

Relationships versus Competition in OTC Markets

Hannes Halder*

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Abstract

This paper provides an explanation as to *why* competition on centralized platforms in OTC markets is low and *why* clients form exclusive relationships with dealers. Leveraging novel quote-level data from a request for quotes (RFQ) platform in which non-financial firms hedge their currency exposure, I find that dealers charge up to 9 basis points more from clients with fewer dealer connections. Because trading on the platform is otherwise frictionless, I argue that clients lack dealer connections because clients need to entertain costly credit lines with each dealer to settle transactions. Consistent with theories of long-run relationships where dealers have the incentive to keep their customer loyal, I find that relationship dealers provide discounts of up to 6 basis points and customer being loyal to their relationship dealer even when an outside dealer sends more favorable prices.

JEL classifications: G14, G15, G18, G32, D4

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*GSEFM Frankfurt and Goethe University Frankfurt: hannes.halder@hof.uni-frankfurt.de
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1 Introduction

Over-the-counter (OTC) markets are gigantic in size. 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). Dealers maintain market power to discriminatorily price against "less sophisticated" clients, which the previous literature mainly associates with search frictions (Duffie, Gârleanu, and Pedersen 2005; Hau et al. 2021; O'Hara, Y. Wang, and Zhou 2018; Hendershott, Li, et al. 2020). 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 because platforms enable clients to solicit quotes from multiple dealers simultaneously which eliminates search problems and intensifies dealer competition.^{1,2} Though, competition appears to be low on more centralized platforms and trading relationships persist (Allen and Wittwer 2023).

This paper jointly explains *why* competition on platforms is low and *why* clients form exclusive relationships with dealer banks. The findings from novel quote level data from a European RFQ platform in which non-financial firms hedge their currency exposure suggest that firms lack dealer connections because of costly settlement

¹In 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 receive from other dealers. On platforms, clients can solicit quotes from multiple dealers simultaneously and select the most favorable price.

²The Dodd-Frank act mandates certain products to be traded via centralized platforms (so-called swap execution facilities) and the MiFID II regulation incentivizes platform trades because clients can proof best execution on platforms. Further, empirical evidence shows that spreads are tighter on platforms compared to bilateral trading (Hendershott and Madhavan (2015), Hau et al. (2021), and Allen and Wittwer (2023)). 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.

requirements and firms form exclusive relationships with dealer banks to mitigate the pervasive effects from low dealer competition.

This paper has three sets of main findings. First, 45% firms concentrate more than half of their trades on one dealer and these firms pay around 3 to 4 basis points wider spreads. The executed prices are higher even when comparing them to prices by the same dealer for the same instrument at the same day indicating that dealers price discriminate against those clients. This finding shows that clients are unable to foster dealer competition which allows dealers to extract markups from their more exclusive customers.

So why would firms not simply request more banks to intensify dealer competition? Because of the novel setup I am able to exclude traditional explanations like search³ or informational⁴ explanations shaping dealer networks. Hence, I conjecture that settlement requirements limit the firms' dealer networks. Before a client can trade with a dealer, both parties need to establish a trading link which typically includes costly lines of credits to guarantee settlement.⁵ Because credit lines are ex-

³See Hendershott, Li, et al. (2020) and Hollifield, Neklyudov, and Spatt (2017) for the related literature. This platform eliminates search problems, because clients can simultaneously request multiple dealers (pre-trade transparency) and the platform sends its customers monthly reports providing transparency about their price quality (post-trade transparency). The monthly reports compares the clients' price qualities across their connected dealers and benchmarks the prices to those of other clients on the platform.

⁴See Kondor and Pinter (2022) and Baldauf and Mollner (2024) for the related literature. Non-financial firms are uninformed clients in the FX market (Ranaldo and Somogyi 2021; Menkhoff et al. 2016, therefore it is unlikely that these clients choose smaller networks to hide information).

⁵The trades on the platform are settled bilaterally and guaranteed through credit lines and in rare cases cash. Under the European Market Infrastructure Regulation (EMIR) non-financial counterparties are generally not subject to central clearing obligations unless their positions exceed certain clearing thresholds. These thresholds are not relevant for the firms in the sample, because their trading activity is too small. Glowka and Nilsson (2022) provide an overview on the FX settlement from the BIS triennial survey.

pensive, clients have a limited set of dealer connections and dealers have substantial market power over clients with few connections allowing dealers to increase markups.

The second set of main findings shows that less connected clients benefit from exclusive dealer relationships. This is similar to the theories by Bernhardt et al. (2005) and Board (2011) where a dealer (agent) has market power to hold-up the client (principal) and the promised loyalty in long-run relationships mitigates the pervasive effects from the dealers' excessive market power. Relationships provide both the firm and the bank long-run incentives to keep the other party loyal, whereas outside dealers follow short-run incentives of trade-by-trade profit maximization. The quote-level evidence reveals that less competitive clients benefit from their main relationship dealers because they provide discounts of up to 6 basis points compared to outside dealers. Zooming further in within each multi-dealer request shows that competition intensifies for larger trades: As the notional size doubles, outside dealers tighten their spreads by around 3 basis points relative to the relationship dealer and their quotes are about 5 percentage points more likely to be executed.

The third set of evidence highlights the clients' loyalty to their relationship dealers. In about 10% of trades, firms execute quotes from their relationship dealer even though outside dealers send more favorable quotes. Though, if loyalty to the relationship dealer is costly due to large trade sizes, firms are tempted to execute the best prices from an outside dealer.

Again, the evidence is consistent with long-run relationships: in return for the client's loyalty, the dealer provides discounts making both parties better off. Though, if the trades size is large, firms are tempted to be disloyal and competing dealers re-

duce their spreads similar to the theory by Bernhardt et al. (2005). Because FX derivatives constitute only a part in a portfolio of services by banks, firm-bank relationships are likely to be formed outside the platform and managed on an institutional level (Qi 2023; Bak-Hansen and Sloth 2023). Therefore, it remains difficult to fully characterize the nature of the relationship which includes its origin and other non-FX-trade related benefits of the relationship such as loan conditions.

Because settlement requirements (credit lines) are closely tied to financial constraints of firms (Sufi 2009), it seems plausible that credit risk drives both the lack of dealer connections and wider markups. To avoid counterparty credit risk as a confounding friction, the main analysis focuses on spot transactions, which are characterized by the absence of credit risk. As robustness check, I repeat the analysis on samples of forwards, swaps and forward swaps. The evidence indicates that credit risk exacerbates the lack of dealer competition.

This paper has important policy implications. Because settlement poses a friction to OTC markets as it requires costly credit relationships, widening the access of clients to multiple dealers is a first step towards more dealer competition. Though, it remains unclear whether clients could benefit from central clearing, for example through the CLS group, because the clearing networks are owned by banks and exhibit expensive fee structures.

Related literature This paper has four contributions: First, this paper provides empirical evidence to theories where long-run relationships mitigate the pervasive effects from low dealer competition (Board 2011; Bernhardt et al. 2005; Desgranges and Foucault 2005). Because of the granularity of the dataset, I can zoom in the

quote-level to uncover relationship discounts, that are not visible on regulatory trade-level data (Hau et al. 2021; Allen and Wittwer 2023). Therefore, this paper provides a new explanation for the fact that most clients in OTC markets trade exclusively with one dealer. Allen and Wittwer (2023) finds that 90% clients trade Canadian government bonds with a single dealer, Hendershott, Li, et al. (2020) find that almost 30% of insurers trade corporate bonds with a single dealer and Hau et al. (2021) show that over 50% of corporates trade FX derivatives exclusively with one dealer. My findings differ from the empirical literature documenting benefits from trading relationships (Di Maggio, Kermani, and Song 2017; Hendershott, Li, et al. 2020; Jurkatis et al. 2023; Hau et al. 2021; Bak-Hansen and Sloth 2023) because I focus on clients' for whom competition is low due to a lack of credit relationships.

Second, I can associate small trading networks to bilateral settlement, because of the otherwise frictionless environment. This friction from settlement requirements offers an alternative explanation to vast literature on search frictions since the seminal work by Duffie, Gârleanu, and Pedersen (2005) or informational frictions shaping trading networks (Kondor and Pinter 2022; Baldauf and Mollner 2024).

Third, the paper adds granular evidence to the vast empirical literature that documents size discounts.⁶ I uncover a mechanism why competition intensifies with trade size by showing that non-relationship dealers tighten their spreads when the trade size is large and clients are more likely to be disloyal. Similar to Bernhardt et al. (2005), the temptation to forgo relationships increases with trade size providing

⁶Schultz (2001), Bessembinder, Maxwell, and Venkataraman (2006), Harris and Piwowar (2006), and Pinter, C. Wang, and Zou (forthcoming) among others document that transaction costs in OTC markets are smaller for large trades.

also an incentive to outside dealers to narrow spreads.

