Relationships versus Competition in OTC Markets

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Abstract

A salient feature in over-the-counter (OTC) markets is that many clients trade exclusively with one dealer. This paper uses a novel quote-level dataset from a request for quotes (RFQ) platform for non-financial firms to discover trading strategies over the entire trading process. Even though firms trade on the platform to foster dealer competition, many firms are locked into exclusive dealer relationships. The data reveal, that is dealers adjust their mark-ups depending on the number of active dealer connections of the requesting client. The evidence points towards regulatory and collateral requirements as the reason why firms lack dealer connections. Further, the results highlight the importance of the firm-bank relationships. Relationship dealers appear to follow a long-run strategy to keep their customers captive, while outside dealers maximize short-term profits.

JEL classifications: G14, G15, G18, G32, D4
Key words: OTC frictions, RFQ platforms, Firm-bank relationships

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1 Introduction

Over-the-counter (OTC) markets are gigantic. For example, the foreign exchange (FX) market, which is the largest financial market, has a daily turnover of \$7.5 trillion (Bank for International Settlements 2022). As such, small price differences in this market can have huge welfare consequences. One such price difference is discriminatory pricing against "less sophisticated" clients, which previous literature mainly associates with search frictions (Hau et al. 2021; O'Hara, Y. Wang, and Zhou 2018). Following the view that the foreign exchange market is intransparent, a centralization through request for quotes (RFQ) platforms is considered as a desirable market mechanism.[1] For example Hau et al. (2021) argue that European firms lose approximately 264 million Euro to their dealer banks yearly in the EUR/USD forward market because they do not move onto platforms.

Given the recent push towards centralizing OTC markets,[2] it is important to understand the underlying frictions governing trading behaviors on those markets and to what extent a centralization increases market efficiency. In this paper, I study the ability of corporate customers to foster dealer competition on a market-leading European FX platform to benefit from more favorable prices. In contrast to previous studies with trade-level data, this paper leverages detailed quote-level data

[1] In OTC markets, clients traditionally approach dealers sequentially over phone or by text. Dealers make take-it-or-leave-it offers which the clients either accept or decline. Therefore, the clients are unaware about the prices that they can potentially receive from other dealers. On platforms, clients can solicit quotes from multiple dealers simultaneously and select the most favorable price. Therefore, the trading mechanism resembles an auction.

[2] The Dodd-Frank act mandates certain products to be traded via centralized platforms (so-called swap execution facilities) and the MiFID II regulation incentives platform trades because clients can proof best execution on platforms. Further, empirical evidence supports this view (Hau et al. (2021) and Wittwer and Allen (2023, forthcoming))

from this platform allowing me to observe the entire trading process and to discover trading strategies in more detailed.[3]

This paper has two sets of main findings. First, many firms trade only with a few dealers and dealers discriminatively widen their mark-ups to firms with only a few dealer connections. This finding suggests that the lack of dealer connections impairs competition leading to bid-shading[4]. Second, the evidence shows that close ties between firms and banks are widespread even on RFQ platforms. The data reveal that less connected firms have a relationship dealer providing more favorable prices compared to those of outside dealers. While the pricing of the main relationship dealer appears to be less sensitive towards the trading volume, outside dealers narrow spreads markedly when the volume is large, which intensifies competition for large trades.[5] This suggests that not only number of dealer connections is important for the price quality but also the dealer's willingness to compete. The evidence of this paper is in line with the view that long-run firm-bank relationship shape the incentives to continuously supply a firm with relatively narrow spreads, whereas outside dealers maximize profits per trade. Though, relationships are likely to be formed outside

[3] Existing literature typically uses regulatory data sets for OTC markets which are all on trade level, see for example Hau et al. (2021), Hendershott, Li, et al. (2020), Jurkatis et al. (2023), and Wittwer and Allen (2023, forthcoming). Though, trades as the outcome of a competitive process show only a part of the picture. For example, relationship dealers appear to charge higher prices in the cross-sectio of trades pointing towards relationship premia (Hau et al. 2021), whereas my quote-level data show that outside dealers tend to quote even less favorable pointing towards relationship discounts. These quotes by outside dealers are not observable in a trade level data set, because they are not executed.

[4] Bid-shading is a term from auction theory describing that bidders adjust their markups in dependence of the number of competing bidders.

[5] This is in line with the evidence of Pinter, C. Wang, and Zou (forthcoming) showing a volume discount in the cross-section of clients. My evidence contributes to that view such that outside dealers improve prices and intensify competition once the volume increases.

the platform, because FX derivatives constitute only a part in a portfolio of services by banks. Therefore, it remains difficult to fully characterize the nature of the relationship.

The aim of this paper is to highlight frictions in relationships leading to different quoting strategies by dealers and price outcomes for clients.This means not only the *quantity* but also the *quality* of dealer connections is relevant to receive narrow spreads in OTC markets. The evidence highlights how both a lack of connections (quantity) and the willingness to compete by dealers (quality) limit competition. Moreover, it is important to highlight the heterogeneity in trading strategies depending on whether they are the main relationship or outside dealer to a less connected client. Therefore, relationship remain central in non-anonymous OTC trading, even centralized venues like the RFQ platform.

The main benefit of my setup is its absence of a search friction[6] which typically dominates OTC markets. Additionally, informational incentives are less likely to shape clients' dealer networks of non-financial firms compared to other clients such as institutinals (asset managers, insurers and hedge funds), because corporate clients trade FX to hedge their FX exposure and their trades carry little information (Ranaldo and Somogyi 2021; Menkhoff et al. 2016). In contrast, more informed institutional clients may choose small networks to reduce informational leakage (Kondor

[6]Pre-trade transparency is improved through the clients ability to simultaneously elicit quotes from multiple dealers in the RFQ auctions. This eliminates search costs from approaching dealers sequentially as model by Duffie, Gârleanu, and Pedersen (2005). To increase post-trade transparency, the platform provides monthly reports to its clients comparing the price quality of the client's trades across its connected banks and the overall price quality compared to other customers on the platform.

and Pinter 2022) or avoid front-running (Baldauf and Mollner forthcoming). Again, this novel setting allows me to document unrecognized relationship frictions in OTC markets. A salient feature of the data set is that 8% of firms exclusively trade with only one dealer and 45% of firms conduct at least half of their trades with one bank. Because firms cannot easily switch to other dealers, banks increase discriminatory markups for these less connected clients.

This study of discriminatory pricing on a RFQ platform captures only the tip of the iceberg of a much wider problem in OTC markets. Usually, the largest and well-connected multinational corporate clients join the platform. These firms are very active traders with multiple bank connections such that they can benefit from the RFQ auctions.[7,8] Hau et al. (2021) find that in the entire universe of European firms, more than 50% of the cooperates trade exclusively with one bank and Hendershott, Li, et al. (2020) document that 30% of US insurers are locked-in with one bank in the corporate bond market. A back-of-the-envelope calculation reveals that less connected clients on the platform lose approximately EUR 22 million yearly because of discriminatory pricing. Again, this is only the tip of the iceberg from a subset of trades and a subset of affected clients consisting mostly of the largest, and therefore least affected, European multinational corporations.

The main reason why firms are unable to add dealer connections can be found

[7] An interview with a manager of the platform reveals that the typical clients of the platform are the major European multinational corporations. For example, almost all of the German blue chip companies (DAX) hedge their foreign exchange exposure through the platform.

[8] The platform offers more benefits to its clients and dealers. For example, the platform increases workflow efficiency for dealers by allowing for straight-through-processing (STP) or to embed any enterprise resource planing (ERP) system. Firms can potentially hedge their currency exposure by just one click. This makes the platform also attractive to smaller clients seeking more automation.

in the clearing requirements. Opposed to central exchange markets, trades in OTC markets are typically cleared bilaterally either through a line of credit or cash at a account with the bank.[9] Therefore, one major contributor to the relationship friction is that setting up a bilateral trading link between a firm and a bank is costly, because it requires the same routines as starting a loan business with a new corporate client.[10] Before a client is able to request a dealer, there are legal hurdles imposing considerable costs on banks.[11] This strictly limits the set of banks a client can query for quotes. Once a connection is established, some dealers may either not quote or send markedly higher prices. For example, when clients have insufficient collateral at the bank, the bank categorically refuses to quote.[12] As consequence, 11% of all bank connections are never quoting, which effectively reduces the set of competing dealers.

To understand the special role of close relationships, this paper borrows insights from Qi (2023) and Bak-Hansen and Sloth (2023) who provide evidence from the inner of one bank. They show that banks foster relationships with profitable customers as an effort to keep them captive. The FX trading is typically only one piece of a

[9]The European Market Infrastructure Regulation (EMIR) imposes central clearing obligations on certain classes of OTC derivatives. The counterparties subject to central clearing obligations are generally financial counterparties (FCs) and non-financial counterparties (NFCs) whose positions exceed certain clearing thresholds. These thresholds are not relevant for the firms in the sample, because their trading activity is too small.

[10]The platform does not help facilitate firm-bank relationships. Instead, firms have to unlock their existing bank connections on the platform to be able to request the bank for a quote. These dealer connections must be established outside the platform.

[11]Section **??** provides a more detailed explanation on the legal requirements.

[12]Collateral is costly to both banks and firms. For example, firms typically pay fees on unused credit lines and banks must set aside regulatory capital even to undrawn credit lines. This suggests that financially constrained firms have fewer active bank connections, which leads to more expensive hedging. Therefore, the evidence suggests that financially constrained firms hedge less is because of the elevated costs (Rampini, Sufi, and Viswanathan 2014).

portfolio of services banks provide to their clients. This view suggests that dealers should offer lower prices to relational customers such that their is no incentive to open a new banking connection. Non-relationship dealers may maximize their profits per transaction without the long-run incentives to foster the relationship with a client. The evidence of this paper is in line with this view. Relational dealers of less connected clients appear to increase discriminatory markups only mildly, whereas outside dealers markedly widen discriminatory spreads. Once trading becomes more profitable due to large volumes, outside dealers narrow discriminatory spreads.[13]

Usually, relationships are viewed as beneficial, especially during periods of crisis (Di Maggio, Kermani, and Song 2017; Petersen and Rajan 1995). This paper exploits the market turmoils during the outbreak of the COVID-19 pandemic as a shock to dealer competition. As traders moved into the home office, uncertainty with regard to credit risk rose and many dealers turned off automatic quoting, the outbreak of the pandemic limits competition highlighting the role of exclusive relationships during the crisis. First, the evidence shows that outside dealers dropped their response rates to less connected clients markedly. While relationship dealers widen spreads only modestly at the spot, outside dealers increase spot prices sharply during March 2020. This suggests that dealers extract higher markups once the disciplining role of competition is impaired. At the forward, the evidence shows that prices increase more dramatically and outside dealers increase prices in a similar order of magnitude compared insight dealers. At long-term forward and swap trades, there is much

[13]This is also in line with the evidence of Pinter, C. Wang, and Zou (forthcoming) showing a volume discount in the cross-section of clients. My evidence contributes to that view such that outside dealers improve prices and intensify competition once the volume increases.

heterogeneity across dealers in their ability to price some currencies. The evidence suggests that the lack of dealer connections impairs the ability of to locate the dealer with the strongest trading ability. Therefore, wider spreads during the shock by exclusive connections may reflect both higher credit risk and the inability of relationship dealers to finance a currency in the FX market. Overall, the evidence shows that the shock hits less connected firms most severely and exclusive relationships mitigate negative effect to competition. Though, less connected clients are less likely to locate the best dealers.

A major concern could be that observed bid-shading pattern reflects the pricing of credit risk. To distinguish between the pricing of counterparty credit risk and pricing to competition, this paper uses a sub-sample analysis for different instruments and tenures which expose dealers to different loads of credit risks. The results discriminatory even at spot which is arguably characterized by the absence of credit risk. The average level of discriminatory markups is roughly comparable across spot and forward trades suggesting that markups are a result of a lack of competition. The documented quoting behavior suggest that quotes are driven by profitability rather than risk considerations. Naturally, as the volume increases dealers should refuse to quote or price in higher risks. On the opposite, the finding that outside dealers narrow their spread with volume rather speaks for profitability considerations instead of risk concerns.

Still, credit risk could exacerbate the lack of dealer competition in the following three ways: First, financially constrained firms may be unable to afford costly collateral at several banks, which narrow the set of quoting banks. Second, banks may restrict trading only to less credit-intense products (i.e. product with short tenure). Therefore, competition may be limited for more credit-intense products. Third, dealers may increase markups for products with longer tenure as a compensation for counterparty credit risk. I find evidence in line with all three channels. First, the share of quoting dealers drops with tenure, which is even more pronounced for less connected clients. Further, the data show that the discriminatory component of spreads widens for forward contracts with longer tenures. Especially during the COVID-19 outbreak, spreads for more credit-intense products widen sharply for relational and outside dealers.

Related literature. The main contribution of this paper is to highlight the unrecognized role of the quantity and quality of relationships in OTC markets leading to distinct trading strategies to different clients. While relational dealers appear extractive on the trade level, the quote level evidence reveals sizable relationship discounts. Similarly, trading relationships are typically viewed beneficial as such there is value to concentrate trades on a main relationship dealer. For example, Di Maggio, Kermani, and Song (2017) document relationship discounts in the US corporate bond inter-dealer market and Jurkatis et al. (2023) show that dealers provide discounts to their most important clients in the European corporate bond market. Hendershott, Li, et al. (2020) find that smaller dealer networks of insurance companies in the US corporate bond market are associated with more favorable prices due to a value of repeated business. There are important differences: First, my setting focuses on relationships to less connected clients, whereas the previous literature focuses on relationships clients as the largest clients of a dealer. Second, this paper studies non-financial firms hedging their FX exposure, which differs from the findings with institutional clients, because trades by non-financial firms are typically valuable to dealers only through the charged markups. This is because of two reasons: First, corporate clients are uninformed (Ranaldo and Somogyi 2021; Menkhoff et al. 2016) compared to dealers or institutional investors. The information from order flows by institutional clients may generate value to dealers (Kondor and Pinter 2022). Second, dealers attract large institutional investors in the European bond market because they can provide liquidity to the dealers (Jurkatis et al. 2023)[14]. Therefore, dealers try to charge markups to their corporate clients as high as the competition allows them.

Discriminatory pricing in OTC markets is typically associated with search problems. Closely related to my work is the paper by Hau et al. (2021). They find that firms with small dealer networks and lower trading volumes are charged higher markups in the FX forward market and these discriminatory markups are markedly smaller on platforms. They argue that the clients' number of dealer connection proxies searching ability and platforms eliminate search frictions. My setting from within one platform allows me to exclude search problems and to attribute smaller dealer networks to the relationship friction. Therefore, in my setting discriminatory pricing is not a result from search problems, but due the relationship friction.

