102.06
Outcome	Dealer bought @ 101.96
CoverPrice	101.92
Trader ID	Trader32
Salesperson ID	Sales5

Table 4. Summary Statistics: Requests-for-quote

	Obs	Traders	Sales	Trade size (EUR m.)	Bidders	Quoted (%)	Traded (%)	Quoted spread (basis points)
Government bonds								
EUR	421,637	34	62	6.6	10.0	62.3	7.2	9.3
SEK	41,291	17	56	5.9	4.1	85.7	33.4	10.1
DKK	27,154	15	50	6.4	4.2	88.4	52.9	2.7
NOK	26,532	13	57	2.8	5.2	82.8	27.2	8.2
USD	2,652	10	37	0.4	7.7	73.4	15.4	51.4
Corporate bonds								
EUR	331,239	20	55	0.6	12.6	38.9	12.8	28.4
USD	38,686	11	42	0.4	9.0	51.0	19.7	48.5
NOK	18,779	13	46	1.7	4.1	84.2	47.3	15.1
SEK	13,293	8	47	3.2	2.4	90.4	59.0	13.0
DKK	1,609	6	29	0.9	1.5	85.8	64.4	29.9
GBP	1,065	7	24	0.7	17.3	10.7	3.6	32.0
Mortgage bonds								
DKK	87,407	17	49	6.1	2.8	93.9	43.6	10.0
EUR	43,191	21	59	1.7	11.3	52.1	10.2	12.3
SEK	40,114	11	62	10.2	3.7	93.6	33.2	3.1
NOK	4,809	4	40	5.5	3.5	92.0	51.2	2.8
Inflation-linked bonds								
EUR	38,581	14	50	2.6	10.2	52.6	4.2	15.1
SEK	15,807	12	53	1.8	3.6	93.1	34.9	14.8
DKK	2,618	10	38	2.4	3.9	84.0	29.2	15.2
Supranational bonds								
EUR	23,190	22	56	6.7	9.5	54.9	10.1	21.5
NOK	13,190	11	42	0.8	6.8	74.4	28.3	13.4
SEK	8,352	13	55	5.5	4.0	87.5	35.5	9.0
TRY	4,293	7	21	0.1	6.7	59.8	9.0	81.5
ZAR	2,587	7	13	0.1	7.3	70.5	13.9	29.4
Interest rate swaps								
EUR	27,483	6	35	69.2	6.1	51.2	10.6	n/a
SEK	16,823	10	26	64.3	3.6	85.3	27.9	n/a
NOK	9,465	8	17	27.3	4.2	84.7	24.1	n/a
GBP	1,040	3	13	46.4	7.1	1.2	0.0	n/a
Total	1,266,043	56	63	6.6	8.9	61.6	17.4	14.2

Table 5. Summary Statistics: Customer tiers

	Customers	Trades per quarter	Trade size ($m.)	Bidders per RFQ	Probability of quote	Probability of trade success	Quoted spread (bps)	Quarterly volume
Bronze	247	152.8	4.8	12.0	43.2	13.6	21.4	840.7
Silver	2,805	38.9	6.8	9.0	62.1	31.5	14.4	139.1
Gold	844	67.3	5.5	8.1	66.9	28.2	12.9	330.4
Platinum	76	131.5	11.1	4.5	84.5	34.0	6.4	1292.7

Table 6. **Cross-market concentration of trading relationships**

This table reports the estimation results from the linear regression:

$$Relationship_{c,d,a,t} = \gamma_0 + \gamma_1 Overall\ Relationship_{c,d,a,t} + \alpha_{d,m} + \varepsilon_{c,d,a,t}$$

Where *Relationships* is share of trading between customer c and dealer t and *Overall Relationship* is calculated by averaging the relationship variable in all other asset classes.

	(1)	(2)	(3)	(4)
Overall Relationship*	0.270**	0.368***		
	(4.08)	(5.24)		
Overall Relationship$^+$			0.335***	0.402***
			(5.17)	(4.63)
Constant	0.150***	0.144***	0.128***	0.125***
	(17.45)	(38.27)	(11.20)	(16.38)
Dealer x Asset Class fixed effects	No	Yes	No	Yes
Observations	1,496	1,418	1,496	1,418
R^2	0.341	0.382	0.288	0.321

* = based on volume, $^+$ = based on orders

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors are clustered on customer, dealer, year and asset class.

Table 7. Monopolist discount and customer timer

Tier	Discount (in bps)	t-stat
Bronze	3.37***	5.12
Silver	0.94	0.48
Gold	6.10***	11.29
Platinum	8.77***	12.93

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard-errors are clustered on ISIN code and date.