Finally, this paper contributes to the understanding of RFQ platforms in OTC markets. Competition appears to be intense for the bulk of firms and response rates are generally quite high. It does not seem that there is a substantial marginal cost to quote FX products to corporate clients (C. Wang 2023; Yueshen and Zou 2022). This paper differs from Riggs et al. (2020) who highlight the role of relationships defined through a clearing membership and past trading activities on platforms for index CDS.

This paper is structured as follows. Section 2 introduces the data. Section 3 documents that clients with small dealer networks pay wider markups. Section 4 discusses frictions why clients fail to connect with multiple dealers. Section 5 provides quote-level evidence on relationship discounts and section 6 documents the customers' loyalty to their relationship dealers. Section 7 concludes.

2 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 2021.⁷ For all trades, more detailed information on the RFQs

⁷An 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. The dealers are the dealer arms of largest global banks. Some banks may have several trading desks and are identified with separate IDs.

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.⁸

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).⁹ 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 tenor of 77 and 44 days, respectively. Forwards are specified with smaller average notional sizes of 2.7 million and longer average tenor of 140 days. In all instruments the notional size and tenor is left-skewed with the bulk of trades been short-term or small in notional.

Generally, the summary statistics suggest fierce dealer competition across all instruments as shown by the number of banks requested and response rates. On

⁸To 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. My data set includes all RFQs that lead to a trade. 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 because trading remains profitable and reputational damages.

⁹The 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.

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
Tenor [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
Tenor [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
Tenor [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
Tenor near lag [in days]	554,384	6.9	0.00	53.95	0.00	3,066.00
Tenor [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.

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 in response rates between firm-bank pairs which will be discussed in section 4.

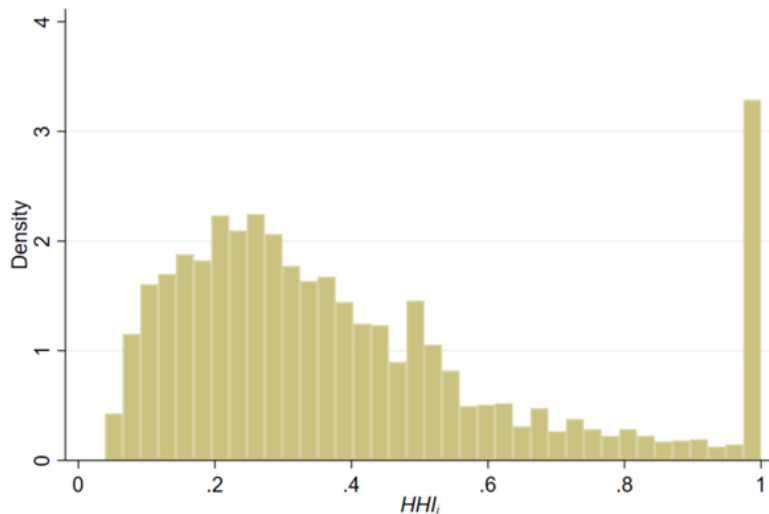
In terms of its daily turnover, the sample is quite significant. In comparison to the Bank for International Settlements (BIS) Triennial Survey, the sample represents approximately 6.5% of the global daily foreign exchange turnover of the non-financial corporate sector. Though, the sample clusters around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

3 Discriminatory pricing

In this section, I document that clients with fewer dealer connections realized wider spreads. 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 ($HHI_j = 1$) 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.

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. $HHI_j = \sum_i \left(\frac{\#trades_{j,i}}{\#trades_j} \right)^2$). The index is calculated on a yearly sample.

Next, I measure the price differentials paid by less competitive firms. To measure spreads, I benchmark quote with 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 provides details on the measurement of spreads for different instruments and a discussion on the robustness of spread measure.

To identify the discriminatory component of the spreads, I use $dealer \times date \times currency\ pair \times direction \times tenor$ fixed effect model similar to Hau et al. (2021). As such, I estimate the extent to which a dealer sends different prices to different clients

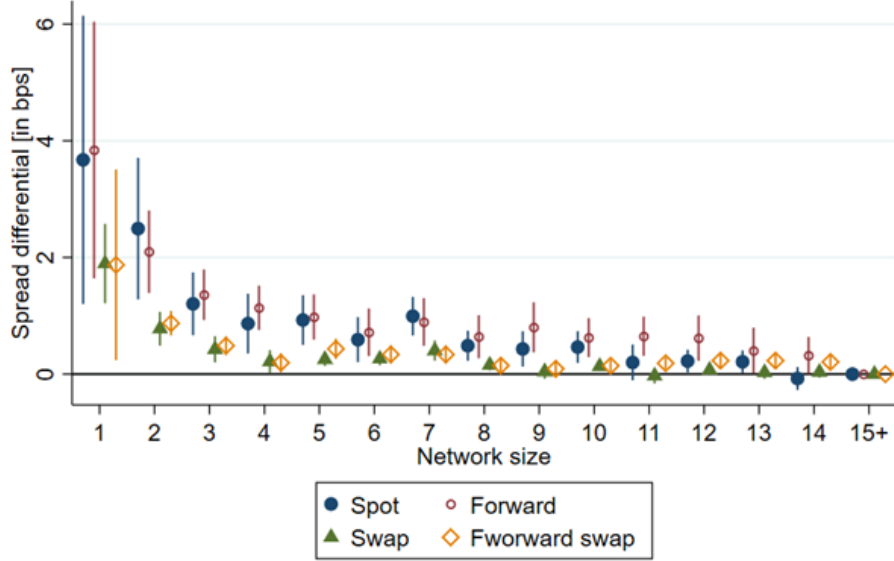
at the same day and for the same instrument (spot, forward, swap or forward swap, currency pair and direction). The estimation model is as follows

$$Spread_{j,i,r} = \sum_{n=1,...,14} \delta_n \times \mathbb{1}_{N_t=n} + \beta \times \ln(Notional_r) + \alpha_{i \times t \times c \times d \times \tau}$$

where $Spread_{j,i,r}$ is the spread sent by bank i to client j in request r . $\mathbb{1}_{N_t=n}$ are 14 dummies equal one if a client trades with $n \in N_t = \{1, ..., 14\}$ dealers during the year. $i \times \alpha_{t \times c \times d \times \tau}$ are the *dealer* $\times$ *date* $\times$ *currency pair* $\times$ *direction* $\times$ *tenor* fixed effects absorbing the bank's ability to quote at a specific product at a certain day. The model controls for the requested trade size (in logs of EUR notional). Because the fixed effects hold the supply constant, the coefficients δ_n estimate the discriminatory component of spreads for clients with n dealer connections compared to the spreads received by clients with a network of 15 or more dealers. Standard errors are clustered two-way at the firm and month. Figure 2 plots the estimated coefficients δ_n from two separate regressions for spot and forward trades. At the spot, forward, swap and forward swap, dealers charge 3.7, 3.8, 1.7 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 shows that clients with larger networks realize tighter spreads. The fact that these markups are discriminatory suggests that dealers adjust spreads depending on the competition that a client imposes on them.

Because credit risk could simultaneously limit the number of dealer connections and drive spreads, this paper estimates models for different instruments which are

Figure 2: Network size and discriminatory pricing



The figure plots estimates from a regressions on the trade-level sample of each product. The estimated model is $Spread_{j,i,r} = \sum_{n=1,\dots,14} \delta_n \times \mathbb{1}_{N_t=n} + \beta \times \ln(Notional_r) + \alpha_{t \times c \times d \times \tau}$, where $\mathbb{1}_{N_t=n}$ are dummies for different network sizes. The plotted coefficients δ_n measure discriminatory markups compared to the base group of clients trading with 15 or more dealers. The regressions include controls for trade size and $dealer \times date \times currency\ pair \times direction \times tenor$ fixed effect as controls with two-way clustered standard errors at the firm and month level.

heterogeneous in credit intensity. Arguably, there is no credit risk at the spot. The figure 2 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.

$$Spread_{j,i,r} = \delta \times HHI_j + \beta \times \ln(Notional_r) + \text{fixed effects}$$

The dependent variable is the spread measure paid by firm j to dealer i in trade t .

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 ($HHI_j = 1$) pays 3.8 bps higher spot spreads compared to the hypothetical firm that equally distributes all its trades among its infinite dealer network ($HHI_j = 0$) holding the controls constant. To see the economic magnitude, consider the median notional size 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 ($HHI_j = .2$). Because less connected firms could be locked-in with dealers with worse funding abilities, column 2 adds $dealer \times date \times currency\ pair \times direction$ 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.