My paper also contributes to the literature on RFQ platforms. In the context

[14]Jurkatis et al. (2023) frame relationships from the dealers' perspective by measuring the importance of one client to a dealer. In contrast, my paper takes the clients perspective by looking at the relevance of one dealer to the trades of the client. Overall, dealers trade with many clients and no client seems particularly important to them.

of index CDS, Riggs et al. (2020) stress the importance of relationships defined through a clearing membership and past trading activities to achieve better execution quality on RFQ platforms. The key differences come from clearing. First, because clearing in my setting is achieved bilaterally, clearing memberships are irrelevant. Second, bilateral clearing requires the setup of a firm-bank relationship, which is costly. Therefore, firms cannot just trade with any dealer as it is assumed in Riggs et al. (2020). Moreover, in contrast to the theories by C. Wang (2023) and Yueshen and Zou (2022), quoting does not appear costly at the margin as response rates are generally quite high (almost 90% on average). Therefore, the platform appears to be working well for many firms and dealers seem to indeed compete for the trades.

This paper is structured as follows. Chapter 2 reviews the literature on frictions in OTC trading and the role of RFQ platforms. Chapter 3 introduces the data. Chapter 4 documents the client's usage of dealer networks and the discriminatory pricing towards clients with small networks. Chapter 5 discusses different sources why clients fail to connect with many dealers. Chapter 6 provides quote-level evidence on relationship discounts and chapter 7 shows how the COVID shock impairs dealer competition. Chapter 8 concludes.

2 Frictions and the role of platforms in OTC markets

Since the seminal work by Duffie, Gârleanu, and Pedersen (2005), the view that search frictions govern trading in OTC markets dominates the literature. Typically, clients in OTC markets approach dealers sequentially and negotiate bilaterally until they find an agreement. O'Hara, Y. Wang, and Zhou (2018) and Hau et al. (2021) associate discriminatory pricing in OTC markets with the opaque nature of the market. Wittwer and Allen (2023, forthcoming) show that price quality markedly improves once a client has access to a centralized platform because platforms eliminate search frictions. Therefore, my data from a RFQ platform in the FX market is ideal to isolate search considerations, because firms can effortlessly send requests to several dealers simultaneously. The platform improves both pre- and post-trade transparency. Pre-trade transparency is achieved through the direct comparison of executable quotes in the RFQ auction. For the post-trade transparency, the platform sends monthly reports to its clients comparing the price quality across all connected dealers and, also, benchmarking executed quotes with those of other clients on the platform. Because the FX market is the largest and most liquid financial market, dealers are able to instantaneously send quotes, hedge themselves without considerable price impacts and, hence, platforms should work effectively (Hendershott and Madhavan 2015). Concerns about the speed of executions like in less liquid bond (Hendershott, Li, et al. 2020) or collateralized default swap markets (Riggs et al. 2020) should not play a role in this setting, because the execution usually takes place seconds after the initiation of the RFQ. Instead, this paper can isolate the relationship friction because of the absence of other frictions interfering in other OTC segments.

To be more precise on the trade mechanism, the trading process of the platform resembles a sealed-bid first-price auction with three stages. At the first stage, the firm specifies the trade details, i.e. product, currency pair, trade direction and notional amount. Also, the firm selects a set of banks to be requested for quotes. The competing dealer banks know the identity of the requesting client, but are unaware about the number and identities of the competitors in the request. At the second stage, the requested banks determine their quotes or do not reply to the request before trade completion. Finally, the firm executes one quote, which usually is the best quote sent by the competing dealers.[15]

Key to this paper is that clients on the platform cannot request any bank and banks do not necessarily want to engage in competition. Firms have to unlock dealer connections prior to being able to request the client. Dealer may also refuse to quote or send wide spreads. Before the limits to dealer competition are explained in section 5, section 2 introduces the data and section 4 highlights the severity of the frictions.

3 Data

This study uses anonymized data from a market-leading RFQ platform on which clients mainly trade FX products with their connected banks. The data set covers around 4.9 million platform trades including anonymous identifiers from 1,478 non-financial corporations (market takers)) and 371 dealers (market makers) between January 2018 and June 2021. For all trades, more detailed information on the RFQs

[15]Banks still have a last look option. Unfortunately, I have no information on the usage of the last-look right. Though, banks should have little incentive to make us of it due to reputational costs.

such as the set of banks requested as well as the quotes (42.8 million) sent by the competing banks are included. This unique information on the request level enables me to document the entire trading process leading to a trade. This study focuses on a subset of trades in five major currency pairs (EUR/USD, EUR/GBP, EUR/CHF, GBP/USD and USD/CHF).

Table 1 provides summary statistics on the 2.9 million trades (corresponding to 17 million quotes). Firms mostly trade in outright forwards (1,487,830 trades), followed by spot trades (669,172 trades) and trades in swap instruments (213,497 outright swaps trades and 554,384 forward swaps trades).[16] The summary statistics show that outright and forward swaps are mainly used for large and short-term transactions with a mean notional size of 4.1 and 5.7 million EUR and mean tenure of 77 and 44 days, respectively. Forwards are specified with smaller average notional sizes of 2.7 million and longer average tenure of 212 days. In all instruments the notional size and tenure is left-skewed with the bulk of trades been short-term or small in notional. Usually, there is fierce dealer competition across all instruments, on spots, forwards as well as outright and forward swaps, on average 7.4, 7.1, 10, and 9.9 banks are requested. In forwards and swaps, there are trades for which up to 65 banks were requested. Though, almost 17.7% of trades are single-bank trades, which means that only one bank was requested. Generally, the response rate as the share of dealers sending a quote after they have been requested is quite high with averages between 85% and 93% across instruments. Though, there is much variation

[16] The difference between the swap instruments is that the first leg is at the spot for outright swaps and at any other future date for forward swaps. The majority of forward swaps are overnight swaps with the first lag today and the second lag is tomorrow.

in response rates between firm-bank pairs which will be exploited in section 5.

In terms of its daily turnover, the sample is quite significant. In comparison to the to the Bank for International Settlements (BIS) Triennial Survey, the sample represents approximately 6.5% of the global daily foreign exchange turnover of the non-financial corporate sector. Though, the sample clusters around European clients because the platform is still expanding to the customer bases on other continents.

4 Discriminatory pricing

In this section, I document realized price differential depending on the clients' identities. That means dealers adjust their markups depending on the competitive pressure a client imposes on its connected dealer. To measure the firm's j ability to foster dealer competition across banks i during the calendar year, I compute a Herfindahl-Hirschman index, which is $HHI_j = \sum_i \left(\frac{\#trades_{j,i}}{\#trades_j}\right)^2$. Figure 1 shows the distribution of this HHI. Saliently, many firms trade exclusively with one bank. In total, 8.3% of firm-year observations are locked-in ($HHI_{j,m} = 1$) and 44.5% trade at least half of their trades with only one dealer. This is the tip of the iceberg of a general problem in OTC trading. Hau et al. (2021) show that over 50% of European corporates trade exclusively with one dealer in the FX market and Hendershott, Li, et al. (2020) show that 30% of insurers are locked-in in the US bond market.

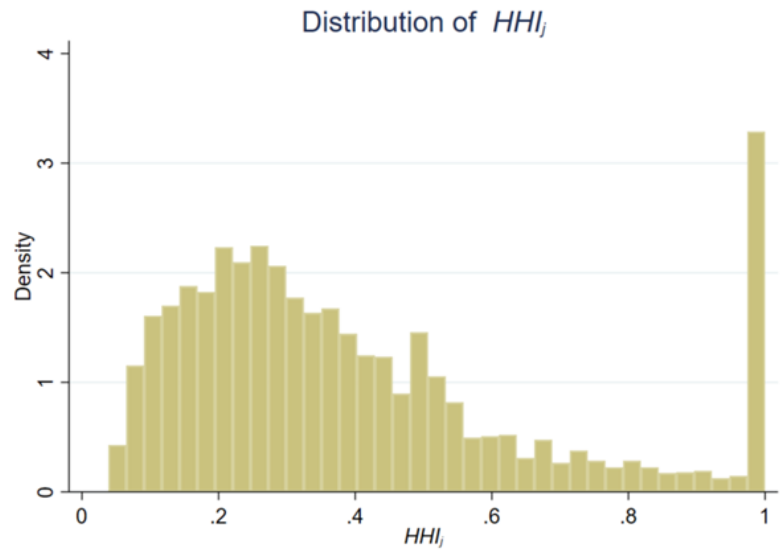
Next, I measure the bid-shading of dealers. To measure spread, use minute level interbank quotes from Refinitive Datascope for five different currency pairs: EUR/USD, EUR/GBP, EUR/CHF, GBP/USD, and USD/CHF. Appendix A pro-

Table 1: Trade level summary statistics

	N	Mean	Med	SD	Min	Max
Spot						
Notional [in mio EUR]	669,123	3.2	0.89	12.71	0.00	1,401.02
Tenure [in days]	669,097	2.9	2.00	1.10	0.00	7.00
#banks requested	669,172	7.4	4.00	8.16	1.00	42.00
Response rate	669,172	.93	1.00	0.13	0.03	1.00
Forward						
Notional [in mio EUR]	1,487,736	2.7	0.42	11.56	0.00	2,844.11
Tenure [in days]	1,487,830	140	58.00	211.68	0.00	7,304.00
#banks requested	1,487,830	7.8	6.00	6.35	1.00	65.00
Response rate	1,487,830	.85	0.94	0.19	0.04	1.00
Swap						
Notional [in mio EUR]	213,483	23	4.06	50.12	0.00	2,259.79
Tenure [in days]	213,497	77	35.00	113.73	1.00	3,655.00
#banks requested	213,497	10	9.00	7.39	1.00	65.00
Response rate	213,497	.87	0.93	0.16	0.04	1.00
Forward-Swap						
Notional [in mio EUR]	554,334	23	5.74	47.81	0.00	2,628.18
Tenure near lag [in days]	554,384	6.9	0.00	53.95	0.00	3,066.00
Tenure [in days]	554,384	44	14.00	109.10	1.00	4,759.00
#banks requested	554,384	9.9	8.00	8.42	1.00	64.00
Response rate	554,384	.86	0.92	0.18	0.03	1.00
Observations	2,924,883					

The table displays trade-level summary statistics on the sample used in this study, which includes trades of non-financial corporations between January 2018 and June 2021. The 2.9 million trades come with 17 million quotes.

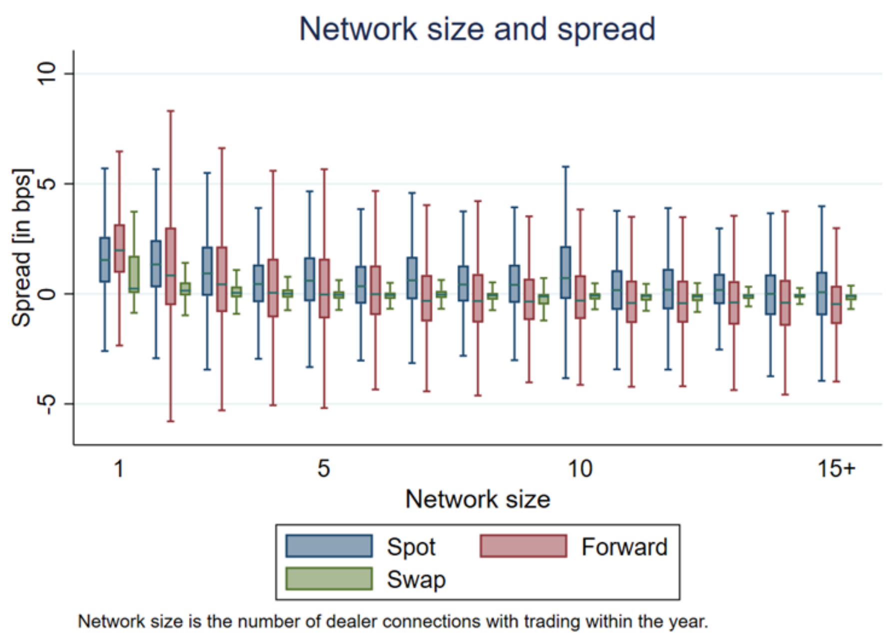
Figure 1: Client's usage of dealer network



The figure plots the distribution of the yearly HHI index of the firms on the platform based on the number of trades by firm j with banks i (i.e. $HHI_j = \sum_i \left(\frac{\#trades_{j,i}}{\#trades_j}\right)^2$).

vides details on the measurement of spreads for different instruments. Figure 2 plots the distribution of realized spot, forward and swap spreads on executed prices received by clients with different numbers of actively trading dealer connections (network size). From the median values of the box plots, the decreasing pattern of spreads become visible. For locked-in clients, the median (mean) spread is 1.76 (5.5) bps at the spot and 2.1 (3.3) bps at the forward. For clients with 15 or more dealer relations, the median (mean) effective spot spread is 0.0 (-0.05) bps and the median (mean) effective forward spread is -0.48 (-0.78) bps. Swap spreads are narrower and price differentials are smaller, falling from a mean of 1 bps for locked-in clients to -0.10 for well connected firms with 15 or more dealer connections. To verify this pattern without need to approximate spreads, I compute a competitiveness index similar to Riggs et al. (2020). This measures the the price differential between the best and second best quote in a request. Figure 12 in the Appendix B exhibits a similar pattern. Requests by firms with fewer dealer connections (high-HHI) appear less competitive with wider price differences. Price variation in swap products are smaller compared to the spot and forward. Overall, there seems to be much

Figure 2: Spread distribution across clients' network sizes



The figure plots the distribution of the effective spread over the client's number of active dealer connections (Network size). Appendix Appendix A provides details on measurement of spreads.

variation in my spread measures.[17] To address this variation, a regression model

[17]Much variation in the spread measure is due to within-minute variation in the spot exchange rates. Because the benchmark prices are only at the minute level, there is measurement noise. This noise is unrelated to discriminatory pricing, therefore regressions