Table 8. **Relationship and quoted bid-ask spreads**

This table reports the estimation results from the linear regression:

$$\begin{aligned} Spread_{a,c,i,t,p} = &\gamma_0 + \gamma_1 Relationship_{t,c} + \gamma_2 Relationship_{t,c} \cdot VIX_t \\ &+ \gamma_3 PastVolume_{t,c} + \beta \mathbf{X} \\ &+ \alpha_i + \omega_p + \phi_{a,t} + \theta_c + \varepsilon_{a,c,i,t,p} \end{aligned}$$

Where *Spread* is the bid-ask spread on a RFQ calculated as the relative difference between the quoted price and the mid-price.

	(1)	(2)	(3)	(4)	(5)	(6)
Relationship	-2.149***	-2.105***	-0.849***	-2.416***	-2.260***	-0.959***
	(-15.16)	(-15.84)	(-7.00)	(-13.66)	(-15.67)	(-7.06)
Relationship × VIX				-0.0647***	-0.0371***	-0.0245**
				(-4.29)	(-3.33)	(-2.42)
Past volume	-0.913***	-0.769***	-0.397***	-0.927***	-0.773***	-0.397***
	(-13.37)	(-11.86)	(-4.23)	(-13.47)	(-11.90)	(-4.22)
Trade size	-0.147	-0.102	0.305***	-0.137	-0.0970	0.307***
	(-1.19)	(-0.84)	(6.14)	(-1.12)	(-0.79)	(6.18)
No. of bidders	1.297***	1.388***	2.238***	1.286***	1.383***	2.236***
	(4.97)	(5.36)	(18.01)	(4.93)	(5.35)	(18.02)
Maturity	7.579***	6.456***	5.526***	7.562***	6.453***	5.523***
	(9.27)	(9.94)	(6.10)	(9.22)	(9.93)	(6.09)
Date FEs	Yes	No	No	Yes	No	No
ISIN FEs	Yes	Yes	Yes	Yes	Yes	Yes
Date x Asset class x Currency FEs	No	Yes	Yes	No	Yes	Yes
Customer FEs	No	No	Yes	No	No	Yes
Platform FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	661,309	659,621	659,169	661,309	659,621	659,169
R^2	0.471	0.549	0.569	0.472	0.549	0.569

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9. **Relationship and Quote frequency**

This table reports the estimation results from the linear probability model:

$$\begin{aligned} Quoted_{a,c,i,t,p} = &\gamma_0 + \gamma_1 Relationship_{t,c} + \gamma_2 Relationship_{t,c} \cdot VIX_t \\ &+ \gamma_3 PastVolume_{t,c} + \beta \mathbf{X} \\ &+ \alpha_i + \omega_p + \phi_{a,t} + \theta_c + \varepsilon_{a,c,i,t,p} \end{aligned}$$

Where *Quoted* is a dummy variable which indicates for a given RFQ whether the dealer showed a quote or not.

	(1)	(2)	(3)	(4)	(5)	(6)
Relationship	2.542***	2.327***	-0.159	2.829***	2.401***	-0.0835
	(11.35)	(12.24)	(-0.70)	(12.03)	(12.39)	(-0.35)
Relationship × VIX				0.102***	0.0267**	0.0216**
				(6.16)	(2.25)	(1.99)
Past volume	0.349	0.764***	0.229	0.357	0.767***	0.230
	(1.02)	(3.58)	(1.29)	(1.04)	(3.60)	(1.30)
Trade size	1.363***	1.194***	0.823***	1.353***	1.192***	0.822***
	(3.24)	(2.98)	(4.45)	(3.23)	(2.98)	(4.45)
No. of bidders	-9.213***	-7.637***	-4.762***	-9.202***	-7.635***	-4.760***
	(-14.59)	(-12.89)	(-19.08)	(-14.56)	(-12.89)	(-19.05)
Maturity	5.083***	2.765***	1.785***	5.107***	2.769***	1.790***
	(4.10)	(3.49)	(3.10)	(4.12)	(3.49)	(3.11)
Date FEs	Yes	No	No	Yes	No	No
ISIN FEs	Yes	Yes	Yes	Yes	Yes	Yes
Date x Asset class x Currency FEs	No	Yes	Yes	No	Yes	Yes
Customer FEs	No	No	Yes	No	No	Yes
Platform FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,201,635	1,199,094	1,198,581	1,201,635	1,199,094	1,198,581
R^2	0.353	0.421	0.453	0.353	0.421	0.453

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10. **Relationship and number of dealers**

This table reports the estimation results from the linear regression:

$$\begin{aligned} NumofDealers_{a,c,i,t,p} = &\gamma_0 + \gamma_1 Relationship_{t,c} + \beta \mathbf{X} \\ &+ \alpha_i + \omega_p + \phi_{a,t} + \theta_c + \varepsilon_{a,c,i,t,p} \end{aligned}$$

Where $NumOfDealers$ is a number of dealers selected to submit quotes for the request-for-quote.