Table 2: Dealer competition and spreads

	(1) Spot	(2) Spot	(3) Forward	(4) Forward	(5) Forward $\tau \geq 90$	(6) Swap	(7) Forward swap
HHI_j	3.782*** (1.167)	3.029*** (0.521)	4.094*** (0.737)	3.871*** (0.627)	14.339*** (2.787)	1.235*** (0.152)	0.661*** (0.099)
Notional	0.011 (0.026)	0.011 (0.011)	0.022 (0.019)	0.008 (0.008)	-0.015 (0.031)	-0.016 (0.010)	-0.012** (0.006)
Obs	454,544	365,684	556,764	245,433	77,103	84,107	266,356
R ²	0.08	0.43	0.58	0.84	0.85	0.96	0.79
Within-R ²	0.03	0.02	0.03	0.02	0.04	0.01	0.01
Fixed effects:							
$t \times c \times d \times \tau$	Yes	No	Yes	No	No	No	No
$i \times t \times c \times d \times \tau$	No	Yes	No	Yes	Yes	Yes	Yes

The table displays results from the regression $Spread_{j,i,r} = \delta \times HHI_j + \beta \times \ln(Notional_r) + fixedeffects$. The dependent variable $Spread_{j,i,r}$ is the positive spread measure as described in Appendix A. The columns 1 and 3 include $date \times currencypair \times direction \times tenor$ fixed affects to absorb effects from the market situation. Columns 2, 4, 5, 6 and 7 include $dealer \times date \times currency pair \times direction \times tenor$ fixed effects to measure discriminatory pricing. The samples are on trade-level and colums 1-2 include spot trade, columns 3-4 includes all forward trades, columns 5 includes forward trades with at least 90 days to maturity and the columns 6 and 7 include swap and forward swap trades, respectively. 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.

Columns 3 and 4 repeat the estimation for forward trades. Here, tenor τ fixed effects are added because forward trades differ in their maturity. Because of little common support, many observations are lost due to the tight fixed effects specification.¹⁰ The evidence shows 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 tenor 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 increases to 14.3 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. (See sections 4 and 5 for further discussions.)

Columns 6 and 7 repeat the analysis for swap instruments. There are two main differences to the previous instruments. First, swap spreads are generally much narrower. Second, unreported results show that including dealer fixed effects shrinks the coefficient while the R^2 increases from 14% to 96%. This suggests that most variation in swap prices is due to different quoting abilities of dealers and less connected clients are unable to switch the dealer.

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

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

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

¹⁰This tight fixed effects specification drops many singletons, especially in long-tenor products. The results are very similar without the inclusion of tenor in the fixed effect.

from columns 2, 4, 6 and 7 of table 2 for all spot, forward, swap and forward swap trades, I estimate an aggregated cost of EUR 89 million. The total costs comprises of EUR 15 million at the spot, EUR 46 million at the forward, EUR 11 million at the swap and EUR 17 million at the forward swap. Again the estimate of EUR 89 million, or EUR 35.6 million yearly, is the tip of the iceberg, because of several reasons. First, the calculation bases only on small estimation sample of trades. The sample, for which I have spot benchmark prices, covers only around 60% of all trades (compared section 2). 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 on the trade level 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 4) and that close ties between firms and banks mitigate the cost due to relationship discounts (5).

4 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 how bilateral settlement limits the clients' dealer networks which impairs dealer competition.

Because trades are settled bilaterally, firms have to setup an account and a line of credit with the banks,¹¹ which requires extensive risk and regulatory checks. Anecdotal evidence from interviews with corporate bankers reveals that the process of know-your-customer (KYC) checks¹² can take up to a few months and requires resources from the banks and firms. Beyond this regulatory costs, lines of credit or revolving credit facilities (RCF) are large and costly. Over 80% of U.S. public firms have credit lines which on average represent 16% of total book assets (Sufi 2009). Berg, Saunders, and Steffen (2016) show that firms pay on average 32 basis points per annum in fees for undrawn credit lines and costs increase for the amount of the drawn credit. In addition, up-front fees are on average 61 basis points (Berg, Saunders, and Steffen 2016). As a consequence, these credit lines determine a substantial cost creating a trade-off of larger bank networks. While firms benefit

¹¹Credit lines are commonly used to settle trades. A few clients hold cash at the bank to settle their trades.

¹²KYCs 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 Prison 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>).

from intensifying competition and bank diversification (Detragiache, Garella, and Guiso 2000), each bank connection entails additional costs.

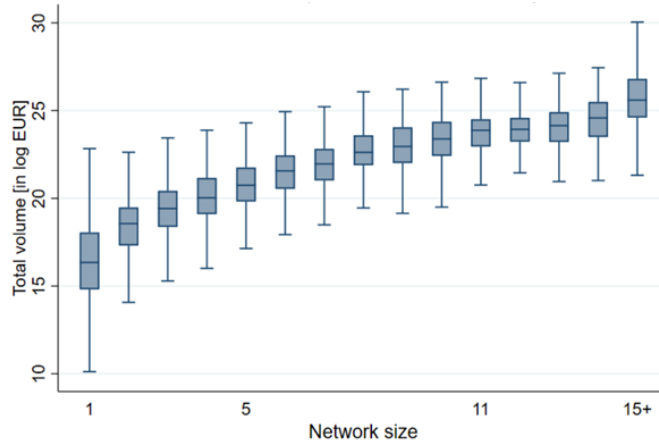
Also, banks want to ensure an overall profitable client relationship. As argued by Qi (2023), firm-bank relationships start with a lending relationship and the portfolios of services will eventually be expanded to extract more rents from their clients.¹³ Therefore, banks may connect to firms only if the overall relation with the client promises a profitable business or terminate relationships if they are unprofitable. For less active firms, providing only FX liquidity may not be profitable enough to justify the setup of a new relationship. As a result, banks are less prone to connect to smaller firms with less trading activity.

Figure 3 illustrates the trade-off between the benefits from more competition of larger dealer networks and the cost of establishing new connections. The firms' dealer networks and the yearly trade volume appear to be monotonically positively related. While the median locked-in firm has a yearly volume of just EUR 13 million, the median firm with 15 or more trading connections has a yearly volume of EUR 131 billion. This is in sharp contrast to the findings of Hendershott, Li, et al. (2020) in bond markets where clients trade-off relationship discounts against search abilities of larger networks which creates a non-monotone relationship in the size of the dealer network and the client's trade volume. Again, my setting is characterized by the absence of search problems and the results from section 3 show that prices improve monotonically with network size.

The previous analysis focuses on dealer connections with trading activity in a

¹³Qi (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.

Figure 3: Trade intensity and network size



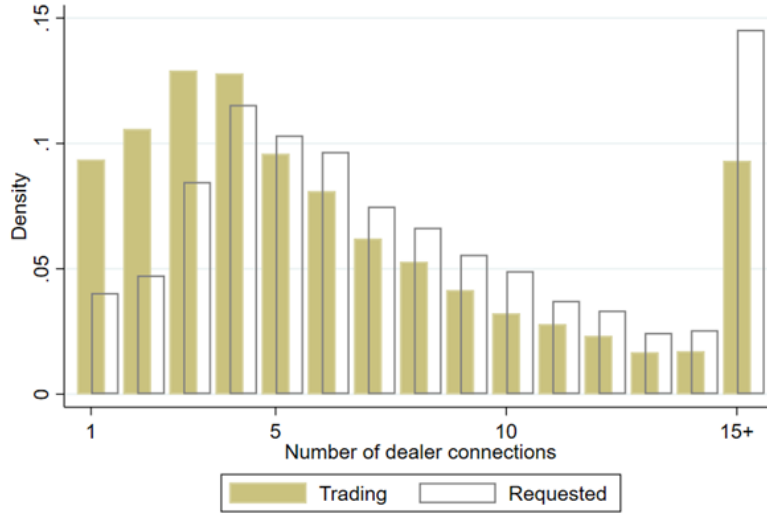
The figure plots the distribution of the client's yearly total trade volume in logs over the clients' number of dealer connections with at least one trade. The figure positive monotonic relation between the network size and trade intensity is consistent with fixed costs of establishing dealer connections.

given year, though many firms have more dealer connections. Figure 4 plots the distribution of the number of trading connections and the number of all dealers queried in a year. 47% of firms trade with two to five dealers, whereas 8.3% trade with only one and 8.6% trade with 15 or more dealers. The distribution of the number of requested dealers is shifted rightwards showing that the average clients is connected to two more dealers, but those connections lack any trading activity.