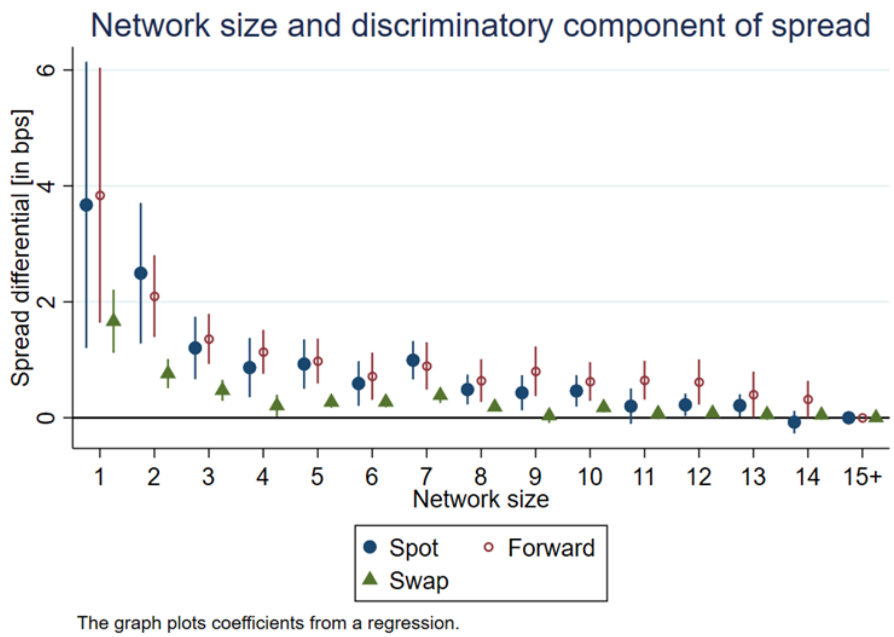
isolates the discriminatory component of the spreads. Following Hau et al. (2021), a *dealer* $\times$ *date* $\times$ *currency pair* $\times$ *direction* fixed effect model estimates the extent to which a dealer sends different prices to different clients at the same day and for the same instrument (spot, forward or swap, currency pair and direction). The estimation model is as follows

$$Spread_{j,i,t} = \sum_{n=1,...,14} \delta_n \times \mathbb{1}_{N_t=n} + \beta_1 ln(Notional\ in\ EUR) + \beta_2 ln(Tenure)$$
$$+\alpha_i \times \alpha_{date} \times \alpha_{currency} \times \alpha_{direction}$$

where $\mathbb{1}_{N_t=n}$ are 14 dummies equal one if a client has $n = 1, ..., 14$ dealer connections in the trade month m. $\alpha_i \times \alpha_{date} \times \alpha_{currency} \times \alpha_{direction}$ are the fixed effects absorbing the bank's funding ability. The model includes controls for trade volume and at the forward for the tenure. Because the fixed effects hold the supply constant, the coefficients δ_n estimate the discriminatory component of spreads for clients with different networks compared to the spreads received by clients with networks of 15 or more dealers. Standard errors are clustered two-way at the firm and month level. Figure 3 plots the estimated coefficients δ_n from two separate regressions for spot and forward trades. At the spot, forward and swap, dealers charge 3.7, 3.8 and 1.7 bps higher spreads to locked-in clients compared to well-connected firms holding all other factors from the regression constant. The downward-sloping pattern mirrors the bid-shading behavior of dealer banks. The evidence shows that dealers adjust spreads depending on the competition that a client imposes on them.

A major concern could be that the coefficients measure the counterparty credit

Figure 3: Discriminatory bid shading



The figure plots estimates from a regression on the sample of spot and forward trades. The estimated model is $Spread_{j,i,t} = \sum_{n=1,...,14} \delta_n \times \mathbb{1}_{N_t=n} + \beta_1 ln(Notional in EUR) + \beta_2 ln(Tenure) + \alpha_i \times \alpha_{date} \times \alpha_{currency} \times \alpha_{direction}$, where $\mathbb{1}_{N_t=n}$ are dummies for different network sizes. The plotted coefficients are $delta_n$ showing discriminatory markups compared to the base clients with 15 or more dealer connections. The regressions include controls for size and tenor and $dealer \times date \times currency pair \times direction$ fixed effect as controls with two-way clustered standard errors at the firm and month level.

risk that dealers price in for the less connected clients. Arguably, there is no credit risk at the spot. On the contrary, the graph shows that the average discriminatory markups are roughly comparable across instruments. To shed more light into the role of credit risk and discriminatory pricing, I repeat the regression analysis with the HHI_j as the main explanatory variable of interest and on instruments with different loads of credit risk.

$$Spread_{j,i,t} = \delta \times HHI_{j,m} + \beta_1 ln(Notional) + \beta_2 ln(Tenure) + \text{fixed effects}$$

Table 2 shows the results from this regression. Column 1 includes results from spot spreads and $date \times currency\,pair \times direction$ fixed effects to control for the market situation in a product. The coefficient shows that a locked-in firm ($HHI_{j,m} = 1$) pays 3.8 bps higher spot spreads compared to the hypothetical firm that equally distributes all its trades among its infinite dealer network ($HHI_{j,m} = 0$) holding the controls constant. To see the economic magnitude, consider the median volume of EUR 233,244 by less connected firms, a locked-in clients pays around EUR 71 more in spread compared to the a well connected firm ($HHI_{j,m} = .2$). Because less connected firms could be locked-in with dealers with worse funding abilities, column 2 adds $dealer \times date \times currencypair \times direction$ fixed effects to control for the dealers' funding abilities. Because the coefficient is only slightly smaller, most of the price differences can be attributed discriminatory pricing.

Columns 3 and 4 repeat the estimation for forward trades and finds discriminatory components of spreads of similar order of magnitude compared to spot trades. Though, most of the forward trades are short-lived with roughly half of the forward trades having tenures shorter than 30 days. To focus on trades that are subject to more credit risk, I restrict the sample to trades with at least 90 days to maturity. The results show that the discriminatory component of spreads is increases to 6.7 bps (column 5). However, it remains unclear whether the widening of spreads is due to credit risk or due to a lack of dealer competition. The evidence suggests that counterparty credit risk may be priced on top of the discriminatory markups. Section 5 provides further discussions between the relationship of credit constraints and the relationship friction.

Columns 6 and 7 repeat the analysis for swap transactions. There are two main differences to the previous instruments. First, swap spreads are generally much narrower. Second, including dealer-date fixed effects shrinks the coefficient while the R^2 increases from 14% to 55%. This suggests that most variation in swap prices is due to different funding abilities by dealers and less connected clients are unable to swift the dealer.

Table 2: Dealer competiton and spreads

	(1) Spot	(2) Spot	(3) Forward	(4) Forward	(5) Forward $\tau \geq 90$	(6) Swap	(7) Swap
HHI_j	3.800***	3.031***	3.495***	3.993***	6.721***	1.457***	0.897**
	(1.160)	(0.520)	(0.945)	(0.893)	(1.698)	(0.329)	(0.339)
Notional	0.012	0.011	0.058*	0.037	0.101**	0.076***	0.072**
	(0.026)	(0.011)	(0.031)	(0.024)	(0.046)	(0.026)	(0.029)
Tenure			−0.398***	−0.350***	−2.152***	−0.292***	−0.242***
			(0.061)	(0.048)	(0.234)	(0.044)	(0.048)
Obs	454,700	365,707	839,358	744,414	323,963	204,546	129,440
R^2	0.08	0.43	0.10	0.41	0.50	0.14	0.55
Within-R^2	0.03	0.02	0.05	0.04	0.06	0.00	0.00
FE: $t \times c \times d$	Yes	No	Yes	No	No	Yes	No
FE: $i \times t \times c \times d$	No	Yes	No	Yes	Yes	No	Yes

The table displays results from the regression $Spread_{j,i,t} = \delta \times HHI_j + \beta_1 ln(Notional) + \beta_2 ln(Tenure) + fixed\,effects$. The dependent variable $Spread_{j,i,t}$ is the positive spread measure ($\frac{S_{j,i,t}-S}{S} \times 10,000 \times (1 - 2\mathbb{1}_{Bid})$ at the spot (columns 1-2) and $\varepsilon \times (1 - 2\mathbb{1}_{Bid})$ at the forward (columns 2-5) and at the swap (colums 6-7), where ε is the (cleaned) spread measure as described in Appendix A. The columns 1, 3 and 6 include *date* $\times$ *currency pair* $\times$ *direction* fixed affects to absorb effects from the market situation. Columns 2, 4, 5 and 7 include *dealer* $\times$ *date* $\times$ *currency pair* $\times$ *direction* fixed effects to measure discriminatory pricing. The columns 5 includes results from a sample of forward trades with at least 90 days to maturity. The main coefficient of interest is δ which measures differential pricing for less connected firms. Two-way clustered standard errors around the firm and month level are in parenthesis. ***, **, * indicate statistical significance at the 1%, 5%, and 10%, respectively.

To gauge the magnitude of the costs from discriminatory pricing, I conduct a back-of-the-envelope calculation. Fore each trade, I calculate the discriminatory costs

$$\text{Discriminatory cost} = \delta \times (HHI_j - HHI_{\text{well-connected firm}}) \times S \times volume$$

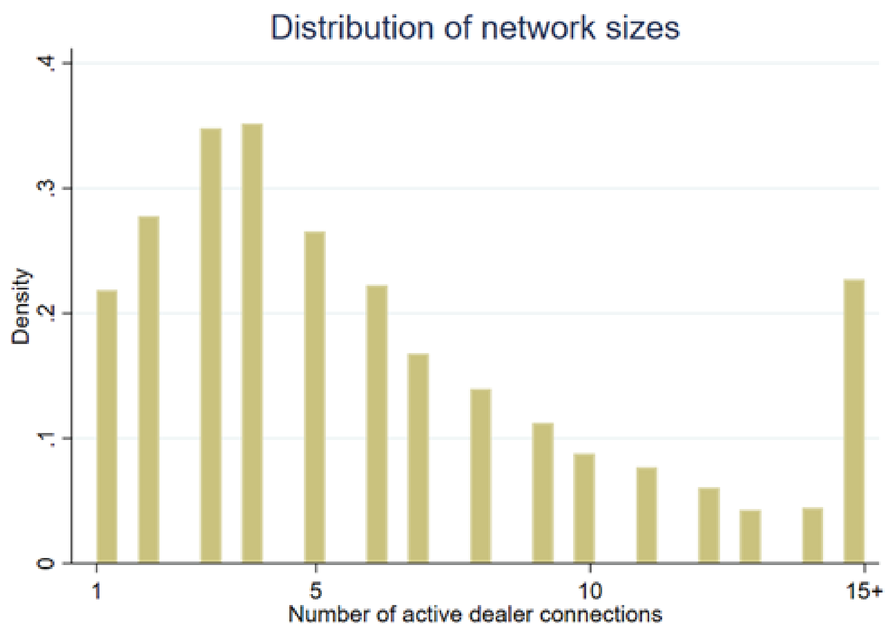
where $HHI_{\text{well-connected firm}} = 0.12$ which is the top percentile of the HHI distribution and S is the spot rate to convert values from bps in EUR. Using the coefficient δ from columns 2, 4 and 7 of table 2 for all spot, forward and swap trades, I estimate an aggregated cost of EUR 19 million at the spot and EUR 55 million at the forward. Again the estimate of EUR 74 million, or EUR 22 million yearly, is the tip of the iceberg, because of several reasons. First, the calculation bases only on around 230,000 spot and 730,000 forward trades. This is a subset of trades for which I have spot benchmark prices. Second, the most affected clients trade outside the platform (compare with Hau et al. 2021. Third, the sample is mostly European, but the relationship friction should apply globally. Further, the frictions in relationships impair competitive pricing for any other financial service especially OTC products from banks.

Overall, the trade-level evidence from this section shows discriminatory price differentials between well- and less-connected firms making dealers in more exclusive relationships look extractive, i.e. there is a relationship premium similar to Hau et al. (2021). The financial cost paid by these firms is substantial. The following sections leverage the quote-level data to shed more light into what limits dealer competition (section 5) and that there are indeed relationship discounts (6).

5 What limits dealer competition?

Given the significant costs of discriminatory price differentials, it is logic to ask why firms are not able to intensify dealer competition and improve price quality. This section provides evidence on the clients' usage of dealer networks and discusses limiting factors of dealer competition. To do so it is important to understand different qualities of dealer connections. The previous section has focused on dealer connections with trading activity in a given year. Figure 4 plots the distribution of this number. 47% of firms trade with two to five dealers, wherase 8.3% trade with only one and 8.6% trade with 15 or more dealers.

Figure 4: Distribution of active trading connections



The figure plots distribution of dealer connection with trading in a year. Most firms trade with between two and five banks, while also many firms trade with only one or 15 or more banks.

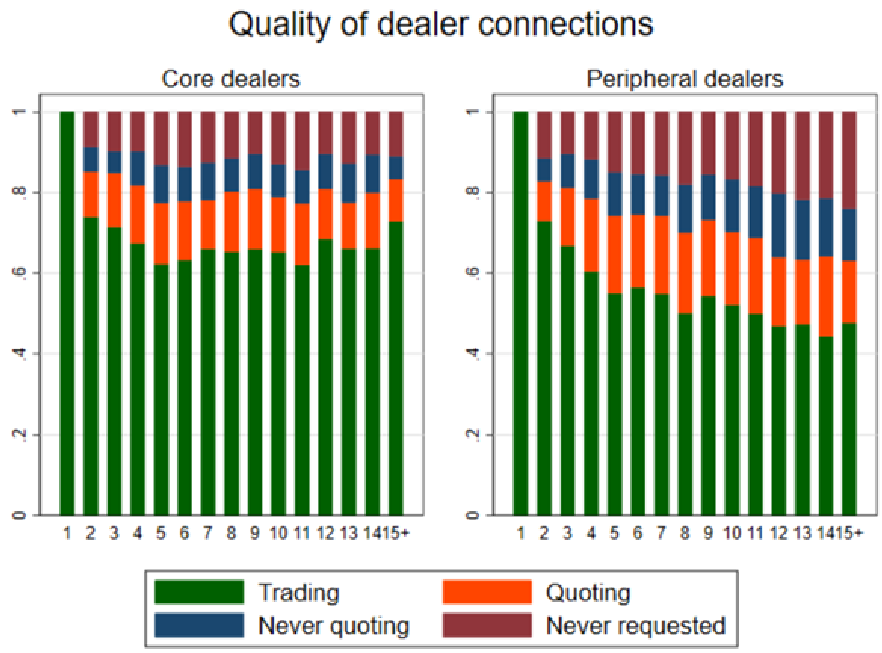
Many clients are actually connected to more dealers, which do not exhibit any trading activity. To distinguish between different qualities of dealer connections, I focus on a monthly relationship level. Let N be the client's number of all bank connections (per year), N_r are the requested dealer, N_n are the dealers that never quote, N_q are the quoting dealers, and N_t are those with trading activity ($N \geq N_r \geq N_n \geq N_q \geq N_t$). Figure 5 plots the share of dealer connections with trading activity ($\frac{N_t}{N}$), the share of connection with only quoting ($\frac{N_q}{N}$), the share of never quoting connections ($\frac{N_n}{N}$), and the share of dealer connections without a request in a month ($\frac{N_r}{N}$) over the number of all connected dealer (N). It becomes visible that many dealer connections are indeed without any trading activity. The average firm requests on 87% of all connected dealers in a month, 78% of connection quote at least once and only 63% of connections exhibit at least one trade. Except for completely locked-in clients, these numbers are roughly in the same order of magnitude across network sizes (N). Though, there are differences deepening on whether the dealer is a core or peripheral dealer.[18] Connections with peripheral dealers are less active, especially in larger networks.