	(1)	(2)	(3)
Relationship	-0.0375***	-0.0293***	-0.0327***
	(-6.96)	(-5.49)	(-8.62)
Trade size	-0.158***	-0.154***	-0.0804***
	(-20.05)	(-20.83)	(-31.84)
Maturity	-0.0245	-0.00313	0.00303
	(-0.85)	(-0.18)	(0.34)
Date FEs	Yes	No	No
ISIN FEs	Yes	Yes	Yes
Date x Asset class x Currency FEs	No	Yes	Yes
Customer FEs	No	No	Yes
Platform FEs	Yes	Yes	Yes
Observations	1,256,191	1,253,496	1,252,959
R^2	0.704	0.728	0.840

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11. **Relationship and Trade failure**

This table reports the estimation results from the linear probability model:

$$\begin{aligned} NoTrade_{a,c,i,t,p} = & \gamma_0 + \gamma_1 Relationship_{t,c} + \\ & + \gamma_2 Spread_{a,c,i,t,p} + \beta \mathbf{X} \\ & + \alpha_i + \omega_p + \phi_{a,t} + \theta_c + \varepsilon_{a,c,i,t,p} \end{aligned}$$

Where $NoTrade$ is a dummy variable that equals 1 if the RFQ did not result in the customer trading with any dealer.

	(1)	(2)	(3)
Relationship	-4.450***	-4.641***	-0.874***
	(-21.69)	(-22.07)	(-4.33)
No. of bidders	-5.566***	-4.873***	-5.047***
	(-13.42)	(-12.52)	(-16.45)
Trade size	5.118***	5.177***	3.318***
	(18.02)	(18.16)	(16.76)
Maturity	-5.142***	-4.446***	-2.867***
	(-5.42)	(-4.69)	(-4.34)
Spread	0.228***	0.231***	0.208***
	(21.83)	(21.45)	(27.79)
Date FEs	Yes	No	No
ISIN FEs	Yes	Yes	Yes
Date x Asset class x Currency FEs	No	Yes	Yes
Customer FEs	No	No	Yes
Platform FEs	Yes	Yes	Yes
Observations	692,719	690,917	690,447
R^2	0.131	0.175	0.271

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12. **Cover deviation and relationship**

This table reports the estimation results from the linear regression:

$$CoverSpread_{a,c,i,t,p} = \gamma_0 + \gamma_1 Relationship_{t,c} + \beta\mathbf{X} + \alpha_i + \omega_p + \phi_{a,t} + \theta_c + \varepsilon_{a,c,i,t,p}$$

Where *CoverSpread* is the price improvement relative to the second-best price (the cover price).

	(1)	(2)	(3)
Relationship	-0.859***	-0.818***	-0.0358
	(-10.49)	(-8.98)	(-0.32)
Trade size	-0.193***	-0.169***	-0.0000447
	(-3.46)	(-2.98)	(-0.00)
No. of bidders	-2.645***	-2.553***	-2.828***
	(-15.51)	(-15.50)	(-14.27)
Maturity	3.427***	3.079***	3.312***
	(9.27)	(8.32)	(9.62)
Date FEs	Yes	No	No
ISIN FEs	Yes	Yes	Yes
Date x Asset class x Currency FEs	No	Yes	Yes
Customer FEs	No	No	Yes
Platform FEs	Yes	Yes	Yes
Observations	91,723	87,225	87,104
R^2	0.379	0.489	0.503

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1. Time-series price plot for a Danish mortgage bond and Bund future