There are two reasons why firm-bank pairs do not exhibit trades. First, quotes by many dealers are too high, hence not executed (see section 5). Second, many dealers refuse to quote, because settlement requirements are not met due to insufficient credit limits.¹⁴ Throughout the sample, never-quoting dealer connections are

¹⁴Interviews with corporate bankers reveal that never-quoting behaviors are mostly due to unmet settlement requirements, which means that the credit line or cash is insufficient to settle the trade. 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 4: Distribution of dealer connections

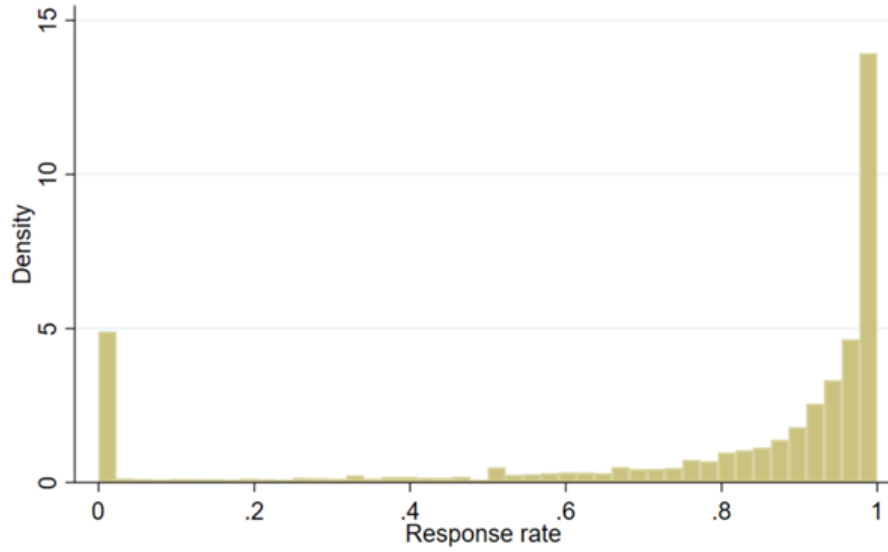


The figure plots distribution of the number of trading and requested dealer connections by a client in a year. An trading dealer refers to a connection with at least one trade and a requested dealer refers to a dealer that was at least once requested. Most firms trade with between two and five banks, while also many firms trade with only one or 15 or more banks. The distribution of requested dealers is shifted right. The average firm has two more dealers which are requested but no request results in a trade.

abundant. Figure 5 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 of 100%), but many do never quote (11% with response rate of 0%). 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. This evidence exemplifies that quoting is automated and if quoting is tuned on, there appears to be no marginal costs of quoting in the sample (compare C. Wang (2023) and Yueshen and Zou (2022)).

Credit is costly and especially firms near distress are less likely to receive it. Rampini, Sufi, and Viswanathan (2014) show that firms near distress hedge less due

Figure 5: 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%).

to costly collateral requirements (under the assumption of central clearing). The fact that competitive firms ($HHI_j < .5$) have only 10% of never-quoting dealer connections and less competitive firms ($HHI_j \geq .5$) have 23% of never-quoting connection illustrates that credit risk may exacerbate the friction of small trading networks. As a consequence, 16% of locked-in firms never receive any quote from second dealer despite their attempts to request multiple dealers. Therefore, firms near distress may face higher hedging costs because of their inability to entertain multiple credit relationships and impose competition.

5 Quoting behavior of relationship and outside dealers

The evidence from the previous section suggests that dealers refuse to quote because settlement may not be guaranteed due to insufficient credit lines or cash. This section zooms into the quote-level to explore different quoting strategies of relationship and outside dealers. The data show the existence of a relationship dealer that quotes more reliably and with tighter spreads compared to outside dealers.

5.1 Relationships and response rates

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

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

where $Quoting_{j,i,r}$ 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 trade size as well as number of dealers requested (n) 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_2 and δ_3 measure

whether less connected clients receive fewer responses, relationship dealer respond more frequently to all clients 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 significantly much less likely to receive a quote (the coefficient is $-.41$). Further, the results show that the relationship dealer is significantly more important to high-HHI firms due to the reliable quoting behavior (with a coefficient of $.34\%$). As demonstrated above, most of the variation in response rates between client-dealer pair. 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 swaps and forward swaps. In contrast to spot trades, the latter products typically include counterparty credit risk. The coefficients show that relationship dealers generally respond more frequently to all clients with estimated coefficient between 2 and 3 percentage points (columns 4-6). The evidence further shows that response rates seem insensitive towards trade size for spot and forwards. For swaps and forward swaps, response rates significantly drop with notional. Moreover, response rates drop significantly with tenor for all three derivative products (forward, swap, forward

swap).

Table 3: Response rates, dealer competition and relationships

	Spot		Forward		Swap	Forward-Swap
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Restricted	All	Restricted	Restricted	Restricted
HHI_j	-0.406*** (0.045)	-0.096*** (0.024)	-0.297*** (0.043)	-0.128*** (0.035)	-0.110*** (0.035)	-0.123** (0.048)
$HHI_j \times RelD_{j,i}$	0.341*** (0.041)	0.078*** (0.025)	0.241*** (0.033)	0.107*** (0.026)	0.036 (0.036)	0.060 (0.039)
$RelD_{j,i}$	-0.018** (0.007)	0.005 (0.005)	0.016* (0.008)	0.026*** (0.007)	0.023*** (0.008)	0.022*** (0.008)
Notional	-0.002 (0.001)	-0.000 (0.001)	0.001 (0.003)	0.002 (0.003)	-0.011*** (0.001)	-0.012*** (0.002)
Tenor			-0.018*** (0.002)	-0.019*** (0.002)	-0.016*** (0.002)	-0.007*** (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 $Quoting_{j,i,r} = \delta_1 \times HHI_j + \delta_2 \times RelD_{j,i} + \delta_3 \times HHI_j \times RelD_{j,i} + \beta_1 \ln(Notional) + \beta_2 \ln(Tenor) + \alpha_n + \alpha_{i \times t \times c \times d}$. The dependent variable $Quoting_{j,i,r}$ 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. $dealer \times date \times currencypair \times direction$ 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.

5.2 Relationship discounts

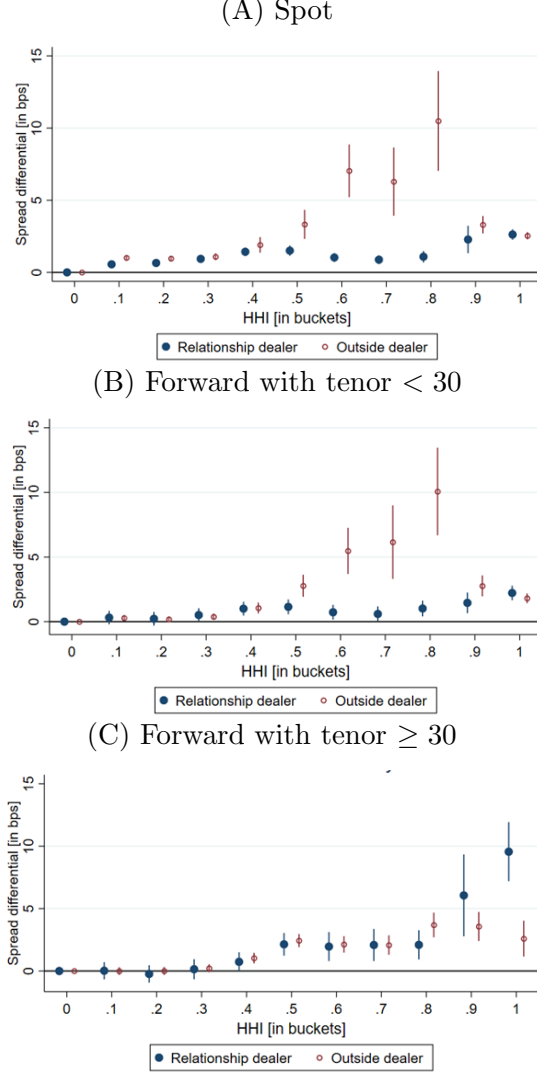
The following quote-evidence documents the relationship discounts. Figure 6 plots coefficient from a regression of spreads on 11 dummies for different buckets of the HHI_j index to measure discriminatory pricing similar as in figure 2. The base dummy represents the most competitive firms ($HHI_j < .05$). Each panel plots coefficients from two samples of the relationship and outside dealers for different instruments. Panel 6A illustrates pricing differentials between both groups of dealers across the HHI_j distribution of firms at the spot. While relationship dealers only slight widen spreads for high- HHI_j firms, outside dealers widen spreads markedly. Firms with an HHI_j index of around 80% receive over 10 bps wider spreads compared to firms with an HHI_j of 0%. Similarly, panel 6B shows that this relationship discount exist with similar order of magnitude for forward trades with short tenor ($\tau < 30$ days). Though, the evidence shows that this relationship discount seems to disappear for more credit intense products. Panel 6C illustrates that there is no differential quoting behavior between relationship and outside dealers for forward trades with longer tenors ($\tau \geq 30$ days). For brevity, the results for swaps are not illustrated as they resemble those of long-tenor forwards.