It is difficult to pin down exact reasons for these different qualities of dealer connections and network sizes, though some institutional background may help explain some of the facts. Because trades are cleared bilaterally, firms have to setup an account and a line of credit with the banks,[19] which requires extensive risk and regulatory checks. Anecdotal evidence from interviews with corporate bankers reveals

[18] I define core dealers as one of the top 30 dealer in total transacted volume in the sample.

[19] Credit lines are commonly used to settle trades. A few clients hold cash at the bank to settle their trades.

Figure 5: Heterogeneity in dealer connections



The figure plots different qualities of dealer connections (defined monthly) over the number of total connections of a client (defined yearly (N)). Panel A is on a sample of connection with core (top 30 dealer in total volume) and panel B with peripheral dealers. Y-Axis is on monthly basis with an indicator equal to one when there is at least one trade, one quote (but no trade), the dealer never quoted during a month, or the dealer is never requested. The different indicators reflect different qualities of a dealer connection.

that the process of know-your-customer (KYC) checks[20] can take up to a few months and requires work from several divisions of the bank. Because of that burden, banks connect to a customer only if they expect a profitable business relation with the

[20]KYCs are regulatory checks requiring banks to verify the identity, sustainability, and risks involved with a client. The goal is to ensure that the bank's clients are compliant with anti-money laundering and other fraudulent business activities. Draconian punishments like fines or potentially prison sentences should discipline bankers globally to conduct KYC checks with due diligence. Prominently, Goldman Sachs was fined $5 billion to federal prosecutors around the globe with one of its bankers being sentenced to 10 years in prison by a US judge in the course of the 1Malaysia Development Berhad (1MDB) scandal. See "Former Goldman Banker Gets 10 Years in Prion in 1MDB Scandal" in New York Times (March 9, 2023; available at https://www.nytimes.com/2023/03/09/business/roger-ng-goldman-sachs-1mdb-sentenced.html).

client. As shown by Qi (2023), firm-bank relationships start with a lending relationship and the portfolios of services will eventually be expanded to extract more rents from their clients.[21] Therefore, banks may connect to firms only if the overall relation with the client promises a profitable business. For less active firms, providing only FX liquidity may not be profitable enough to justify the setup of a new relationship.

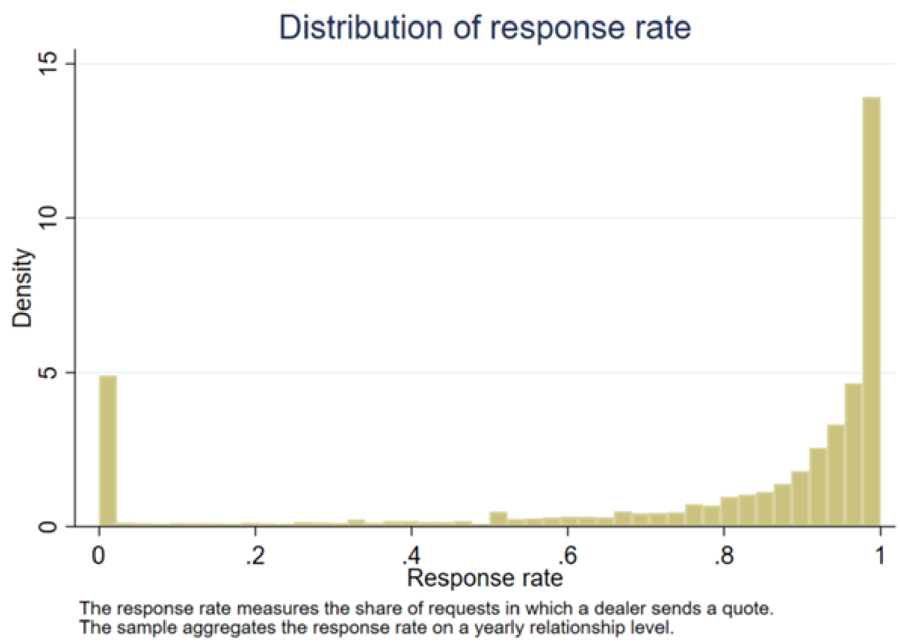
Besides the fixed costs of establishing a trading connection, the evidence shows that dealers tend to refuse quoting to the less connected clients. Around 38% of firms that trade exclusively with one dealer do request only one dealer. 16% of locked-in firms never receive any quote from another dealer despite their attempts to request multiple dealers. Throughout the sample never-quoting dealer connections are abundant. Figure 6 plots the distribution of response rates in yearly firm-bank pairs. The distribution is bimodal with most dealers quoting always to their client (18% with response rate = 1), but many do never quote (11% with response rate = 0). 10% of connected dealers to competitive firms ($HHI_j < .5$) never quote and 23% of connected dealers to less competitive firms ($HHI_j \geq .5$) never quote. A variance decomposition shows that response rates are quite persistent within the firm-bank pair. 60% variation in response rates is between client-dealer pairs instead of within the pair.

Interviews with corporate bankers reveal that never-quoting behaviors are mostly due to unmet collateral requirements.[22] The firm either has no cash or no active line of credit. Collateral is costly and especially firms near distress are less likely to af-

[21]Qi (2023) argues that customers attract firms with cheap loans (loss-leaders) and cross-subsidize the loans with profits from their non-loan businesses such a foreign exchange transactions.

[22]Other reasons include changes in the KYC status or the emergence of political risk, eg. a business person is added to a sanctions list.

Figure 6: Distribution of response rates



The figure plots the distribution of the response rates within a yearly firm-bank pair. The response rate is the share of non-empty prices. The distribution is bimodal, with most response rates being 100%, though there are many never quoting relationships (response rate being 0%).

ford collateral. Rampini, Sufi, and Viswanathan (2014) show that firms near distress hedge less due to costly collateral requirements. My evidence suggests that unmet collateral requirements diminish competition leading to less favorable prices.

In parallel to the banking literature[23], a key finding of this paper the existence of a close ties between firms and banks that prevail even in the competitive auction environment. The following evidence shows a unique role of the relationship dealer

[23]Important papers include Sharpe (1990), Rajan (1992), and Petersen and Rajan (1995). This literature argue that lending relationships are beneficial to firms with credit risk. Independent from credit risk, my evidence shows the existence of close trading relationships.

to reliably provide FX liquidity to less connected clients. Throughout this paper, I define the relationship dealer as the dealer with the largest trade share to a client in a year. To estimate the differential quoting behavior of relationship dealers, following linear probability model is estimated

$$
\begin{aligned}
Quoting_{j,i,r} = \delta_1 \times HHI_j + \delta_2 \times RelD_{j,i} + \delta_3 \times HHI_j \times RelD_{j,i} + \\
\beta_1 ln(Notional) + \beta_2 ln(Tenure) + \alpha_n + \alpha_{i \times t \times c \times d}
\end{aligned}
$$

where $Quoting_{j,i,t}$ is a dummy equal one if if dealer i sends a quote to the requesting client j at request r and $RelD_{j,i}$ is a dummy indicating whether dealer is the relationship dealer to the client. The regression includes controls for tenor and volume as well as number of dealers requested fixed effects α_n to absorb effects from large requests and dealer times date times product fixed effects $\alpha_{i \times t \times c \times d}$ to absorb the dealers quoting capabilities. The main coefficients of interest δ_1, δ_1 and δ_1 measure whether less connected clients receive fewer responses, relationship generally respond more frequently and relationship dealers quote more frequently to less competitive clients. Standard errors are two-way clustered at the firm and month level. Table 3 includes the results for different samples. Columns 1-2 are for requests at the spot, columns 3-4 at the forward, column 5 at the swap and column 6 at the forward swap. Column 1 show substantial differences in the quoting behavior of banks for different client groups with high-HHI firms are much less likely to receive a quote (the coefficient is -.41). Further, the results show that the relationship dealer is more important to high-HHI firms due to the reliable quoting behavior (with a coefficient of .34%). As demonstrated above, much of the variation in response rates in client*dealer specific. Column 2 excludes never-quoting connections from the sample. The coefficient shows that relationship dealers remain more reliable in the supply of quotes to less competitive firms. Column 3 and 4 repeat the analysis for forward trades. For brevity, the columns 5 and 6 include estimates for the restricted sample that excludes never-quoters for swap and forward swaps. In contrast to spot trades, the latter products are typically include counterparty credit risk, therefor, relationships may be more central. The coefficients show that relationship dealers generally respond more frequently to all clients with estimated coefficient between 2 and 3 percentage points.

Table 3: Response rates, dealer competition and relationships

	Spot		Forward		Swap	Forward-Swap
	(1) All	(2) Restricted	(3) All	(4) Restricted	(5) Restricted	(6) Restricted
HHI_j	-0.406^{***}	-0.096^{***}	-0.297^{***}	-0.128^{***}	-0.110^{***}	-0.123^{**}
	(0.045)	(0.024)	(0.043)	(0.035)	(0.035)	(0.048)
$HHI_j \times RelD_{j,i}$	0.341^{***}	0.078^{***}	0.241^{***}	0.107^{***}	0.036	0.060
	(0.041)	(0.025)	(0.033)	(0.026)	(0.036)	(0.039)
$RelD_{j,i}$	-0.018^{**}	0.005	0.016^{*}	0.026^{***}	0.023^{***}	0.022^{***}
	(0.007)	(0.005)	(0.008)	(0.007)	(0.008)	(0.008)
Notional	-0.002	-0.000	0.001	0.002	-0.011^{***}	-0.012^{***}
	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.002)
Tenure			-0.018^{***}	-0.019^{***}	-0.016^{***}	-0.007^{***}
			(0.002)	(0.002)	(0.002)	(0.002)
Obs	4,450,629	4,321,343	10,576,869	10,260,310	1,941,241	5,043,085
R^2	0.44	0.38	0.41	0.37	0.47	0.36
Within-R^2	0.02	0.00	0.02	0.01	0.01	0.01
FE: n	Yes	Yes	Yes	Yes	Yes	Yes
FE: $i \times t \times c \times d$	Yes	Yes	Yes	Yes	Yes	Yes

The table displays results from the regression
$Quoting_{j,i,r} = \delta_1 \times HHI_j + \delta_2 \times RelD_{j,i} + \delta_3 \times HHI_j \times RelD_{j,i} + \beta_1 ln(Notional) + \beta_2 ln(Tenure) + \alpha_n + +\alpha_{i \times t \times c \times d}$.
The dependent variable $Quotingj, i, r$ is dummy equal to one if dealer i sends a quote to client j in request r. $RelD_{j,i}$ is a dummy equal to one for the relationship dealer as measured as the most active dealer of firm j in a year. Number of dealer requested n fixed effects extract effects from the RFQ size. *dealer* $\times$ *date* $\times$ *currency pair* $\times$ *direction* fixed effects are included to extract discriminatory component of spreads. Column 1 and 3 include the entire sample, while the other columns include a restricted sample that excludes never quoting relationships. The sample excludes trades in which only one bank is requested. The main coefficient of interest is δ_1 which measures differential response rate for less connected firms. Two-way clustered standard errors around the firm and month level are in parenthesis. ***, **, * indicate statistical significance at the 1%, 5%, and 10%, respectively.

6 Relationship discounts

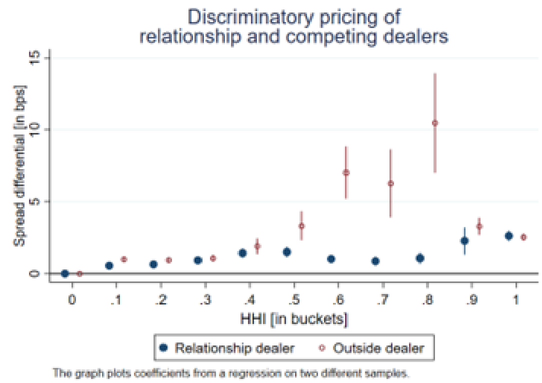
The evidence from the previous section suggests that dealers refuse to quote because of unmet collateral requirements. Moreover, the data show the existence of a relationship dealer that quotes more reliably compared to outside dealers. This section explores different pricing strategies of relationship and outside dealers. Figure 7 plots coefficient from a regression of spreads on 11 dummies for different buckets of the HHI_j index to measure discriminatory pricing similar as in figure 3. Each panel plots coefficients from two samples of the relationship and outside dealers for different instruments. Panel 7A illustrates pricing differentials between both groups of dealers across the HHI distribtuion of firms at the spot. While relationship dealers only slight widen spreads for high-HHI firms, outside dealers widen spreads markedly. Firms with an HHI index of around 80% receive over 10 bps wider (half) spreads compared to firms with an HHI of 0%. Similarly, panel 7B shows that this relationship discount exist with similar order of magnitude for forward trades with short tenor. Though, the evidence shows that this relationship discount seems to disappear for more credit intense products. Panel 7C illustrates that there is no differential quoting behavior between relationship and outside dealers for forward trades with longer tenures. For brevity, the the results for swaps are not illustrated as the mirror those of long-tenure forwards.