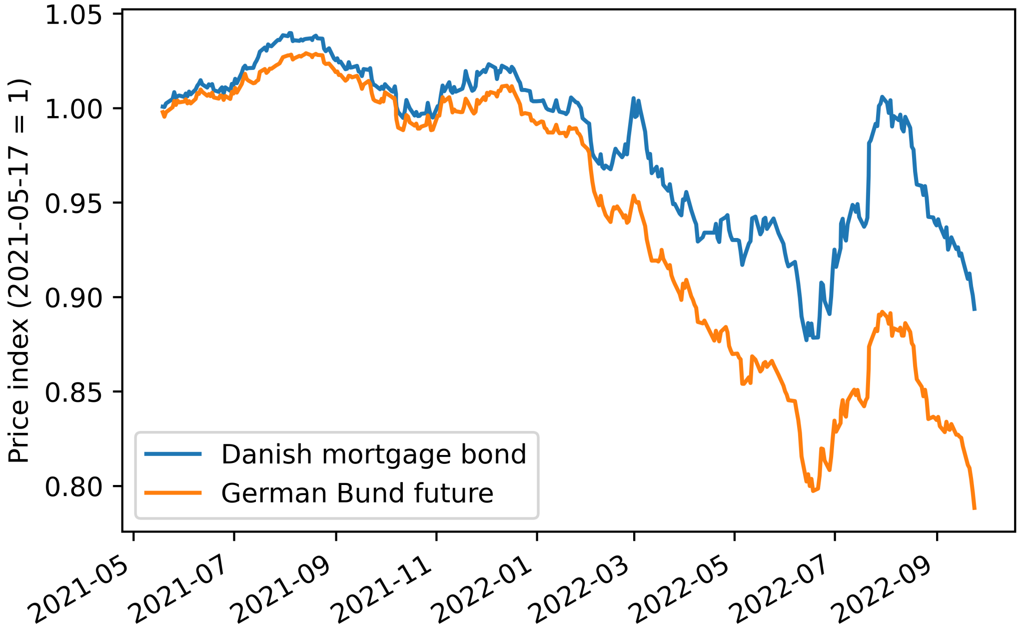


Table 13. **Relationship and Informativeness**

This table reports the estimation results from the linear regression:

$$DealerLoss_{a,c,i,t,p} = \gamma_0 + \gamma_1 Relationship_{t,c} + \gamma_2 NoTrade + \beta \mathbf{X} + \alpha_i + \omega_p + \phi_{a,t} + \theta_c + \varepsilon_{a,c,i,t,p}$$

Where *DealerLoss* is the customer's 1-day return on a trade (marked to the end-of-day reference price on the following day) if the bid-ask spread had been 0.

	(1) DL	(2) DL	(3) DL	(4) Adj. DL	(5) Adj. DL	(6) Adj. DL
Relationship	-0.178	-0.131	-0.105	-0.104	-0.100	0.101
	(-1.14)	(-0.80)	(-0.34)	(-0.91)	(-0.84)	(0.44)
No. of bidders	-0.0739	-0.0168	0.266	0.0892	0.0788	-0.0215
	(-0.31)	(-0.07)	(1.16)	(0.56)	(0.51)	(-0.13)
Trade size	0.215***	0.213***	0.232***	0.235***	0.207***	0.271***
	(2.82)	(2.91)	(2.78)	(4.73)	(4.47)	(4.75)
Maturity	-0.313	-0.196	0.0749	-0.0799	0.0615	0.203
	(-0.47)	(-0.33)	(0.13)	(-0.16)	(0.13)	(0.40)
No trade	2.831***	2.638***	2.639***	2.733***	2.632***	2.524***
	(8.26)	(8.05)	(8.12)	(9.41)	(9.62)	(9.23)
Date FEs	Yes	No	No	Yes	No	No
ISIN FEs	Yes	Yes	Yes	Yes	Yes	Yes
Date x Asset Class x Currency	No	Yes	Yes	No	Yes	Yes
Customer FEs	No	No	Yes	No	No	Yes
Platform FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	996,128	994,161	993,690	996,128	994,161	993,690
R^2	0.045	0.093	0.097	0.053	0.110	0.114

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14. **Bid-ask spreads and new client**

This table reports the estimation results from the linear regression:

$$\begin{aligned} Spread_{a,c,i,t,p} = & \gamma_0 + \gamma_1 Relationship_{t,c} + \gamma_2 Relationship_{t,c} \cdot NewClient_{t,a,c} \\ & + \gamma_3 NewClient_{t,a,c} + \beta \mathbf{X} \\ & + \alpha_i + \omega_p + \phi_{a,t} + \theta_c + \varepsilon_{a,c,i,t,p} \end{aligned}$$

Where *Spread* is the quoted bid-ask spread and where $NewClient$ is a dummy variable which is equal to 1 if the customer did not send any RFQs in the given asset class in the previous quarter (we exclude observations from a customer's first quarter of trading)