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

$$\begin{aligned} Spread_{j,i,r} = & \delta_1 \times HHI_j + \delta_2 \times RelD_{j,i} + \delta_3 \times HHI_j \times RelD_{j,i} \\ & + \beta \times \ln(Notional_r) + \alpha_{i \times t \times c \times d \times \tau} \end{aligned}$$

Table 4 presents the results. Column 1 is estimated on spot quote-level data and column 2 includes executed prices only (trade-level). While the coefficient show large and highly significant discriminatory spreads against low-HHI firms (coefficient of

Figure 6: Discriminatory spreads of relationship versus outside dealers



The figure plots estimates from a regression on the quote-level sample of spots, short-tenor forwards ($\tau < 30$ days) and long-tenor forwards ($\tau \geq 30$ days). The estimated model is $Spread_{j,i,r} = \sum_{b=0,0.1,\dots,1} \delta_b \times \mathbb{1}_{|HHI_j - b| < .05} + \beta \times \ln(Notional_r) + \alpha_{i \times t \times c \times d \times \tau}$, where $\mathbb{1}_{|HHI_j - b| < .05}$ are 11 dummies dividing firms into HHI buckets. The plotted coefficients are δ_b showing discriminatory markups compared to the base clients with 15 or more dealer connections. The regressions include controls for trade size and $dealer \times date \times currency\ pair \times direction \times tenor$ fixed effect as controls with two-way clustered standard errors at the firm and monthly date level.

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). On the trade level (column 2), I fail to find relationship discounts significantly different from zero (coefficient of -0.4). 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). Again, the result highlight the importance of quote-level data to study the effects of relationships, because these effects are not visible on regulatory trade-level data (Hau et al. 2021; Allen and Wittwer 2023).

The columns 3 and 4 repeat the analysis for forward transactions. Overall, the pattern are in parallel to the spot. Though, discriminatory pricing by outside dealers seem less severe and relationship discounts appear smaller. The results of column 5 show that the relationship discounts to less connected clients turn into a relationship premium (coefficient of 4.2), while the relationship dealers generally send narrower spreads (coefficient of (-1.6). Columns 6 and 7 repeat the analysis for swap instruments at the quote level. Again, the evidence at the swap exhibit much fewer variation with significant relationship premia (coefficient of .45). In contrast, the evidence points toward mild relationship discounts for forward swaps (coefficient of -.17).

Table 4: Relationship discounts

	(1) Spot	(2) Spot	(3) Forward	(4) Forward	(5) Forward $\tau \geq 90$	(6) Swap	(7) Forward swap
HHI_j	9.244*** (0.816)	3.214*** (0.161)	9.375*** (0.708)	3.751*** (0.371)	7.936*** (0.492)	0.337*** (0.070)	0.449*** (0.038)
$RelD_{j,i}$	0.408*** (0.093)	0.152*** (0.058)	0.704*** (0.138)	0.030 (0.110)	-1.610*** (0.226)	-0.092*** (0.018)	-0.002 (0.008)
$HHI_j \times RelD_{j,i}$	-6.432*** (0.829)	-0.389 (0.264)	-6.156*** (0.747)	-0.018 (0.393)	4.226*** (0.935)	0.453*** (0.103)	-0.170*** (0.048)
$Notional_r$	-0.153*** (0.020)	0.016*** (0.005)	-0.162*** (0.015)	0.009* (0.005)	-0.166*** (0.023)	-0.049*** (0.004)	-0.038*** (0.003)
Obs	2,801,761	365,663	2,523,278	245,335	763,019	546,398	1,298,819
R ²	0.35	0.41	0.68	0.81	0.78	0.91	0.84
Within-R ²	0.05	0.02	0.04	0.02	0.03	0.01	0.01
FE: $i \times t \times c \times d \times \tau$	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The table displays results from the regression $Spread_{j,i,r} = \delta_1 \times HHI_j + \delta_2 \times RelD_{j,i} + \delta_3 \times HHI_j \times RelD_{j,i} + \beta \ln(Notional_r) + \alpha_{i \times t \times c \times d \times \tau}$. The dependent variable $Spread_{j,i,r}$ is the positive spread measure as described in Appendix A. $RelD_{j,i}$ is a dummy equal to one for the relationship dealer as measured as the most active dealer of firm j in a year. $dealer \times date \times currency\ pair \times direction \times tenor$ fixed effects are included to extract discriminatory component of spreads. The columns 1-2 include spot transactions, columns 3-4 includes all forward trades, columns 5 includes forward transactions with at least 90 days to maturity and the columns 6 and 7 include swap and forward swap transactions, respectively. All samples are on the quote level, except the columns 2 and 4 include only executed prices. The main coefficient of interest is δ_3 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.

From the above evidence, it remains unclear why there is a relationship premium for forwards with long tenor and swaps. 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 try to intensify competition and banks to be more eager to compete. Instead the evidence indicates that clients that depend on their relationship may be unable to locate the dealer with the strongest ability to quote. The international finance literature establishes that there is strong pressure on US Dollar financing and some bank may be in a particular need for Dollar (Du, Tepper, and Verdelhan 2018; Cenedese, Della Corte, and T. Wang 2021; Rime, Schrimpf, and Syrstad 2022). Table 8 in the Appendix D repeats the analysis for long-tenor product on a sample with trades that resemble US Dollar financing through the FX market and otherwise.¹⁵ The results show that the premium is large and significant for US Dollar funding at the quote and trade level (columns 3-4), while it disappears other products (columns 1-2). In sum, the evidence indicates that the relationship premium reflects the inability of captive clients to locate the dealer with best quoting ability. This premium is paid above and beyond credit risk as indicated by wider discriminatory spreads for long-tenor forwards.

5.3 Trade size and competition

This papers argues that relationship dealers have the incentives to keep their customers captive, while non-relationship dealers may maximize profits on a trade-by-

¹⁵Synthetically financing US Dollar through the FX markets means that the bank borrows Dollar to lend it to the customer. At the future leg, the client returns the Dollars and the dealer can pay back the Dollar debt. This is the case for the EUR/USD at the ask, GBP/USD at the ask and USD/CHF at the bid.

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 interacting the HHI_j index with the requested volume:

$$Spread_{j,i,r} = \delta_1 \times HHI_j + \delta_2 \times HHI_j \times \ln(Notional_r) + \beta \times \ln(Notional_r) + \alpha_{i \times t \times c \times d \times \tau}$$

Table 5 presents the results. Column 1 includes the estimates of spot trades with relationship dealers. The results show only mild general size penalty (coefficient of 0.06) and size 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 of outside dealers depends more heavily on the trade size as the within- R^2 increase from 1% to 12%. While the size penalty generally increases for outside dealers,¹⁶ outside dealers heavily narrow their spreads to less connected clients as the trade size increases (coefficient of -4.5). The results are economically and statistically significant. Columns 3 and 4 repeat the analysis for the forward. The numbers mirror those of the spot, though with a somewhat smaller order of magnitude. For brevity, the results for swap instruments are in table 9 of the Appendix D. For outright swaps, the results draw a different picture. Here, the relationship dealer is appears to price more favorably to less competitive clients with larger notional sizes. For forward swaps, the relationship dealer seems insensitive towards trade size, while outside dealers provide sizeable size discounts to their less connected clients. Again, all swap

¹⁶This is in line with asymmetric information motive as argued by Pinter, C. Wang, and Zou (forthcoming).

instruments exhibit little variation in pricing as indicated by small within-R².