Following estimation model repeat the analysis with interaction effects of the HHI index and the relationship dummy:

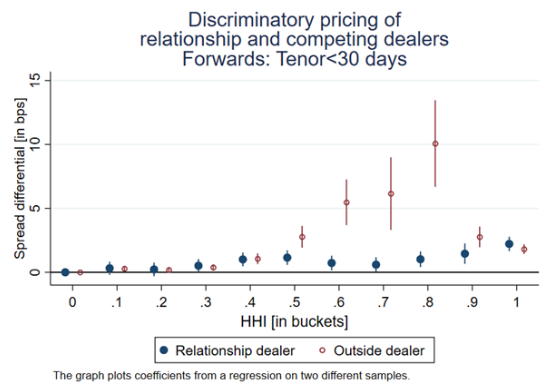
$$\begin{aligned} Spread_{j,i,t} = {} & \delta_1 \times HHI_j + \delta_2 \times RelD_{j,i} + \delta_3 \times HHI_j \times RelD_{j,i} \\ & + \beta_1 ln(Notional) + \beta_2 ln(Tenure) + \alpha_{i \times t \times c \times d} \end{aligned}$$

Table 4 presents the results. Column 1 is estimated on spot quote-level data and column 2 includes executed prices only. While the coefficient show large and highly significant discriminatory spreads against low-HHI firms (coefficient of 9.2), the coefficient shrinks to almost a third in magnitude on a trade level (coefficient of 3.2). The interaction effect of the HHI index with the relationship dummy shows large and highly significant relationship discounts (coefficient of -6.4) while they almost disappear on a trade level (coefficient of -0.4) and become insignificant. This is because the high prices by outside dealers are rarely executed, and therefore are only visible on a quote level. Interestingly, the coefficient of the relationship dummy shows that relationship dealers, measured as the most active dealer, generally tend to send modestly and highly significantly wider spreads (coefficient of 0.4). The columns 3 and 4 repeat the analysis for the forward. Overall, the pattern are in parallel to the spot. Though, discriminatory pricing by outside dealers seem less severe and relationship discounts appear smaller. Column 5 measures a relationship premium for long tenured forwards at the quote level. The results show that the relationship discounts to less connected clients turn into a relationship premium (coefficient of 2.3), while the relationship dealers generally send narrower spreads (coefficient of (-1.1). Columns 6 and 7 repeat the analysis for swap transactions. Again, the evidence at the swap exhibit much fewer variation with only mild relationship premia (significant at the 10% level). The evidence is unclear why there are relationship premia for forwards with long tenure and swap products. Unreported results indicate that less connected clients even try to request more dealers in an effort to intensify competition while response rates by outside dealers slightly increase at long tenors. This result is at the odd credit risk explanations because it shows both firms to intensify competition and also banks to be more willing to engage in competition. An unreported subsample analysis points towards heterogeneity in funding ability of banks across different currencies. For example, European bank charge relationship premia to their captive clients for synthetic USD funding through the FX market (EUR/USD at the ask), while the premium almost disappears for synthetic USD dollar lending (EUR/USD at the bid). In contrast, US and British banks generally provide relationship discounts to their captive clients independently of the trading direction. In sum, the evidence indicates that relationship premia reflect the inability of captive clients to locate the natural counterparty (dealer with best quoting ability) instead of credit risk.

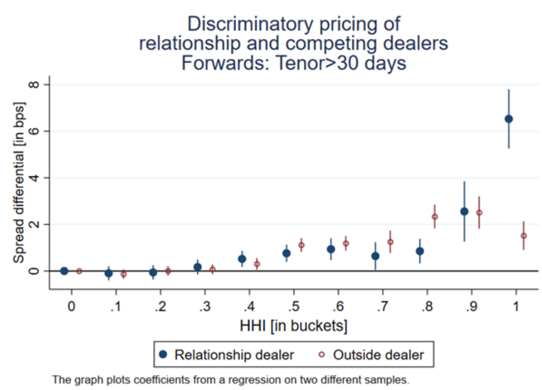
Figure 7: Discriminatory spreads of relationship versus outside dealer



(A) Spot



(B) Forward with tenure < 30



(C) Forward with tenure ≥ 30

The figure plots estimates from a regression on the sample of spot and forward trades. The estimated model is $Spread_{j,i,t} = \sum_{b=0,0.1,\ldots,1} \delta_b \times \mathbb{1}_{|HHI_j-b|<.05} + \beta_1 ln(Notional\ in\ EUR) + \beta_2 ln(Tenure) + \alpha_i \times \alpha_{date} \times \alpha_{currency} \times \alpha_{direction}$, where $\mathbb{1}_{|HHI_j-b|<.05}$ are 11 dummies dividing firms into HHI buckets. The plotted coefficients are $delta_b$ showing discriminatory markups compared to the base clients with 15 or more dealer connections. The regressions include controls for size and tenor and $dealer \times date \times currency\, pair \times direction$ fixed effect as controls with two-way clustered standard errors at the firm and date level.

Table 4: Relationship discounts

	(1) Spot	(2) Spot	(3) Forward	(4) Forward	(5) Forward $\tau \geq 90$	(6) Swap	(7) Swap
HHI_j	9.243***	3.214***	5.160***	4.071***	3.025***	0.296***	0.799***
	(0.815)	(0.161)	(0.376)	(0.236)	(0.236)	(0.068)	(0.107)
$HHI_j \times RelD_{j,i}$	−6.426***	−0.386	−2.025***	−0.344	2.274***	0.167*	0.034
	(0.829)	(0.264)	(0.430)	(0.307)	(0.506)	(0.096)	(0.143)
$RelD_{j,i}$	0.407***	0.152***	−0.161**	0.140**	−1.103***	−0.124***	0.007
	(0.093)	(0.058)	(0.069)	(0.070)	(0.103)	(0.019)	(0.033)
Notional	−0.153***	0.016***	−0.056***	0.032***	−0.009	0.017***	0.037***
	(0.020)	(0.005)	(0.008)	(0.007)	(0.008)	(0.004)	(0.005)
Tenure			−0.143***	−0.343***	−0.118***	0.140***	−0.294***
			(0.010)	(0.012)	(0.026)	(0.019)	(0.012)
Obs	2,801,834	365,686	5,642,064	744,110	2,363,178	1,675,307	129,398
R^2	0.35	0.41	0.25	0.43	0.35	0.39	0.59
Within-R^2	0.05	0.02	0.02	0.05	0.01	0.00	0.04
FE: $i \times t \times c \times d$	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The table displays results from the regression
$Spread_{j,i,t} = \delta_1 \times HHI_j + \delta_2 \times RelD_{j,i} + \delta_3 \times HHI_j \times RelD_{j,i} + \beta_1 ln(Notional) + \beta_2 ln(Tenure) + fixed\,effects.$
The dependent variable $Spread_{j,i,t}$ is the positive spread measure ($\frac{S_{j,i,t}-S}{S} \times 10,000 \times (1 - 2\mathbb{1}_{Bid})$ at the spot (columns 1-2) and $\varepsilon \times (1 - 2\mathbb{1}_{Bid})$ at the forward (columns 2-5) and at the swap (colums 6-7), where ε is the (cleaned) spread measure as described in Appendix A. $RelD_{j,i}$ is a dummy equal to one for the realtionship dealer as measured as the most active dealer of firm j in a year. *dealer* $\times$ *date* $\times$ *currency pair* $\times$ *direction* fixed effects are included to extract discriminatory component of spreads. The columns 5 includes results from a sample of forward trades with at least 90 days to maturity. The main coefficient of interest is δ which measures differential pricing for less connected firms. Two-way clustered standard errors around the firm and month level are in parenthesis. ***, **, * indicate statistical significance at the 1%, 5%, and 10%, respectively.

Relationship bank are generally viewed to have the incentives to keep their customers captive, while non-relationship dealers may maximize profits on a trade-by-trade level. To shed more light into the differences in quoting strategies by inside and outside dealers, I test whether their quoting changes as trades become more profitable by intereacting the HHI index with the requested volume:

$$Spread_{j,i,t} = \delta_1 \times HHI_j + \delta_2 \times \times HHI_j \times ln(Volume)$$
$$+\beta_1 ln(Notional) + \beta_2 ln(Tenure) + \alpha_{i \times t \times c \times d}$$

Table 5 presents the results. Column 1 includes the estimates of spot trades with relationship dealers. The results show only mild general volume premia (coefficient of 0.06) and volume discounts for less connected clients (coefficient of -0.2). Column 2 repeats the analysis for spot quotes by outside dealers. It becomes visible that the pricing depends more heavily on the volume as the within-R^2 increase from 1% to 12%. While volume premia generally increase for outside dealers,[24] outside dealers heavily narrow their spreads as the volume increases (coefficient of -4.5). Columns 3 and 4 repeat the analysis for the forward. The results are in parallel, though with a somewhat smaller order of magnitude. For brevity, I omit the results at the swap as they, again, exhibit little variation in pricing.

Figure 13 illustrates relationship discounts from within the request, where positive numbers indicate that the relationship dealer sends more favorable prices in bps. Even though, there are significant relationship discounts for swaps and forward swap, the figure shows that the pricing differentials are markedly narrower for swap products compared to spots and forwards. The provide more robust evidence on the

[24]This is in line with asymmetric informatin motive as argued by Pinter, C. Wang, and Zou (forthcoming).

Table 5: Competition and volume

	Spot		Forward	
	(1) RelD	(2) OutD	(3) RelD	(4) OutD
HHI_j	4.790^{***}	65.795^{***}	2.811^{***}	36.082^{**}
	(1.694)	(18.000)	(0.989)	(15.053)
Notional	0.056^{*}	0.540^{***}	0.027	0.297^{**}
	(0.031)	(0.179)	(0.029)	(0.145)
$HHI_j \times$ Volume	-0.202^{*}	-4.523^{***}	0.096	-2.451^{**}
	(0.114)	(1.175)	(0.078)	(1.062)
Tenure			-0.203^{***}	-0.138^{***}
			(0.032)	(0.046)
Obs	255,249	2,483,030	670,960	4,908,642
R^2	0.45	0.41	0.40	0.27
Within-R^2	0.01	0.12	0.03	0.03
FE: $i \times t \times c \times d$	No	Yes	Yes	Yes

The table displays results from the regression
$Spread_{j,i,t} = \delta_1 \times HHI_j + \delta_2 \times HHI_j \times ln(Volume) + \beta_1 ln(Notional)$
$+ \beta_2 ln(Tenure) + fixed\,effects$.
The dependent variable $Spread_{j,i,t}$ for the spot (columns 1-2) and for the forward (columns 3-4) as described in Appendix A. Colums 1 and 3 base on the sample of relationship dealers and columns 2 and 4 on a sample of outside dealers. $dealer \times date \times currency\,pair \times direction$ fixed effects are included to extract discriminatory component of spreads. The main coefficients of interest are δ_1 and δ_2 which measures differential pricing for less connected firms and how this pricing differential changes with volume. Two-way clustered standard errors around the firm and month level are in parenthesis. ***, **, * indicate statistical significance at the 1%, 5%, and 10%, respectively.

differential quoting strategies, following within-request model is estimated

$$Y_{r,i} = \alpha_r + \beta_1 RelD + \beta_2 RelD \times ln(notional) + \varepsilon$$

where α_r are request fixed effects to absorb all demand related factors and focus on the differential quoting of dealers for the exact same request. This model resembles the method of Khwaja and Mian (2008) at the high-frequency level. The coefficients β_1 and β_2 measure differences in the quoting behavior of the relationship dealer to the outside dealers and how it changes as volume rises. The dependent variables $Y_{r,i}$ are a dummy, whether the dealer i is quoting in the request r ($P(Quote_i)$), the dealer's quote is executed ($P(Exec_i)$), and the quote in basis points ($Quote_i$).

Table 6 presents the results. Throughout all samples, the relationship dealer appears more competitive compared to outside dealers. That means the relationship dealer is more likely to quote (column 1), more likely to be executed (column 2), and prices are more favorable (column 3) at the spot as well as at the forward (columns 4-6) and forwards with long-tenor (columns 7-9). Though the competitive edge narrows when the volume is high. The relationship dealer becomes less likely to be executed and the relationship discount shrinks at all instruments. Though, the evidence on the probability to quote appears different. At the spot, outside dealers are less likely to quote with larger volume (column 1), there is no effect at full sample of forwards (column 2), and a highly significant negative effect for forwards with long tenors (colmn 7). When the volume is large, potential competitors start to quote for long tenured forwards. Again, this evidence is in line with the idea of locating the natural counterparty, i.e. the bank with the best funding ability in a currency. This may not coincide with the relationship dealer who most likely is a European bank.

Table 6: Within-request dealer competiton and volume

	Spot			Forward			Forward $\tau > 90$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$P(Quote_i)$	$P(Exec_i)$	$Quote_i$	$P(Quote_i)$	$P(Exec_i)$	$Quote_i$	$P(Quote_i)$	$P(Exec_i)$	$Quote_i$
RelD	0.040***	1.093***	−38.452***	0.111***	1.076***	−22.798***	0.308***	1.137***	−9.807***
	(0.006)	(0.010)	(0.399)	(0.006)	(0.007)	(0.161)	(0.010)	(0.013)	(0.232)
RelD × Notional	0.001**	−0.050***	2.848***	0.001	−0.050***	1.629***	−0.014***	−0.055***	0.624***
	(0.000)	(0.001)	(0.033)	(0.000)	(0.001)	(0.013)	(0.001)	(0.001)	(0.018)
Obs	331,853	331,853	191,025	928,875	928,875	333,164	373,639	373,639	154,687
R^2	0.32	0.28	0.44	0.32	0.25	0.54	0.34	0.25	0.39
Within-R^2	0.01	0.23	0.07	0.03	0.21	0.11	0.04	0.20	0.05
Request FE:	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The table displays results from the regression $Y_{r,i} = \alpha_r + \beta_1 RelD + \beta_2 RelD \times ln(notional) + \varepsilon$. The model resembles a high frequency version of the method by Khwaja and Mian (2008) to absorb all effects related to the demand using a request fixed effects α_r. The idea of the within-request estimator is to compared the quoting behavior of different dealers in the same request. The dependent variables $Y_{r,i}$ are a dummy whether the dealer is quoting (columns 1,4, and 7), a dummy whether the dealer's quote is executed (columns 2, 5, and 8) and the actual quote send by the dealer in bps (columns 3, 5, and 8). The dummy $RelD$ is equal one for the dealer i with the largest trade share of the requesting firm. This dummy is interacted with the log of the notional size in EUR to test how the competitive edge of the main dealer changes with volume. If potential competitors are concerned about credit risk, they shy away from competition as the notional size increases. If profitability considerations dominate, dealers enter the competition with larger volumes. Further separations into subsamples help to understand the impact of different loads of credit risks associated with different products. The columns 1-3 bases on spot trades, columns 4-6 on forward, and the columns restrict the sample to forward trades with over 90 days to maturity. The sample only includes RFQs from less competitive firms ($HHI_{j,m} > .375$). Because the identification of the coefficients requires within variation, the sample excludes single-bank trades. Robust standard errors are in parenthesis. ***, **, * indicate statistical significance at the 1%, 5%, and 10%, respectively.

7 COVID-19

The previous analysis highlights differential quoting behaviors of inside and outside dealers to less connected clients. The results show relationship discounts at the spot and forwards with short tenor. For forwards with long tenor and swaps, cross-request evidence show relationship premia. The evidence indicates that less connected clients suffer not only from discriminatory pricing but also from an impaired ability to locate the dealer with the strongest ability to finance in a currency. This section exploits the outbreak of COVID-19 as an exogenous shock on dealer competition. As I show, during March 2020, dealers' response rates to less connected firms dropped markedly and dealer competition deteriorated for those clients. This can be because of a combination of a few reasons. First, dealers turned off automatic quoting because of elevated uncertainty. Second, a sudden shift towards trading in the home office slowed traders down and they could not reply requests for quotes. Third, uncertainty with regard to the firm's credit risk elevated and dealers refuse to quote with the clients. In sum, less connected firms suffer from three effects. First, competition deteriorated allowing more space to extract rents from less connected clients. Second, the ability to locate the natural counterparty shrinks as some dealers stopped quoting. Third, credit risk may be higher and dealers price the risk.