	(1)	(2)	(3)
Relationship	-2.124***	-2.076***	-0.811***
	(-14.13)	(-14.91)	(-6.48)
New Client	2.632***	2.206***	2.472***
	(7.06)	(7.26)	(7.99)
Relationship × New Client	-0.0968	-0.190	-0.106
	(-0.44)	(-0.89)	(-0.54)
No. of bidders	1.454***	1.549***	2.193***
	(5.53)	(5.89)	(17.93)
Trade size	-0.248**	-0.186	0.306***
	(-2.00)	(-1.52)	(6.07)
Maturity	7.554***	6.418***	5.559***
	(9.27)	(9.91)	(6.15)
Date FEs	Yes	No	No
ISIN FEs	Yes	Yes	Yes
Date x Asset class x Currency FEs	No	Yes	Yes
Customer FEs	No	No	Yes
Platform FEs	Yes	Yes	Yes
Observations	661,309	659,621	659,169
R^2	0.472	0.549	0.569

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 2. Trade requests in a German inflation-linked government bond maturing in 2026

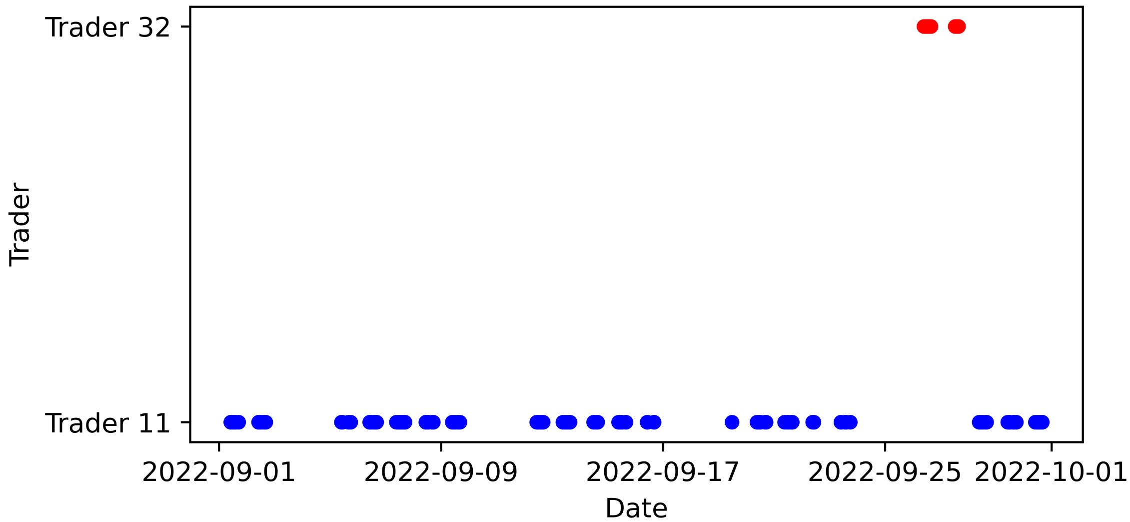


Table 15. **Relationship effects and salesperson monitoring**

This table reports the estimation results from the linear regression:

$$\begin{aligned} Spread_{a,c,i,t,p} = &\gamma_0 + \gamma_1 Relationship_{t,c} + \beta \mathbf{X} \\ &+ \gamma_2 NonSpecialist_{t,i,a} + \gamma_3 NonSpecialist \cdot Relationship_{t,c} \\ &+ \gamma_4 OutsideTrader_{t,i,a} + \gamma_5 OutsideTrader \cdot Relationship_{t,c} \\ &+ \alpha_i + \omega_p + \phi_{a,t} + \theta_c + \varepsilon_{a,c,i,t,p} \end{aligned}$$

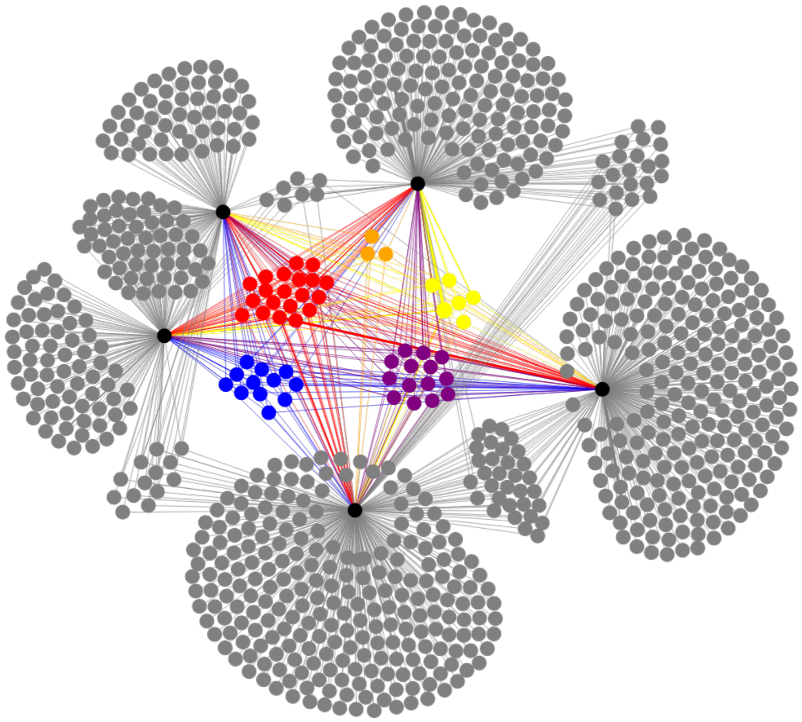
Where $NonSpecialist$ is a trader active in the same asset class as the specialist trader, but not specialised in the particular bond and where $OutsideTrader$ is a trader who is not normally active in the asset class.