Table 5: Competition and volume

	Spot		Forward	
	(1) RelD	(2) OutD	(3) RelD	(4) OutD
HHI_j	4.788*** (1.695)	65.806*** (17.999)	3.319*** (1.059)	48.804*** (10.288)
$Notional_r$	0.056* (0.031)	0.540*** (0.179)	-0.010 (0.020)	0.318** (0.119)
$HHI_j \times Notional_r$	-0.202* (0.114)	-4.524*** (1.175)	0.038 (0.049)	-3.146*** (0.610)
Obs	255,230	2,483,023	273,224	2,134,379
R ²	0.45	0.41	0.77	0.71
Within-R ²	0.01	0.12	0.01	0.07
FE: $i \times t \times c \times d \times \tau$	Yes	Yes	Yes	Yes

The table displays results from the regression $Spread_{j,i,r} = \delta_1 \times HHI_j + \delta_2 \times HHI_j \times \ln(Notional_r) + \alpha_{i \times t \times c \times d \times \tau}$. The dependent variable $Spread_{j,i,r}$ for the spot (columns 1-2) and for the forward (columns 3-4) as described in Appendix A. Columns 1 and 3 base on the sample of relationship dealers and columns 2 and 4 on a sample of outside dealers. $dealer \times date \times currency\ pair \times direction \times tenor$ 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 trade size. 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 verify how the competition changes with trade size, the following analysis zooms further in requests where the relationship dealer is exposed to competing outside dealers. Compared to the pooled regression analysis from above, this setup rules out the possibility that relationship dealers are selectively requested, where they

would quote with tight spreads anyways. Figure 12 in the Appendix C illustrates relationship discounts from within the request, where positive numbers indicate that the relationship dealer sends more favorable prices. The pattern mirror the evidence from the pooled quote level regressions above showing that relationships dealers send more favorable prices to their less connected clients compared to outside dealers. Even though, there are relationship discounts for swaps and forward swaps, the figure shows that the pricing differentials are markedly narrower for swap products compared to spots and forwards. Following within-request model provides more robust evidence on the differential quoting strategies

$$Y_{r,i} = \alpha_r + \beta_1 RelD_{j,i} + \beta_2 RelD_{j,i} \times \ln(Notional_r)$$

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 relative to the outside dealers and how it changes as the notional size increases. 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 ($Quote_i$).¹⁷ The sample includes requests from less competitive firms ($HHI_j > .375$).

Table 6 presents the results. Throughout all samples, the relationship dealer appears more competitive compared to outside dealers. That means the relation-

¹⁷The regression does not rely on the spread measure. Ask prices are in negatives. Therefore, positive values indicate less competitive quotes by the relationship dealer compared to the competitor.

ship dealer is significantly more likely to quote (column 1), significantly more likely to be executed (column 2), and prices are significantly 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 trade size is large. 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 trade size (column 1), there is no effect at full sample of forwards (column 2), and a highly significant negative effect for forwards with long tenors (column 7). When the notional size is large, potential competitors start to quote for long tenor forwards. Again, this evidence is in line with the idea that less connected clients try to locate the bank with the best funding ability in a currency.

Table 6: Within-request dealer competition and trade size

	Spot			Forward			Forward $\tau > 90$		
	(1) $P(Quote_i)$	(2) $P(Exec_i)$	(3) $Quote_i$	(4) $P(Quote_i)$	(5) $P(Exec_i)$	(6) $Quote_i$	(7) $P(Quote_i)$	(8) $P(Exec_i)$	(9) $Quote_i$
RelD	0.040*** (0.006)	1.093*** (0.010)	-38.452*** (0.399)	0.111*** (0.006)	1.076*** (0.007)	-22.798*** (0.161)	0.308*** (0.010)	1.137*** (0.013)	-9.807*** (0.232)
RelD $\times$ Notional	0.001** (0.000)	-0.050*** (0.001)	2.848*** (0.033)	0.001 (0.000)	-0.050*** (0.001)	1.629*** (0.013)	-0.014*** (0.001)	-0.055*** (0.001)	0.624*** (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 $Y_{r,i} = \alpha_r + \beta_1 RelD_{j,i} + \beta_2 RelD_{j,i} \times \ln(Notional_r)$. 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 dealer i 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 $RelD_{j,i}$ is equal one for the dealer i with the largest trade share of the requesting firm. This dummy is interacted with the trade size (log of the notional size in EUR) to test how the competitive edge of the main dealer changes with size. 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 trade sizes. A subsample analysis helps 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 ($HHI_j > .375$). 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.

6 Loyalty

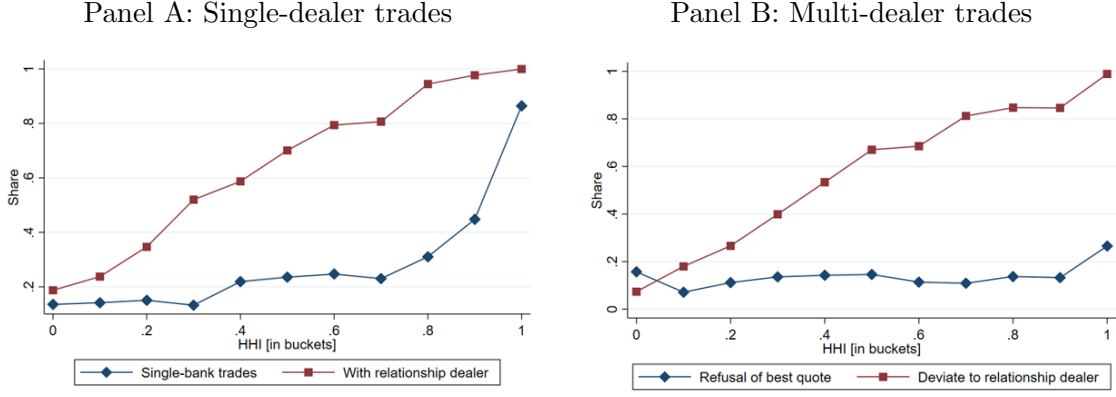
Relationship dealers provide discounts to their loyal customers which mitigates the pervasive effects from low competition. In return for the price concessions, clients remain loyal to their relationship dealers.¹⁸ This section documents this loyalty and the temptation of clients to execute an alternative offer from an outside dealer if loyalty is too costly.

Figure 7 illustrates the less connected clients' patronage with their relationship dealers. Panel A plots the share of trades that are single-bank trades (only one bank is requested), and the share of those trades with the relationship dealer. The graph shows High-HHI firms are requesting almost only their relationship dealer suggesting that these firms cannot or do not want to impose dealer competition. Panel B restricts to a sample of multi-dealer trades (more than one bank requested). It plots the share of trades in which the client does not execute the the best prices (refuse of best quote) and the share of these trades in which the relationship dealer's quote is executed. This shows that clients are willing to pay a price to support their relationships. In sum, less competitive firms exhibit loyalty to their relationship dealers as they tend to either do single-bank trades with them or they execute the relationship dealers' quotes even though an outside dealer sends a more favorable price.

Though, loyalty does not appear to be guaranteed. Under the assumption that relationships break up in case of disloyalty, theories of long-run relationships pos-

¹⁸Firms may nurture the profitability considerations of their relationship dealer. Beyond that, firms may have an incentive to trade with their relationship dealer as they know that the settlement and payment systems are intact.

Figure 7: Clients' patronage with their relationship dealer



The figure illustrates the loyalty of clients to their main relationship dealer. Panel A plots the share of single-bank trades of all trades and the share of trades with the relationship dealer of all single-bank trades. Panel B restricts the sample to only multi-dealer trades (more than one dealer is requested). It plots the share of multi-dealer trades in which the client does not execute the best price (refusal of best quote) and the share of trades with the relationship dealer from all trades in which the client refuses to execute the best quote (Deviations to ReD). The figure shows less connected clients patronize their relationship dealer, because they do not request other dealer (large share of single-bank trades with relationship dealer) or execute quotes from the relationship dealer even though outside dealers quote more favorably.

tulate the trade-off of the current gains from disloyalty against the future value of relationships (Bernhardt et al. 2005; Board 2011). Concretely, whenever a client receives a more favorable quote from an outside dealer, the client trades off the cost from executing the quote by the relationship dealer against the future value of the relationship. To test the theory, I run the following regression on all quotes by the relationship dealer of less competitive firms ($HHI_j > .375$) when an outside dealer sends a more favorable price.

$$\mathbb{1}_{Exec_i|Not\ Best} = \gamma \times X_r + \beta \times \log(Tenor_r) + \alpha_j$$

the dummy $\mathbb{1}_{Exec_i|Not\ Best}$ is equal to one if the quote is executed even though a competing quote is better (higher bid or lower ask). The variables of interest (X_r) are the trades size (in logs), the distance between the best quote and the relationship dealers quote (in basis points) and the direct cost of execution the relationship dealer's quote (in logs). Firm fixed effects (α_j) absorb time-constant effects related to the firm.

Table 7: Determinants of loyalty

	(1)	(2)	(3)
Notional	-0.023** (0.010)		
Quote disance		-0.012*** (0.003)	
Cost			-0.047*** (0.013)
Tenor	-0.014 (0.013)	-0.010 (0.013)	-0.005 (0.013)
Obs	31,130	31,137	31,128
R ²	0.38	0.38	0.41
Within-R ²	0.01	0.01	0.06
FE: j	Yes	Yes	Yes

The table displays results from the regression $\mathbb{1}_{Exec_i|Not\ Best} = \gamma \times X + \beta \times \log(Tenor) + \alpha_j$, where $\mathbb{1}_{Exec_i|Not\ Best}$ is a dummy equal to one if the quote is executed even though a competing quote is better (higher bid or lower ask). The sample includes quotes from high-HHI firms ($HHI_j > .375$) by relationship dealers which are not the best quote in a request. The variable of interests X are measures of the temptation to disloyalty towards the relationship, that means to execute the competition dealer. In column 1-3, the variables are the trade size (in logs), the quote distance (in bps) and the direct cost from executing the relationship dealer instead of the best quote (in logs). Firm fixed effects (α_j) are included. Standard errors clustered around the firm and month level are in parenthesis. ***, **, * indicate statistical significance at the 1%, 5%, and 10%, respectively.