To understand what was happening during the COVID outbreak, I focus on the responses during the shock. The following regression estimates how response rates changed during that period

$$Quoting_{i,j,n} = \sum_{m \in \{11/2019-06/2020\}} \delta_m \times \mathbb{1}_{\{if\, month\, m\}} \times HHI_j$$
$$+\beta_1 ln(Notional\ in\ EUR) + \beta_2 ln(Tenure) + \alpha_n + \alpha_i \times \alpha_j$$

where $\mathbb{1}_{\{if\, month\, m\}}$ are monthly indicator to measure how response rates changes monthly. α_n and $\alpha_{i,j}$ are request size and firm times dealer fixed effects to absorb effects related to the request size and relationship. Table **??** includes the results for the four different instruments excluding quotes by the main dealer who (almost) always quotes. It shows that response rates drop markedly for less connected firms for all instruments. This suggest that dealers become less willing to quote to those firms at the crisis breaks out.

Also, the pricing changed during the shock. Figure 8 plots average forward bid and ask prices for competitive and less competitive firms. While ask prices are generally higher for high-HHI firms, and bids are lower, the pricing differential widens at the outbreak of the pandemic.

To isolate the effect that is due to an widening of the discriminatory component or different quoting abilities, the following regression model is estimated:

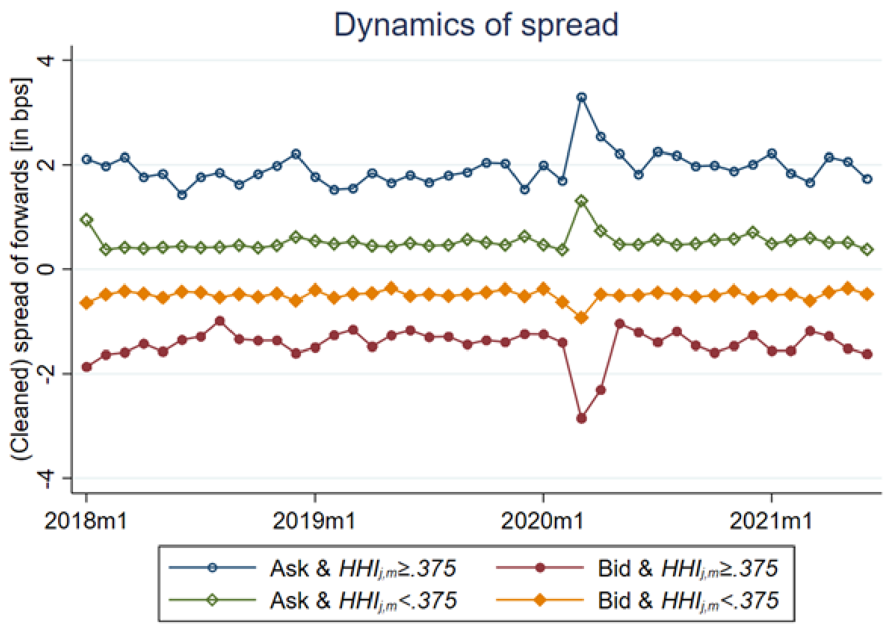
$$Spread_{j,i,t} = \sum_{m \in \{11/2019-06/2020\}} \delta_m \times \mathbb{1}_{\{if\, month\, m\}} \times HHI_j$$
$$+\beta_1 ln(Notional\ in\ EUR) + \beta_2 ln(Tenure) + \alpha_i \times \alpha_{date} \times \alpha_{currency} \times \alpha_{direction}$$

Table 7: Relationships during market turmoil: response rate

	Spot		Forward		Swap		Forward-Swap	
$HHI_{j,11-2019}$	-0.05	(0.03)	-0.13^{***}	(0.03)	0.01	(0.05)	-0.09^{*}	(0.05)
$HHI_{j,12-2019}$	-0.06^{*}	(0.03)	-0.14^{***}	(0.04)	-0.03	(0.04)	-0.08	(0.05)
$HHI_{j,01-2020}$	-0.05	(0.03)	-0.10^{**}	(0.03)	0.03	(0.05)	0.00	(0.05)
$HHI_{j,02-2020}$	-0.03	(0.03)	-0.08^{**}	(0.03)	0.03	(0.05)	-0.00	(0.05)
$HHI_{j,03-2020}$	-0.11^{***}	(0.03)	-0.23^{***}	(0.04)	-0.15^{**}	(0.05)	-0.24^{***}	(0.06)
$HHI_{j,04-2020}$	-0.11^{***}	(0.03)	-0.20^{***}	(0.04)	-0.07	(0.05)	-0.13^{*}	(0.05)
$HHI_{j,05-2020}$	-0.10^{***}	(0.03)	-0.15^{***}	(0.04)	-0.03	(0.05)	-0.08	(0.05)
$HHI_{j,06-2020}$	-0.07^{**}	(0.02)	-0.17^{***}	(0.05)	-0.00	(0.05)	-0.06	(0.06)
Notional	-0.00^{**}	(0.00)	-0.00^{*}	(0.00)	-0.01^{***}	(0.00)	-0.01^{***}	(0.00)
Tenure	-0.00	(0.00)	-0.02^{***}	(0.00)	-0.02^{**}	(0.01)	-0.00	(0.00)
Obs	516,354		1,251,782		263,937		615,479	
R^2	0.34		0.43		0.38		0.33	
Within-R^2	0.00		0.02		0.01		0.01	
FE:	n		n		n		n	
FE:	$i \times j$		$i \times j$		$i \times j$		$i \times j$	

The table displays results from the following regression:
$Spread_{j,i,t} = \sum_{m \in \{11/2019-06/2020\}} \delta_m \times \mathbb{1}_{\{if\ month\ m\}} \times HHI_{j,m} +$
$\beta_1 ln(Notional\ in\ EUR) + \beta_2 ln(Tenure) + \alpha_i \times \alpha_{date} \times \alpha_{currency} \times \alpha_{direction}$
The dependent variable $Spread_{j,i,t}$ is the positive spread measure at the spot (columns 1,5) and at the forward (columns 2-4,6-7) as described in section **??**. All columns include *dealer* × *date* × *currency pair* × *direction* fixed effects to measure discriminatory pricing. The main coefficient of interest is δ which measures the discriminatory component of spreads charged to less connected firms. Because different products are associated with different loads of credit risk, the columns include different subsample like columns 1 and 5 displays results at the spot, columns 2 and 6, at the forward, column 3 for forwards with between 30 and 90 days to maturity and column 4 with at least 90 days to maturity. Columns 1-4 bases on trades of non-financial firms and columns 5-7 on trades by institutional clients. Monthly subsamples are winsorized at the 0.5 and 99.5 level Standard errors clustered around the firm level are in parenthesis. ***, **, * indicate statistical significance at the 1%, 5%, and 10%, respectively.

Figure 8: Dynamics of (cleaned) forward spreads



The figure plots average quotes over time for four sample, at the bid and ask as well as for competitive and less competitive firms. The figure illustrates that ask prices are above bid prices and less connected firms generally pay higher ask prices (receive lower bid prices). Bid-ask spreads widen in march 2020, though the pricing differential between well and less connected firms widens as well.

Here the HHI_j is interacted with monthly dummies such that the respective coefficients δ_m absorb the dynamics of the discriminatory component of spreads. The results are in table 8. As shown in column 1, the discriminatory component of spreads by relationship dealers widens during March 2020 to an estimated coefficient of 2 bps compared to 1.27 bps in November 2019, even at the spot which is absent of credit risks. Outside dealers seem to widen their spreads towards less connected firms even more severely (column 2). This suggests that the absence of competition allows inside dealers to extract modestly higher markups from their captive clients. At the forward, the dynamics of the price discrimination seem to be more pronounced. Column 3 shows the results for forward trades by relationship dealers with an estimated coefficient of 9.8 bps in March 2020 compared to 3.6 in November 2019. In contrast to the spot, outside dealers (column 4) do widen spreads only with a comparable magnitude as inside dealers (column 3). To provide insights into whether the increase in discriminatory pricing is due to credit risk or the inability to locate the natural counterparty, unreported results repeat the analysis on a sample with at least 30 days to maturity. The results show that discriminatory markups for long term products widen much more severely for inside dealers, while widening of discriminatory spreads by outside dealers is less pronounced. This suggests that both elevated credit risk as well as the inability (of mostly European) relationship banks to fund in the currency deteriorate prices for captive clients.

Table 8: Relationships during market turmoil: quotes

	Spot				Forward			
	RelD		OutD		RelD		OutD	
$HHI_{j,11-2019}$	1.27***	(0.29)	6.73**	(3.12)	3.58***	(1.12)	3.63**	(1.77)
$HHI_{j,12-2019}$	1.16***	(0.28)	6.89**	(4.85)	3.50***	(0.86)	2.52**	(1.21)
$HHI_{j,01-2020}$	1.05***	(0.26)	6.83**	(3.17)	4.11***	(1.37)	4.59*	(2.35)
$HHI_{j,02-2020}$	1.35***	(0.27)	11.78**	(5.38)	2.84***	(0.93)	3.67**	(1.63)
$HHI_{j,03-2020}$	2.02***	(0.27)	12.92**	(6.18)	9.78*	(5.79)	8.93***	(3.44)
$HHI_{j,04-2020}$	1.53***	(0.30)	9.73*	(5.01)	4.75***	(1.60)	5.06***	(1.87)
$HHI_{j,05-2020}$	1.37***	(0.29)	8.30**	(4.77)	1.61	(1.13)	3.33*	(1.72)
$HHI_{j,06-2020}$	1.86***	(0.31)	7.78**	(3.76)	3.19***	(1.15)	3.16*	(1.72)
Notional	0.01	(0.01)	−0.24***	(0.06)	0.08***	(0.02)	−0.04**	(0.02)
Tenure					−0.26***	(0.05)	−0.12***	(0.03)
Obs	46,036		451,222		131,753		955,988	
R^2	0.34		0.38		0.42		0.25	
Within-R^2	0.01		0.08		0.03		0.01	
FE:	$i \times t \times c \times d$		$i \times t \times c \times d$		$i \times t \times c \times d$		$i \times t \times c \times d$	

The table displays results from the following regression:
$Spread_{j,i,t} = \sum_{m \in \{11/2019-06/2020\}} \delta_m \times \mathbb{1}_{\{if\ month\ m\}} \times HHI_{j,m} +$
$\beta_1 ln(Notional\ in\ EUR) + \beta_2 ln(Tenure) + \alpha_i \times \alpha_{date} \times \alpha_{currency} \times \alpha_{direction}$
The dependent variable $Spread_{j,i,t}$ is the positive spread measure at the spot (columns 1,5) and at the forward (columns 2-4,6-7) as described in section **??**. All columns include *dealer* × *date* × *currency pair* × *direction* fixed effects to measure discriminatory pricing. The main coefficient of interest is δ which measures the discriminatory component of spreads charged to less connected firms. Because different products are associated with different loads of credit risk, the columns include different subsample like columns 1 and 5 displays results at the spot, columns 2 and 6, at the forward, column 3 for forwards with between 30 and 90 days to maturity and column 4 with at least 90 days to maturity. Columns 1-4 bases on trades of non-financial firms and columns 5-7 on trades by institutional clients. Monthly subsamples are winsorized at the 0.5 and 99.5 level Standard errors clustered around the firm level are in parenthesis. ***, **, * indicate statistical significance at the 1%, 5%, and 10%, respectively.

8 Conclusion

Request for quotes (RFQ) platforms are considered as an ideal mechanism to centralize of OTC markets because it eliminates search costs and decreases the market power of dealers. Because of the recent push towards centralized markets, it is important to understand the frictions governing the trading behaviors on OTC markets. Using detailed quote level-data from market leading European FX platform for corporate clients, this paper has two novel main findings. First, many firms have only a few active dealer connections and those firms pay wider spreads which are discriminatory. Therefore, dealers maintain substantial market power over their customers even on centralized RFQ platforms. The inability of firms to connect with multiple dealers can be found in the bilateral clearly. Usually firms have an account with the bank and a credit line to settle trades. This requires costly regulatory and credit risk checks. It can be seen that many of the less connected firms are also unable to request multiple dealers because of the lack of connections. Though, once the trading link is established, firms must fulfill collateral requirements. The data show that some dealers never quote even though they are frequently requested.

The second main set of finding highlights the special role of relationship dealers. Less connected firms tend to have one dealer who reliably supplies quotes. Moreover, these quotes are more favorable compared to those of outside dealers, suggesting relationship discounts. These relationship discounts turn into relationship premia for long-tenured forwards and swaps. The evidence suggests that there is more dealer heterogeneity in the ability to supply these products and captive clients pay this relationship premium due to their inability to locate the dealer with the strongest ability to supply the product.

Pricing strategies between relationship and outside dealers appear distinct. The evidence show that relationship dealer quote reliably with constantly narrow spreads which is in line with the notion that relationship dealers follow a long-term strategy to keep their customers captive. In contrast, outside dealers markedly wider spreads to less connected firms, though these spreads narrow with volume, leading to more executions as well. This suggests that outside dealers maximize short-term trading profits.

Rel contr: Hau: 1. discri on platform, 2. rel discounts visible b/c

The paper has several novel contributes to the literature. The main contribution is the introduction of a new relationship frictions in OTC markets, which, to the best of my knowledge, has not been previously addressed in the literature and provide new insight into the special role of main relationship dealers. The unique quote-level data set from a market-leading European FX multi-dealer platform provides an ideal setup to isolate search frictions that are typically prevalent in OTC markets. Therefore, this study can uncover novel facts about the entire trading process. The idea that firms are captive and cannot request any dealer is new to the literature on OTC markets. In contrast, previous literature associates small networks with search frictions (Hau et al. 2021), incentives to concentrate trades on a dealer to receive discounts from repeated business (Hendershott, Li, et al. 2020) or assumes that clients can request any dealer (Riggs et al. 2020). Though, captivity of clients is well studied in the firm-bank lending relationship literature, where firms are locked-in because of informational reasons (Rajan 1992; Sharpe 1990; Petersen and Rajan

1995; Von Thadden 2004; Ioannidou and Ongena 2010). While the origin of the relationship remains unclear, FX is only a part from a portfolio of services by banks, therefore, it seems likely that these relationships originate in the lending relationship (Qi 2023).