	(1)	(2)	(3)
Relationship	-2.264***	-2.241***	-0.952***
	(-15.41)	(-15.85)	(-7.82)
Non-specialist trader	0.716**	0.953***	1.046***
	(2.51)	(3.86)	(4.40)
Non-specialist trader × Relationship	0.168	0.157	0.0729
	(1.23)	(1.31)	(0.64)
Outside trader	-0.836*	-0.610	-0.128
	(-1.68)	(-1.26)	(-0.30)
Outside trader × Relationship	1.038***	0.900***	0.546***
	(4.12)	(3.87)	(2.71)
Controls	Yes	Yes	Yes
Date FEs	Yes	No	No
ISIN FEs	Yes	Yes	Yes
Date x Asset class x Currency FEs	No	Yes	Yes
Customer FEs	No	No	Yes
Platform FEs	Yes	Yes	Yes
Observations	692,719	690,917	690,447
R^2	0.470	0.548	0.568

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 3. Customer, salesperson and trader network



Note: The figure shows the structure of the network for the 5 most important salespeople, which are represented by the black nodes. The gray nodes are the customers, while the coloured nodes are traders (each colour representing one asset class)

Table 16. **Bid-ask spreads and sales-trader relationship**

This table reports the estimation results from the linear regression:

$$\begin{aligned} Spread_{a,c,i,t,p} = &\gamma_0 + \gamma_1 Relationship_{t,c} \\ &+ \gamma_2 SalesTraderRelationship_{t,a} + \beta\mathbf{X} \\ &+ \alpha_i + \omega_p + \phi_{a,t} + \theta_c + \varepsilon_{a,c,i,t,p} \end{aligned}$$

Where $SalesTraderRelationship$ measures the relationship between the salesperson and the trader involved in the RFQ.

	(1)	(2)	(3)
Relationship	-2.159***	-2.116***	-0.860***
	(-15.23)	(-15.97)	(-7.08)
Sales-trader relationship	-0.681***	-0.683***	-0.387***
	(-8.27)	(-9.14)	(-4.98)
No. of bidders	1.409***	1.474***	2.234***
	(5.35)	(5.64)	(18.36)
Trade size	-0.190	-0.125	0.302***
	(-1.57)	(-1.04)	(6.01)
Maturity	7.488***	6.412***	5.511***
	(9.18)	(9.91)	(6.10)
Date FEs	Yes	No	No
ISIN FEs	Yes	Yes	Yes
Date x Asset class x Currency FEs	No	Yes	Yes
Customer FEs	No	No	Yes
Platform FEs	Yes	Yes	Yes
Observations	661,309	659,621	659,169
R^2	0.471	0.549	0.569

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

References

Afonso, Gara, Anna Kovner, and Antoinette Schoar, "Trading Partners in the Interbank Lending Market," *FRB of New York Staff Report*, 2013, *620.*

Allen, Jason and Milena Wittwer, "Centralizing Over-The-Counter Markets?," *Journal of Political Economy*, 2023.

Asquith, Paul, Thom Covert, and Parag Pathak, "The Effects of Mandatory Transparency in Financial Market Design: Evidence from the Corporate Bond Market," Working Paper 19417, National Bureau of Economic Research September 2013.

Bernhardt, Dan, Vladimir Dvoracek, Eric Hughson, and Ingrid M. Werner, "Why Do Larger Orders Receive Discounts on the London Stock Exchange?," *The Review of Financial Studies*, 08 2004, *18* (4), 1343–1368.

Bessembinder, Hendrik, William Maxwell, and Kumar Venkataraman, "Market transparency, liquidity externalities, and institutional trading costs in corporate bonds," *Journal of Financial Economics*, 2006, *82* (2), 251–288.

Biais, Bruno and Richard Green, "The microstructure of the bond market in the 20th century," *Review of Economic Dynamics*, 2019, *33*, 250–271. Fragmented Financial Markets.