Table 7 presents the results from the regression. Column 1-3 show that high-HHI firms are significantly less likely execute the relationships dealers’ quotes if the trade size is large, the quote distance is large or the costs from trading with the relationship dealer is high. A doubling in the cost of loyalty is associated with a decrease of about 5 percentage points in the likelihood of trading with the relationship dealer (column 3). The Within- R^2 increase from about 1% in columns 1 and 2 to 6% in column 3, which indicates that loyalty is driven by the combination of both size and quote distance (or the costs). Overall, the evidence shows that firms remain loyal to their relationship dealer. Though, as loyalty is too costly, the temptation to execute alternative offers increases.

7 Conclusion

Given the recent push towards centralized markets, it is important to understand the frictions governing the trading behaviors in OTC markets. Even on centralized platforms competition appears to be low and clients are captive in relationships (Allen and Wittwer 2023). This paper provides an answer as to *why* competition remains low for some clients and *why* these clients stick with their relationship dealer. Using novel quote-level data from a platform on which non-financial firms trade FX products to hedge their currency exposure, this paper argues that bilateral settlement poses a friction to dealer competition because clients need to entertain costly credit relationships to guarantee settlement with each dealer. The bilateral settlement requirement strictly limits the set of dealers a client can query and gives dealers

excessive market power over clients with few dealer connection.

This paper further documents that clients enter long-run relationships with their dealers to mitigate the pervasive effects from low dealer competition. Similar to the theories by Bernhardt et al. (2005) and Board (2011), where relationship dealers (agents) provide price concessions in exchange for the client's (principal) loyalty, I find that relationship dealers quote prices high enough to capture some rents and low enough to keep their customer captive. Less connected clients honor their relationships by executing the quote by relationship dealers even though outside dealers send more favorable prices. Outside dealers seem to maximize short-term profits, that means they narrow spreads only if profit opportunities from large trade sizes open up. At the same time, customers are tempted to be disloyal by executing more favorable quotes from outside dealers because the costs of loyalty increase in trade size.

Bilateral settlement requires customers to establish credit relationships which includes credit lines to secure transactions. This is costly and likely affects smaller and financially constrained firms more. Enabling clients to access multiple dealer, for example through central clearing, is a first step towards more competitive markets. If competition was high, perhaps more firms would enter the platform. My finding that trading strategies are asymmetric and only rationalised in repeated games can inform future theoretical work in OTC markets.

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Appendix A Measuring spreads

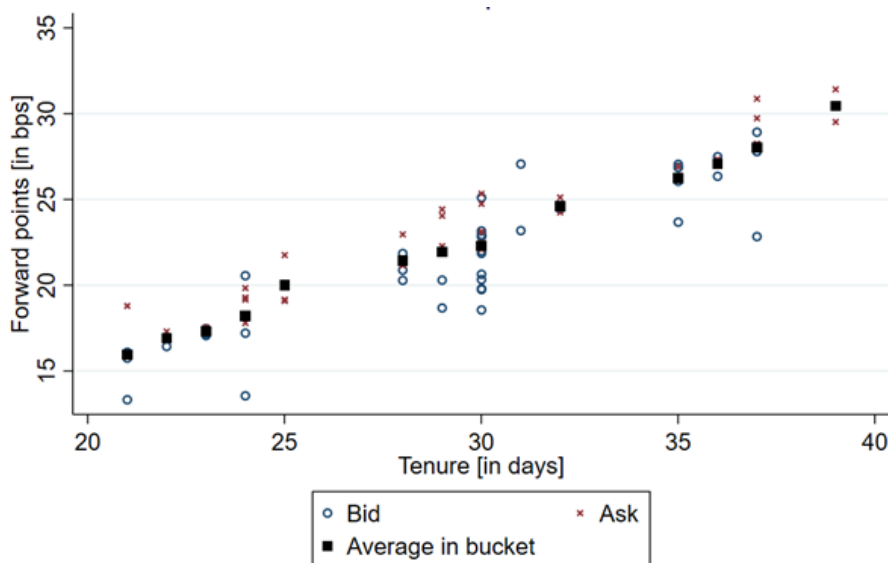
This appendix provides detailed explanations on the spread measures. Measuring spot spreads is straightforward using minute level interbank quotes from Refinitive Datascope for five different currency pairs: EUR/USD, EUR/GBP, EUR/CHF, GBP/USD, and USD/CHF. Spot spreads are $\frac{S_{j,i}-S}{S} \times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

For derivative instruments such as forwards and swaps, measuring spreads is somewhat more complicated. I exploit the fact that all derivative contracts obligate the future exchange currencies and future exchange rates are determined by interest rate differentials between the two currencies. Similar to the method by Abbassi and Bräuning (2021), I implement fixed effects estimators to extract the forward curve (interest rate differential). At the forward, I calculate (cleaned) forward spreads in bps as the residuals ε from the fixed effects regression $\frac{F_{j,i}-S}{S} \times 10,000 = \alpha_{\text{currency pair}} \times \alpha_{\text{tenor}} \times \alpha_{\text{date}} + \varepsilon$, where $F_{j,i}$ is the executed forward rate and $\alpha_{\text{currency pair}} \times \alpha_{\text{tenor}} \times \alpha_{\text{date}}$ are fixed effects. This fixed effects estimator extracts the forward curve from the quoted forward rate ($F = S \times \frac{i^{\text{quote currency}}}{i^{\text{base currency}}}$), to make trades comparable across currency pairs, tenors 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 8 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 and forward swaps works very similarly compared to forwards, because swaps are already quoted with a swap rate (i.e.

$(F_{j,i} - S) \times 10,000$). Therefore, the price fluctuations do not depend linearly on the spot rate. The fixed effects regression can extract the forward curve and residuals approximate spreads. For forward swaps, the fixed effects additionally estimator interacts the tenor of the first leg, because the tenor of the first leg may vary compared to outright swaps.

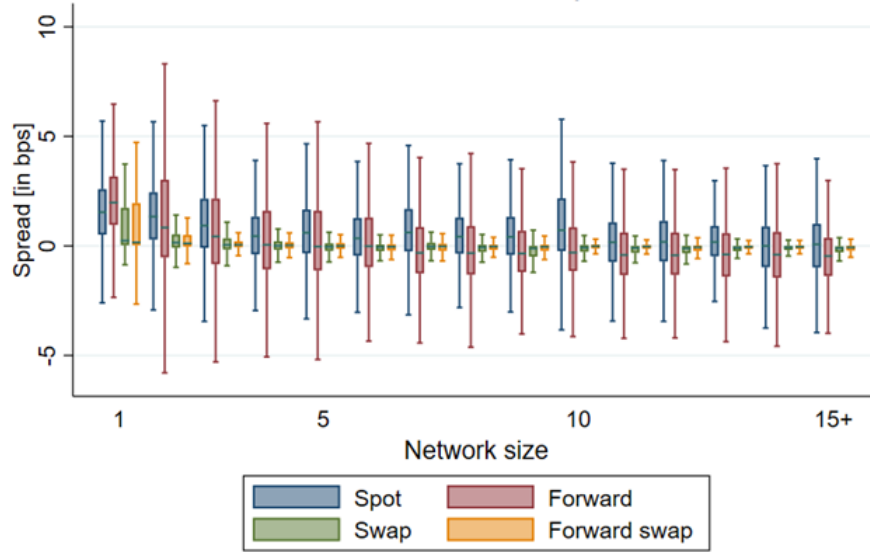
Figure 8: Measuring (cleaned) forward spreads



To estimate spreads, the fixed effects bases on a common support assumption. That means that in each date-currency-tenor bucket, there have to be at least two data points. The advantage of the quote-level data is that there are for most trades at least two quotes, hence there is common support. Though, the calculated averages in date-currency-tenor buckets may be prone to outlying quotes. I repeat all the analysis of the paper using spread estimates based on a trade-level estimation sample. The results are very similar while samples are smaller.

Figure 9 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

Figure 9: 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).

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 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. Forward swap spreads are almost identical to swap spreads. To verify the pattern without need to approximate spreads or interbank benchmark prices, I compute a competitiveness index similar to Riggs et al. (2020). This index measures the the price differential between the best and second best quote in a request. Larger values indicate less competition. Figure 11 in the Appendix C 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.