The role of relationships in OTC markets is mainly studied with regulatory trade-level data. On a trade-level, exclusive relationships appear extractive in the FX market (Hau et al. 2021), while my quote level data reveal the existence of relationship discounts. Di Maggio, Kermani, and Song (2017) and Jurkatis et al. (2023) document relationship discounts for institutional clients in the bond, the main difference to this work is the measurement of relationships. While these paper focus on the largest clients, my work studies relationships to more captive clients. Moreover, the quote-level data enables me to discover different trading strategies shedding new light into the relationship between volume and prices (Pinter, C. Wang, and Zou forthcoming).

This study has important policy implications opposing those from search frictions. Instead of imposing tighter transparency regulations, the frictions in relationships suggests a reduction in compliance costs to make competing by outside dealers more profitable and increase competition. High relationship setup costs from regulatory requirements such as know-your-customer checks may reinforce the relationship friction leading to less competitive pricing for a set of vulnerable firms. The full nature of the relationship and the welfare effects remain elusive.

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Appendix A Measuring spreads

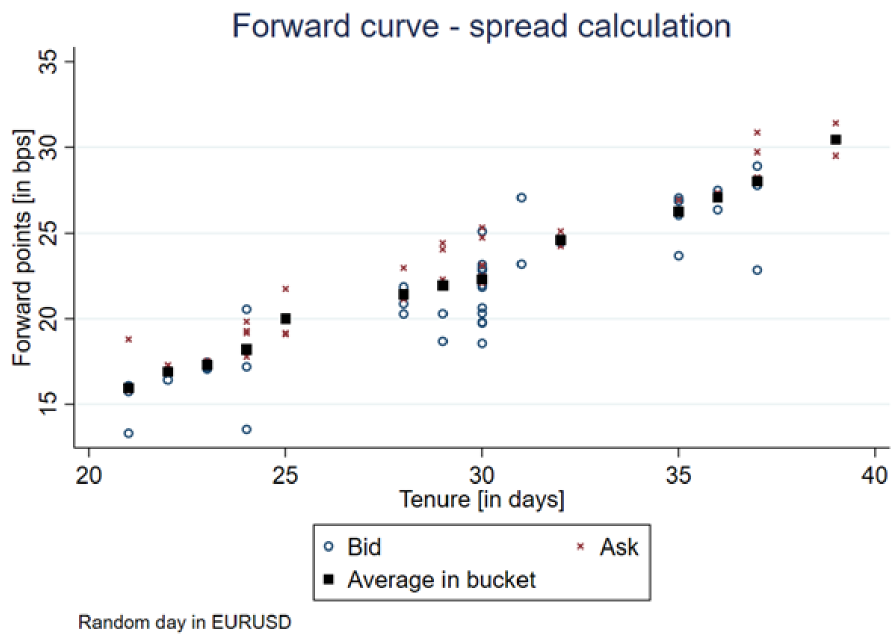
This appendix provides detailed explanations on the spread measures. Measureing spot spreads is straightforward using minute level interbank quotes from Refinitive Datascope for five different currency pairs: EUR/USD, EUR/GBP, EUR/CHF, GBP/USD, and USD/CHF. Spot spreads are $\frac{S_{j,i}-S}{S} \times 10,000$, where $S_{j,i}$ is the trade price in basis points [bps] by bank i executed by firm j and S is the inter-bank benchmark.

For derivative instruments such as forwards and swaps, measuring spreads is somewhat more complicated. Similar to the method by Abbassi and Bräuning (2021), I calculate (cleaned) forward spreads in bps as the residuals ε from the fixed effects regression $\frac{F_{j,i}-S}{S} \times 10,000 = \alpha_{currency\,pair} \times \alpha_{tenure} \times \alpha_{date} + \varepsilon$, where $F_{j,i}$ is the executed forward rate and $\alpha_{currency\,pair}$, α_{tenure}, α_{date} are fixed effects. This fixed effects estimator extracts the forward curve from the quoted forward rate ($F = S \times \frac{i^{quote}}{i^{base}}$), to make trades comparable across currency pairs, tenures and dates. As in Abbassi and Bräuning (2021), the method takes fluctuations in the spot at a high-frequency level into account, but assumes the slope of the forward curve (interest rate differential) to only change on a daily basis. Figure 9 provides a visualization of this method. At a random day of the sample period, there are trades at the bid (blue dots) and ask (red dots) in the EUR/USD pair. The positive trend of forward points in bps ($\frac{F_{j,i}-S}{S} \times 10,000$) mirrors the upward-sloping forward curve. The black dots are the average trade prices in the respective maturity bucket estimated from the fixed effects. The residuals are the spreads which are mainly positive at the ask and negative at the bid. To get a positive spread measure, I calculate the effective (cleaned) spread by multiplying bid prices by minus one.

Measuring spreads for outright swaps works very similarly compared to forwards, because swap are already quoted with a swap rate (i.e. $(F_{j,i} - S) \times 10,000$). The fixed effects regression can extract the forward curve and residuals approximate spreads. Unfortunately, for the fixed effects estimator has little common support for forward swaps, because the method requires trades with identical tenures at the same date

Overall, the methods quite successfully measures spreads. At the spot, spreads

Figure 9: Measuring (cleaned) forward spreads



are identified in 97% of trades. At the forward and swap, the method identifies spreads in only 78% and 83% of trades, respectively. One drawback of the method is its common support requirements. For each $date \times currencypair \times tenure$ bucket, there have to be at least two trades to extract an average price. Especially, in the comparably less liquid pairs such as the USD/CHF and in longer maturity buckets fewer spreads are identified.[25]

[25]Because the discriminatory pricing tends to widen with tenure, the bias resulting from the spread estimation method leads to an underestimation of the price discrimination.

Appendix B Supporting figures

In this section, I introduce seven stylized facts from the data to characterize firm-bank connections on the platform. Relationships are defined through the execution of at least one trade in a dealer-client pair on a monthly basis. To measure the firm's j ability to foster dealer competition across banks i during month m, I compute a Herfindahl-Hirschman index, which is $HHI_{j,m} = \sum_i \left(\frac{\#trades_{j,i,m}}{\#trades_{j,m}}\right)^2$. Figure 1 shows the distribution of this HHI. Most saliently, is the fact that many firms trade exclusively with one bank (fact 1). In total, 13% of firm-month observations are completely locked-in ($HHI_{j,m} = 1$) and 43% trade at least half of their trades with only one dealer. Again, this is the tip of the iceberg of a general problem in OTC trading. Hau et al. (2021) show that over 50% of European corporates trade exclusively with one dealer in the FX market and Hendershott, Li, et al. (2020) show that 30% of insurers are locked-in in the US bond market.

Fact 2 provides a mechanical answer as to why firms are unable to impose dealer competition. Figure 10B plots the distribution of the $HHI_{j,m}$ across different network sizes[26], illustrating that the dealer competition decreases with the number of connected dealers (network size). Firms utilize their network to distribute their trades across the connected dealers. Fact 3 demonstrates that dealer banks should be well aware of the intensity of the competition in requests from a specific client. Figure 10C plots the execution rate, measured as the fraction of executed quotes over all quotes sent, across network sizes. It shows that the execution rates tend to be smaller for dealers in larger networks. Consequently, dealer banks perceive the competition through the requesters' networks to adjust markup accordingly.

Theoretical OTC literature usually bases on the assumption that clients can trade with any dealer. For example, the seminal random search model by Duffie, Gârleanu, and Pedersen (2005) assumes that firms can search the entire universe of dealer for the most favorable prices or in the auction model by Riggs et al. (2020), clients can effortlessly request all dealers. Fact 4 is not in line with this idea. The figure 10D plots the transition of network sizes of clients over months and shows that firms stick

[26]The network size is the number of dealer relationship of a client in a month.

to the same dealer over time. Persistent dealer networks are inconsistent with the idea that clients can easily search or request the entire universe of dealers. Similar to the argument of Hendershott, Li, et al. (2020), dealer networks are formed endogenously and clients are restricted to trade only within the set of connected dealers.

The last three facts provide some indication of how networks are formed. Fact 5 establishes that less connected firms tend to trade less. Figure 11A plots the distribution of the monthly log trading volume in EUR over the network size. It shows that well-connected clients tend to exhibit larger trade intensities. Unreported results show that larger networks are associated with larger trade intensities at the intensive (average trade volume) and extensive (average number of trades) margins. This suggests that more active firms have larger networks which points towards a fixed relationship setup costs as argued in this paper.

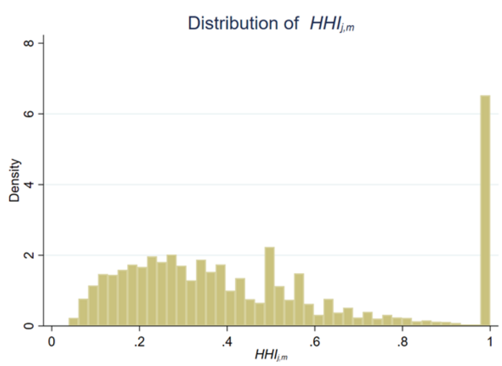
Besides the relationship setup costs, firms also need some sort of collateral for which the counterparties usually agree on a line of credit. As such, the bank must conduct costly credit quality checks. Fact 6 states that less-connected firms tend to be related to local banks defined as being from the same country. Figure 11B plots the share of relationships that are with banks that are headquarted in the same country as the firm over different network sizes. It can be seen that smaller networks are more regional which is in line with the relationship lending literature that argues that geographic proximity lower informational costs (Degryse and Ongena 2005; Petersen and Rajan 2002).

The idea that firms with fewer banking relationships exhibit larger information problems matches fact 7, which states that fewer relationships in smaller networks involve trades with longer tenures compared to relationships in larger networks. As illustrated in Figure 11C, there are relatively fewer relationships in smaller networks that involve trades with tenures longer than 90 days.[27] The evidence corroborates the idea that less connected firms tighter credit limits as such banks in such networks

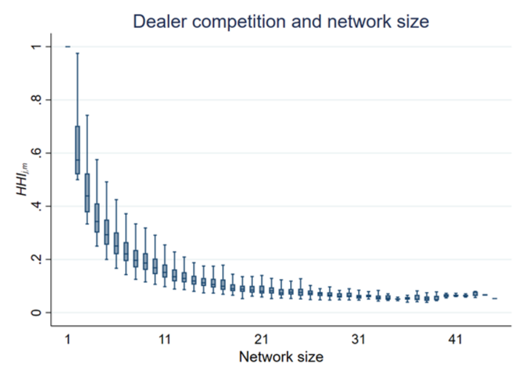
[27]Less connected firms have relatively fewer connected dealers through which they execute contracts with longer tenures. Interviews with corporate bankers show that each firm has only a certain credit limit for FX products which is also in line with the evidence of Qi (2023).

refuse to trade more credit intense products. Though, this could also be rooted in less demand for long-tenured products in less connected firms. The marginal firm choosing to enter the platform may have less sophisticated routines for hedging long-term risks compared to more active platform users. In sum, the evidence points towards both a fixed relationship setup cost and credit limits as determinants of the network size.

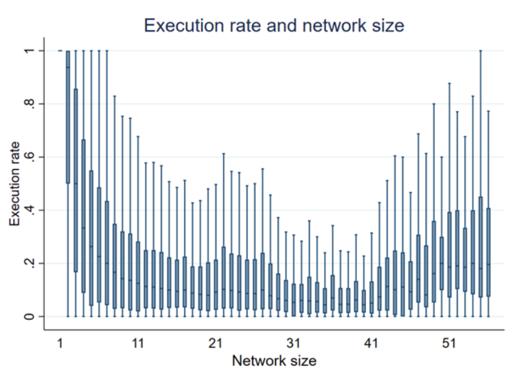
Figure 10: Relationship characteristics I



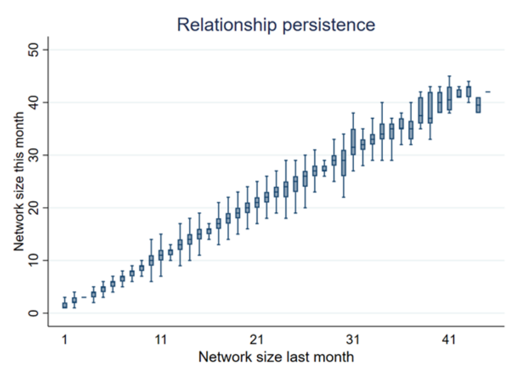
(A) Fact 1: Many firms is locked-in



(B) Fact 2: Large network are more competitive

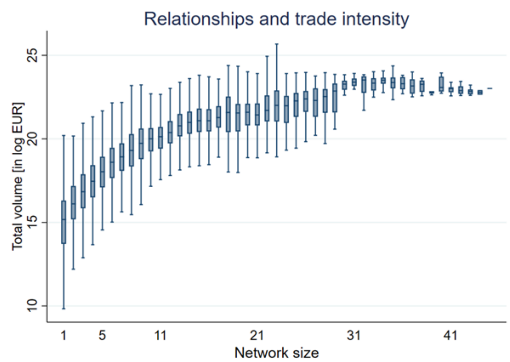


(C) Fact 3: Dealers perceive competition and the lack thereof

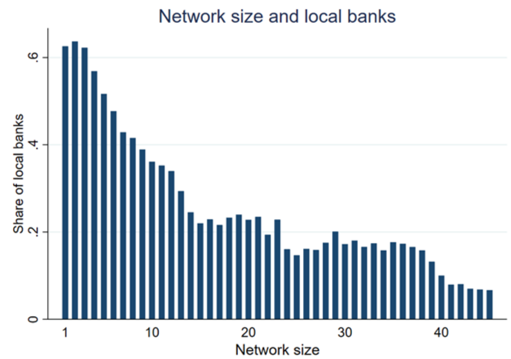


(D) Fact 4: Networks persist over time

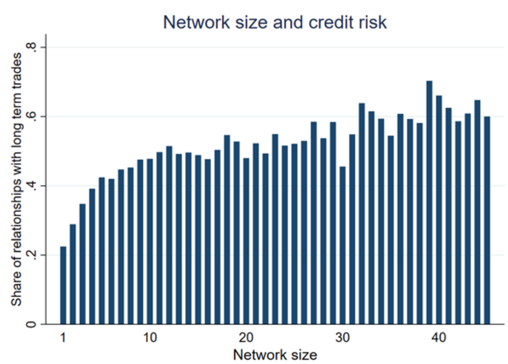
Figure 11: Relationship characteristics II