Czech, Robert and Gabor Pinter, "Informed Trading and the Dynamics of Client-dealer Connections in Corporate Bond Markets," *Bank of England Working Paper*, 2022.

Duffie, Darrell, Nicolae Gârleanu, and Lasse Heje Pedersen, "Over-the-Counter Markets," *Econometrica*, 2005, *73* (6), 1815–1847.

Edwards, Amy K., Lawrence E. Harris, and Michael S. Piwowar, "Corporate Bond Market Transaction Costs and Transparency," *The Journal of Finance*, 2007, *62* (3), 1421–1451.

Financial Times, "AMG chief slams asset management industry deal wave," *https://www.ft.com/content/5a5398f6-987f-477d-b557-37cfede66e69*, 2021.

Glode, Vincent and Christian C Opp, "Over-the-Counter versus Limit-Order Markets: The Role of Traders' Expertise," *The Review of Financial Studies*, 06 2019, *33* (2), 866–915.

Goldstein, Michael A., Edith S. Hotchkiss, and Erik R. Sirri, "Transparency and Liquidity: A Controlled Experiment on Corporate Bonds," *The Review of Financial Studies*, 07 2006, *20* (2), 235–273.

Haddad, Valentin, Alan Moreira, and Tyler Muir, "When Selling Becomes Viral: Disruptions in Debt Markets in the COVID-19 Crisis and the Fed's Response," *The Review of Financial Studies*, 01 2021, *34* (11), 5309–5351.

Hau, Harald, Peter Hoffmann, Sam Langfield, and Yannick Timmer, "Discriminatory Pricing of Over-the-Counter Derivatives," *Management Science*, 2021, *67* (11), 6660–6677.

Hendershott, Terrence and Ananth Madhavan, "Click or Call? Auction versus Search in the Over-the-Counter Market," *The Journal of Finance*, 2015, *70* (1), 419–447.

_ , Dan Li, Dmitry Livdan, and Norman Schürhoff, "Relationship Trading in Over-the-Counter Markets," *The Journal of Finance*, 2020, *75* (2), 683–734.

Jurkatis, Simon, Andreas Schrimpf, Karamfil Todorov, and Nicholas Vause, "Relationship Discounts in Corporate Bond Trading," *Working paper*, 2022.

Kargar, Mahyar, Benjamin Lester, David Lindsay, Shuo Liu, Pierre-Olivier Weill, and Diego Zúñiga, "Corporate Bond Liquidity during the COVID-19 Crisis," *The Review of Financial Studies*, 05 2021, *34* (11), 5352–5401.

Lee, M. and C. Wang, "Why Trade Over the Counter?," *Working paper*, 2022.

Maggio, Marco Di, Amir Kermani, and Zhaogang Song, "The value of trading relations in turbulent times," *Journal of Financial Economics*, 2017, *124* (2), 266–284.

O'Hara, Maureen and Xing (Alex) Zhou, "The electronic evolution of corporate bond dealers," *Journal of Financial Economics*, 2021, *140* (2), 368–390.

_ and Xing (Alex) Zhou, "Anatomy of a liquidity crisis: Corporate bonds in the COVID-19 crisis," *Journal of Financial Economics*, 2021, *142* (1), 46–68.

Pinter, Gabor, Chaojun Wang, and Junyuan Zou, "Size Discount and Size Penalty: Trading costs in bond markets," *Working paper*, 2022.

Riggs, Lynn, Esen Onur, David Reiffen, and Haoxiang Zhu, "Swap trading after Dodd-Frank: Evidence from index CDS," *Journal of Financial Economics*, 2020, *137* (3), 857–886.

Risk.net, "Rates flow market-maker of the year: Citadel Securities," *https://www.risk.net/awards/5362966/rates-flow-market-maker-of-the-year-citadel-securities*, 2017.

Wang, Chaojun, "The limits of multi-dealer platforms," *Journal of Financial Economics*, 2023, *149* (3), 434–450.

Yueshen, Bart Zhou and Junyuan Zou, "Less is More," *Working paper*, 2023.