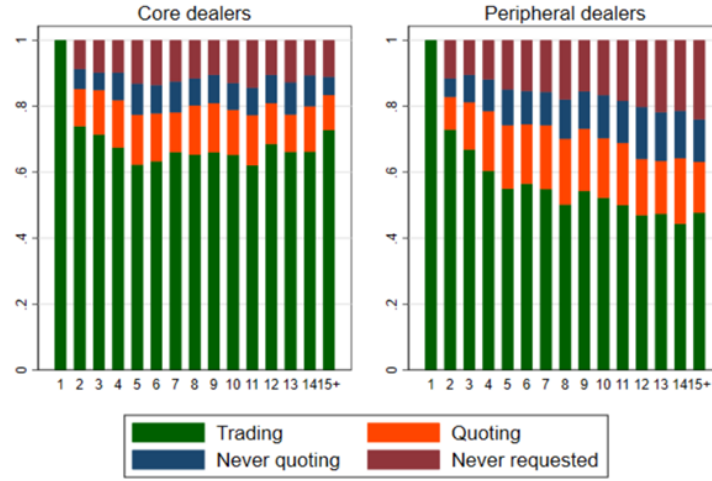
Appendix B Qualities dealer connections

This section zooms in the monthly firm-bank pair to distinguish between different qualities of dealer connections, I focus on a monthly firm-bank pairs. 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 10 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 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,¹⁹ 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.²⁰ Connections with peripheral dealers are less active, especially in larger networks.

¹⁹This is mechanical. Without any trade, the client would not appear in the dataset.

²⁰I define core dealers as one of the top 30 dealer in total transacted volume in the sample.

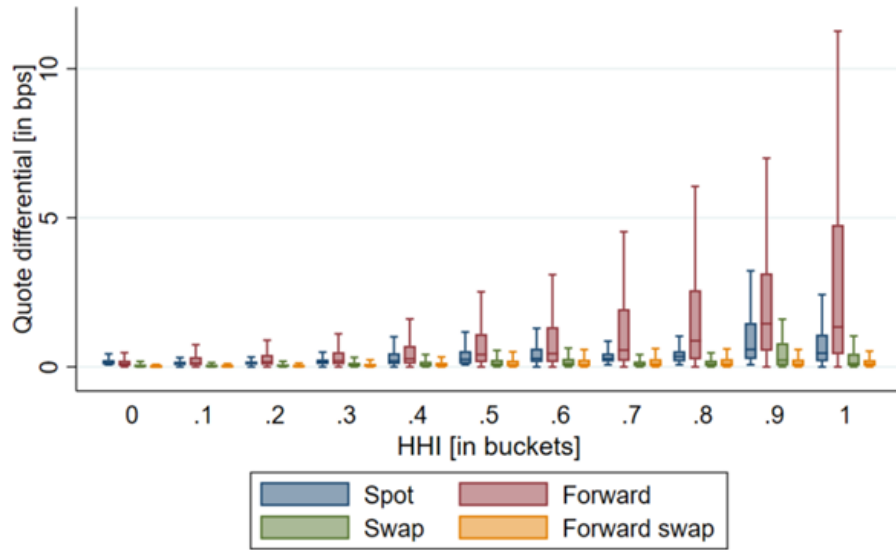
Figure 10: Heterogeneity in dealer connections



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.

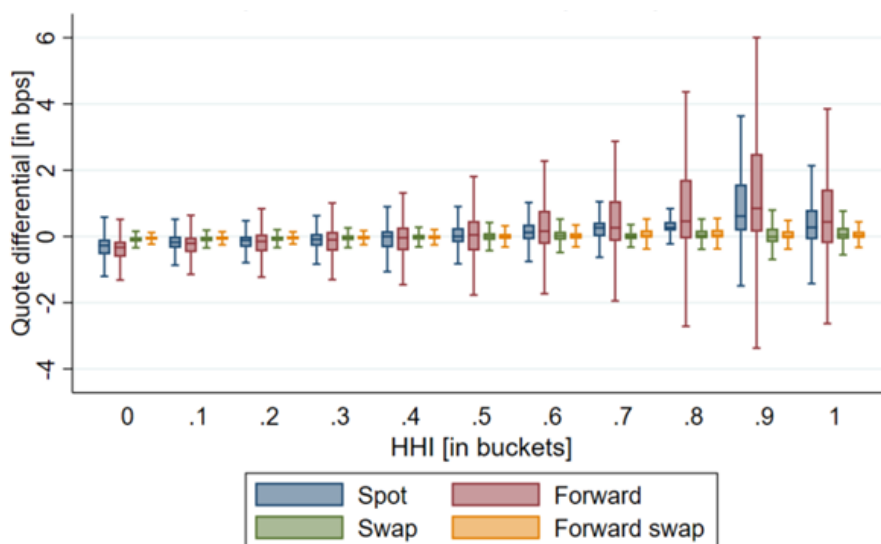
Appendix C Supporting figures

Figure 11: Within request: competitiveness index



The figure plots the distributions of the competitiveness index over the client's HHI_j index in 11 buckets. The competitiveness index is the price differential between the best and the second best quote in a request at the bid and vice versa at the ask. Higher values imply less competition. The measure follows Riggs et al. (2020).

Figure 12: Within request: relationship discounts



The figure plots the distributions of the within-request relationship discounts over the client's HHI_j index in 11 buckets. The within-request relationship discounts are the price differentials between the relationship dealer and the best quote by a outside dealer in a request at the bid and vice versa at the ask. Higher values imply that the relationship dealer faces less competition.

Appendix D Supporting tables

Table 8: Relationship premium for long-tenor forwards

	USD lending		USD funding	
	(1)	(2)	(3)	(4)
HHI_j	8.435*** (0.619)	12.497*** (2.895)	7.029*** (0.731)	9.607*** (2.264)
RelD	-0.914*** (0.248)	-0.349 (0.572)	-2.279*** (0.356)	-1.665* (0.888)
$HHI_j \times \text{RelD}$	0.990 (1.022)	-0.389 (3.080)	7.492*** (1.434)	6.205** (2.859)
Volume	-0.192*** (0.027)	0.003 (0.020)	-0.087*** (0.030)	-0.029 (0.074)
Obs	555,545	56,473	207,474	20,189
R ²	0.77	0.85	0.79	0.85
Within-R ²	0.03	0.04	0.04	0.06
FE: $i \times t \times c \times d \times \tau$	Yes	Yes	Yes	Yes

The table displays results from the regression $Spread_{j,i,r} = \delta_1 \times HHI_j + \delta_2 \times RelD_{j,i} + \delta_3 \times HHI_j \times RelD_{j,i} + \beta \times \ln(Volume) + \alpha_{i \times t \times c \times d \times \tau}$. The dependent variable $Spread_{j,i,r}$ is the spread measure as described in Appendix A. This table includes only quotes from forward transactions with at least 90 days to maturity. Columns 1-2 includes instruments which synthetically lend USD in the FX market and columns 3-4 with sythetic USD funding (i.e. EUR/USD at the ask, GBP/USD at the ask and USD/CHF at the bid) . Columns 1 and 3 base on the quote-level sample and columns 2 and 4 on the trade-level sample. $dealer \times date \times currency\ pair \times direction \times tenor$ 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.

Table 9: Competition and volume

	Swap		Forward swap	
	(1) RelD	(2) OutD	(3) RelD	(4) OutD
HHI_j	1.884*** (0.622)	1.440 (1.306)	0.882* (0.456)	6.616*** (1.693)
Volume	0.011** (0.005)	-0.046*** (0.015)	0.002 (0.005)	0.009 (0.013)
$HHI_j \times \text{Volume}$	-0.078** (0.036)	-0.079 (0.085)	-0.040 (0.031)	-0.405*** (0.109)
Obs	42,82	486,98	486,98	1,136,995
R ²	0.97	0.91	0.89	0.85
Within-R ²	0.01	0.01	0.00	0.01
FE: $i \times t \times c \times d \times \tau$	Yes	Yes	Yes	Yes

The table displays results from the regression $Spread_{j,i,r} = \delta_1 \times HHI_j + \delta_2 \times HHI_j \times \ln(Volume_r) + \beta \times \ln(Volume_r) + \alpha_{i \times t \times c \times d \times \tau}$. The dependent variable $Spread_{j,i,r}$ for swaps (columns 1-2) and for forward swaps (columns 3-4) as described in Appendix A. Columns 1 and 3 base on the sample of relationship dealers and columns 2 and 4 on a sample of outside dealers. $dealer \times date \times currencypair \times direction \times tenor$ 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.