(A) Fact 5: More trade flow in larger networks

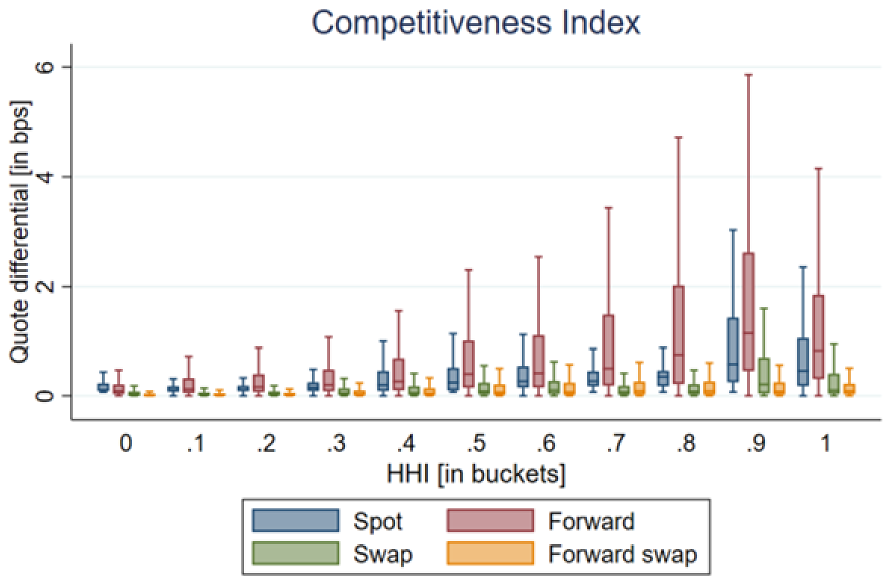


(B) Fact 6: Smaller network are more likely with local banks



(C) Fact 7: Smaller network are less likely to exhibit long term trades

Figure 12: Within request: competitiveness index



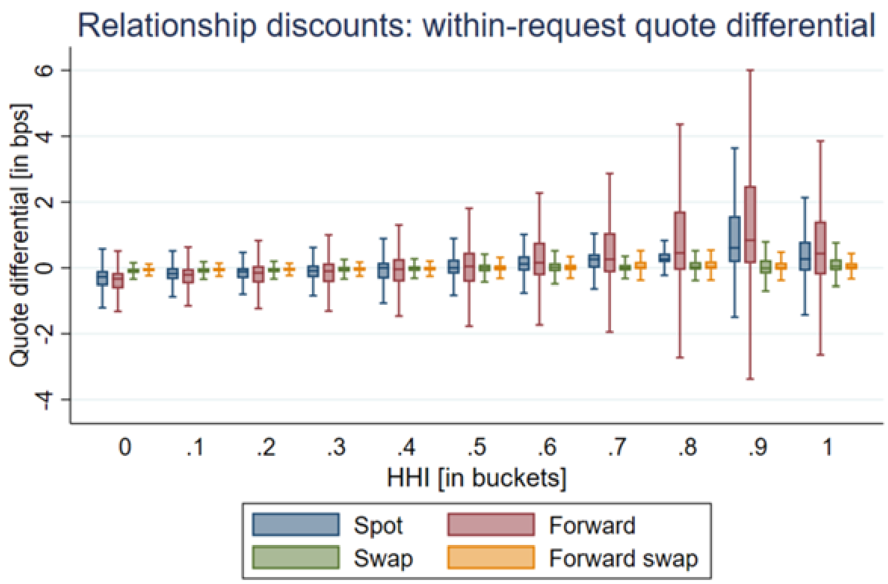
The competitiveness index measures the quote differential between the best and second best quote in basis points.

Appendix C Supporting tables

Appendix D Simple model of bid-shading

Building on the seven relationship facts of the Appendix B, this chapter introduces a parsimonious theoretical framework of platform OTC trading in which firms send RFQs to a set of connected dealer banks to satisfy their exogenous hedging demand. The optimal quoting strategy in the first-price sealed auction mechanism is to shade the bid by an amount depending on the intensity of the dealer competition. Therefore, banks endogenously price-discriminate against less connected firms, because of their inability to impose dealer competition. Firms with larger dealer networks can profit from smaller markups and from higher chances of requesting a dealer with larger inventories. In contrast to classical search models, well-connected firms can effortlessly find a dealer bank with a large inventory quoting more favorable prices

Figure 13: Within request: relationship discounts



The y-axis plots the quote differential between the quote of the relationship dealer and best competing quote in basis points.

compared to the market. Hence, the discriminatory component of spreads depends on the number of connected dealer banks. Opposed to search models in which firm can trade with the entire universe of dealers, firms are limited to trade only with connected banks.[28]

As a next step, I provide a theoretical foundation on bank's profitability considerations leading to the endogenous relationship formation. The main idea is that dealers invest in a connection to a client only if the expected profit is positive. The expected profit is determined by a combination of the firm's pre-existing relationships, the trade intensity, and the relationship setup cost.

[28] In Duffie, Gârleanu, and Pedersen (2005), clients are assumed to be able to approach any dealer and Riggs et al. (2020) assumes that clients can request the universe of all banks.

Quoting strategy

Starting with the primitives of the model, a firm j chooses to request a set of connected dealer banks $M_j \subseteq N_j \subseteq \mathbf{N}$ where N_j depicts the set of all connected banks to firm j which is a subset of the universe of banks $\mathbf{N}$. For simplicity, let us assume that the firm requests all connected firms $M_j = N_j$.[29]

The RFQ procedure resembles a sealed-bid first price auction, in which the firm j chooses the lowest price p_i of quotes received by $n = |M_j|$ requested banks:

$$P_j = min[p_1, ..., p_n]$$

Banks strategically send quotes to maximize the expected trade profits. A key determinant of trade profits in the model is their competitive position π_i which summarizes the inventory position as well as their quoting ability (i.e. access to the money market and interconnectedness on the inter-bank market). More precisely, bank i has some monetary gain by laying off the some of the inventory π_i, where the inventory is drawn from an i.i.d. uniform distribution with support $\pi_i \in [0, 1]$.[30] Therefore, the expected trade profits are

$$\mathbb{E}_i[G_i] = q(p_i)[p_i - s + \pi_i]Q - c$$

where $q(p_i)$ represents the likelihood of winning the auction and $(p_i - s + \pi_i)Q$ is bank i's gain if its quote is executed. More precisely, bank i receives the price p_i at the cost of providing the financial instrument with notional size Q at its fair market-value or inter-bank spot price s. c is a small fixed cost of sending a quote, which includes administrative or informational costs.

Note that higher quotes have two opposing effects on the expected profits: first, increasing the quote decreases the likelihood to win the auction and, second, increases the gain from an execution. The bank chooses a price strategy $p(\pi_i|n)$ to maximize

[29] Unreported results show that less connected firms indeed always request all connected dealers. Only, firms with large networks request a subset of connected banks.

[30] This assumption comes without a loss of generality, since the results can be replicated with any other continuous distribution.

expected profits.

Banks have partial information about their competitors. While they are unaware of the quotes sent by competitors, they known the number of competing banks requested n and that all $n-1$ competitors draw their inventories from the same uniform distribution. [31]

To find an equilibrium strategy, two assumption are necessary. First, all dealers follow the same pricing strategy $p(\pi_i|n)$, which is strictly decreasing in π_i and differentiable. Second, dealers quote only if they expect a non-negative trade profit ($\mathbb{E}_i[G_i] \geq 0$). Because $p(\pi_i|n)$ is decreasing in π_i, the dealer with the highest inventory will send the lowest price to win the auction. As all competitors draw their inventory from the uniform distribution with $\pi \in [0, 1]$, the likelihood of winning is $q(p(\pi_i|n)) = \pi_i^{n-1}$.

The equilibrium strategy can be found using the Revelation Principle. If each bank sets its price according to their true inventory value, the expected profit is $\mathbb{E}_i[G_i] = \pi_i^{n-1}[p(\pi_i|n) - s + \pi_i] - c$. An equilibrium strategy is defined such that no bank has an incentive to deviate from the strategy and pretend to have $\tilde{\pi}$:

$$\pi_i^{n-1}[p(\pi_i|n) - s + \pi_i] \geq \tilde{\pi}^{n-1}[p(\tilde{\pi}|n) - s + \pi_i]$$

This is the case for the value of $\tilde{\pi}$ that maximizes the right-hand side. After taking the first order condition, setting $\tilde{\pi} = \pi_i$ as the banks reveals its true value in the equilibrium and solving the differential equation problem, the equilibrium strategy

[31] In fact, banks do not know the number of competitors requested, though, they can infer n by from the past execution rates (ER) of their quotes ($\tilde{n} = 1/ER_{i,j}$) as shown in figure 10C.

is:[32][33]

$$p_i^*(\pi_i|n) = s - \frac{n-1}{n}\pi_i \tag{1}$$
$$= s + (HHI_j - 1)\pi_i \tag{2}$$

The optimal pricing strategy is a bid shading strategy, in which banks increase their prices in proportion to the competitive pressure the firm imposes through the auction. To see the effect clearer, the optimal pricing strategy can be separated into three components: the inter-bank price s, the monetary value of laying off the inventory $-\pi_i$ and a discriminatory surcharge $HHI_j\pi_i$. This discriminatory surcharge decreases with the intensity of the competition ($\frac{\partial p_i^*(\pi_i|n)}{\partial n} \leq 0$). To exemplify the discriminatory pricing, consider two firms A and B with $n_A > n_B \geq 2$ requesting the same bank i holding the inventory $0 < \pi_i < 1$ constant. The pricing differential is $p_i^*(\pi_i|n_A) - p_i^*(\pi_i|n_B) = (HHI_A - HHI_B)\pi_i < 0$. Firm A pays a lower discriminatory surcharge than B, only because its dealer banks face more intense competition from other dealers.

The positive price effect of more bank relationships goes beyond shrinking discriminatory surcharges. This can be most easily seen from the firm's expected best quote received:

$$\mathbb{E}_i[P_j^*] = \mathbb{E}[min[p_i^*(\pi_i|n)]] \qquad \forall i \in M_j$$
$$= s - \frac{n-1}{n}\mathbb{E}[max[\pi_i]]$$

Because $p_i^*(\pi_i, n)$ is a decreasing function in π_i, the lowest price is sent by the bank

[32] The first order condition to the maximization problem is $\frac{\partial(\cdot)}{\partial\tilde{\pi}} = (n-1)\tilde{\pi}^{n-2}[p(\tilde{\pi}|n) - s + \pi_i] + \tilde{\pi}^{n-1}\frac{\partial p(\tilde{\pi}|n)}{\partial\tilde{\pi}} = 0$. The equilibrium strategy is is defined such that the bank has no incentive to deviate. Therefore, the optimal strategy is characterized by $\tilde{\pi}_i = \pi_i$ and the first order condition can be rewritten as an ordinary differential equation $\frac{\partial p(\tilde{\pi}|n)}{\partial\tilde{\pi}} = -(n-1)\left[\frac{p(\tilde{\pi}|n)-s}{\tilde{\pi}} + 1\right]$.

[33] Locked-in firms ($n = 1$) are a special case. The banks charges the reservation value r as markup, such that $p_i^*(\pi_i|n) = s + r$.

with the strongest competitive capability of π_i of all banks $i \in M_j$, which is

$$\begin{aligned}\mathbb{E}[max[\pi_i]] &= \int_0^1 \underbrace{Prob(max[\pi_i] < y)}_{=y^{(n-1)}} \times ny\, dy \\ &= \int_0^1 y^n \times n\, dy \\ &= \frac{n}{n+1}\end{aligned}$$

and results in an expected price received by the firm j:

$$\mathbb{E}[P_j^*] = s - \frac{n-1}{n+1} \tag{3}$$

Prices received by firms become more favorable as more dealers are requested because of two reasons: First, requesting more banks shrinks the markup $\frac{\partial \frac{\pi_i}{n}}{\partial n} = -\frac{\pi_i}{n^2} < 0$. Second, the firm finds in expectation a dealer with more favorable inventory $\frac{\partial \mathbb{E}[max[\pi_i]]}{\partial n} = \frac{1}{(n+1)^2} > 0$. Note that the firm can effortlessly find the bank with the highest inventory, which defines the main difference to classical search models in OTC markets.

In terms of the variance, requesting more dealer banks leads to more reliable spreads: The variance $Var(P_j^*) = \left(\frac{n-1}{n+1}\right)^2 \left[\frac{n}{n+2} - \left(\frac{n}{n+1}\right)^2\right]$ is decreasing in n, because the variance of the most favorable inventory decreases with more banks requested.[34]

Bank profitability considerations

Building on the theoretical foundation, it is easy to understand the bank's decision of whether to supply international liquidity to the client. First, banks quote only if they expect a profit from responding to the RFQ, which is the case for $\pi_i^n \frac{1}{n} Q > c$. Therefore, the probability of the bank to quote is:

$$Probability(Quoting) = 1 - \left(\frac{cn}{Q}\right)^{1/n}$$

[34]This holds only true if $n \leq 3$.

As section **??** will establish empirically, response rates to RFQs increase with volume (Q), and decrease with competition (n) or the quoting costs (c). For example, the informational costs of quoting for institutional clients may be larger compared to non-financial corporate clients with an exogenous hedging demand. As such, the response rates may be lower for these clients.

Before banks can receive RFQs from clients, the two parties have to establish a trading infrastructure which requires a relationship investment. Banks enter new relationships only if they expect trade profits from the trades with the firm

$$\text{Relationship Profit}_i = \eta_j E[E[G_i|Q]] - \underbrace{K_{i,j}}_{\text{firm-bank specific cost}} \geq 0$$

where η_j and Q are the extensive and intensive margins of the trade intensity, respectively. $K_{i,j}$ is a firm-bank specific relationship setup cost reflecting the fact that regional banks face lower informational costs or cross-sales opportunities. If a lending relationship already exists, cross-selling FX products may be associated with negligible setup costs. The generic formulation set-up costs accomodates any heterogeneities between firm-bank pairs such as whether relationships outside the platform exists, the geographic distance, and the firm's credit risk. It can be seen that three factors determine the bank's relationship investment decision. First, a large number of pre-existing relationships shrink the expected trade profits, because the bank expects to be able to charge only low markups. Second, high trade intensities increase the expected profits. Note the effects of the intensive (Q) and extensive margins (η_j) of the trade intensity. After initial negotiations between the counterparties, the bank may be able to gauge the average trade volume and the intensity of the competition by the firm to predict its average response rate and expected profits. Third, the fixed and firm-bank specific setup cost decreases the propensity to invest.

Again, the idea of this parsimonious theoretical framework is to guide the empirical work. It bases on standard auction theory and builds on the stylized facts from section **??**. Despite its parsimony, the theoretical predictions matches several dimensions of the empirical findings.