A Reducing noise in one-day price changes

A.1 Concept

Consider the following decomposition of bond price changes into two parts: an exposure to price changes in liquid government bond futures and an idiosyncratic component. Formally, we model a bond's price change as:

$$\Delta P_t = \beta_0 + \beta_{1,t}\Delta X_t + \Delta\gamma_t + \varepsilon_t$$

Where X_t is a price vector of 6 European government bond futures and where γ_t is the bond's idiosyncratic component. Note that $\beta_{1,t}$ is time-varying and may depend on X_t and other features such as the bond's currency, asset class, issuer and time to maturity. Since the government bond futures futures are exchange-traded and very liquid, we assume that no customer has private information with respect to price changes in these futures. We therefore isolate the change in the idiosyncratic component by estimating the exposure to government bond futures:

$$\Delta\hat{\gamma}_t = \Delta P_t - \hat{\beta}_0 - \hat{\beta}_{1,t}\Delta X_t$$

Using $\Delta\hat{\gamma}_t$ as an estimate of the component of a bond's price change that is uncorrelated with the government bond futures, we calculate the adjusted dealer loss as:

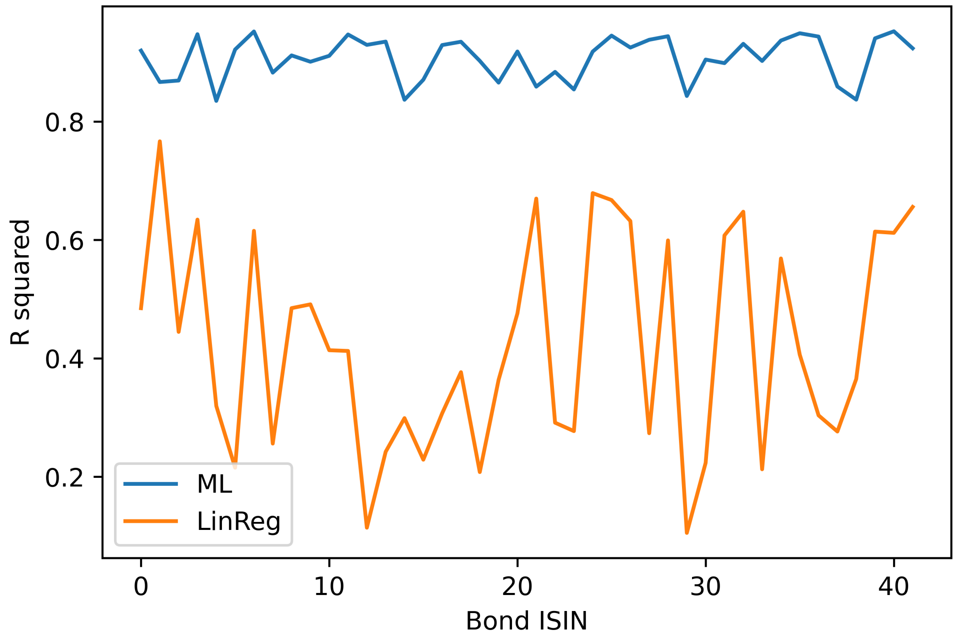
$$Adj\ DealerLoss_{i,t} = \frac{\Delta\hat{\gamma}_t}{MidPrice_{i,t}} \cdot D$$

A.2 Implementation

To estimate $\{\beta_0, \beta_{1,t}\}$ we employ LightGBM, a popular machine learning based on a gradient boosting network. We motivate the choice of a gradient boosting model over a linear regression by the fact that a gradient boosting model can encompass more flexible and potentially non-linear functional forms. To compare the out-of-sample performance of an ML model and a linear regression, we train both a LightGBM model and a ridge regression model[10] using data prior to 2022. We then test the out-of-sample performance in 2022 for 42 German government bonds whose R^2 is shown in Figure A1.

[10] Ridge regression is a linear regression which incorporates a penalty on the square of coefficient estimates.

Appendix Figure A1. Out-of-sample performance of a LightGBM Gradient boosting model and ridge regression on predicting German bond prices in 2022



A.3 Data

We combine our RFQ data set with end of day bond prices from Bloomberg, which in total yields 5,526,285 1-day price changes. We also obtain 1-minute spaced price data on government bond futures from firstratedata.com. We match the futures data to the 1-day price day, so that each observation of a change in bond prices is matched to a corresponding time-stamped change in futures prices. We also include the following features: currency, time to maturity, $dv01$, issuer and country. We estimate a different LightGBM model for each asset class. A summary of the estimation results are show in Table A1. The ML model succesfully reduced noise in *DealerLoss* without a significant change in the mean value.

Appendix Table A1. Comparison of unadjusted and adjusted *DealerLoss* in bps

	Mean		Std. Dev.	
	DL	*Adj.DL*	*DL*	*Adj.DL*
Corporate	6.942	7.375	41.519	38.924
Government bonds	1.039	1.670	51.626	35.128
Inflation-linked bonds	4.627	3.807	48.778	34.118
Mortgage bonds	0.832	1.032	24.408	19.729
Supranational bonds	0.557	0.689	44.955	38.799