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Abstract

New regulatory data reveal extensive price discrimination against non-financial clients in the FX derivatives market. The client at the 90th percentile pays an effective spread of 0.5%, while the bottom quarter incur transaction costs of less than 0.02%. Consistent with models of search frictions in over-the-counter markets, dealers charge higher spreads to less sophisticated clients. However, price discrimination is eliminated when clients trade through multi-dealer request-for-quote platforms. We also document that dealers extract rents from captive clients and market opacity, but only for contracts negotiated bilaterally with unsophisticated clients.

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1 Introduction

Many of the world's largest financial markets are decentralized, with trading taking place over-the-counter (OTC). Unlike in centralized markets, prices are typically negotiated bilaterally, giving rise to search frictions. Duffie, Gârleanu & Pedersen (2005) predict that this market structure entails price discrimination. In their model, less sophisticated clients with worse access to alternative dealers and weaker bargaining power pay higher prices for the same contract. While existing empirical research on bond markets has found evidence of price *dispersion*, it has not quantified the scope of price *discrimination* in OTC markets more generally. Until now, researchers have either been unable to identify counterparties, or they have done so in settings with little identifying variation in client sophistication. Despite the lack of available evidence, a global policy agenda on derivatives markets is premised on the assumption that OTC market quality is poor and in need of reform (Financial Stability Board, 2017b). Hence, both theory and policy on price discrimination in OTC markets currently lack empirical support.

With new data, we precisely measure the scope of price discrimination in the OTC market for foreign exchange (FX) derivatives. Owing to the opacity of many OTC markets, this is already a significant contribution: as Angus Deaton remarked in his Nobel Prize speech (2015), "measurement [...] can be of great importance in and of itself—policy change is frequently based on it". We measure price discrimination by analyzing more than half a million EUR/USD forward contracts. Importantly, we observe the identity of the market participants trading these contracts: in our sample, 204 banks (henceforth "dealers") trade with 10,087 non-financial firms ("clients"), which vary from large multinationals to small import-export companies. This key feature of the FX derivatives market allows us to test the Duffie et al. (2005) prediction that dealers price-discriminate based on client sophistication. While anecdotal evidence suggests that small and medium sized enterprises lack financial expertise,[1] rendering them susceptible to price discrimination by dealers, we are the first to examine this systematically in the data.

We find that transaction costs—measured by the effective spread of contractual forward rates relative to interdealer quotes—are highly heterogeneous across clients. The corporate client at the 90th percentile of the spread distribution pays 0.5% on average over the market mid-price, which in the EUR/USD cross corresponds to a spread of 52 pips, while clients in

[1]See, for example, "Many SMEs fail to grasp foreign exchange risk", *Financial Times*, September 26, 2013, available at https://www.ft.com/content/338d3d5a-269c-11e3-bbeb-00144feab7de.

the bottom quarter of the distribution pay no more than 2 pips.[2] However, spread dispersion could simply reflect differences in contract characteristics or dealer efficiency. To identify price discrimination, we control for these characteristics as well as dealer and time fixed effects. We find that spreads vary systematically with the level of client sophistication, which we measure empirically using five proxies: the number of dealers with which a client trades; the concentration of a client's trades across dealers; the total notional of a client's trades; the number of a client's trades; and the number of a client's non-FX derivatives trades. These variables aim to capture ρ (the intensity with which clients encounter dealers) and $1 - z$ (clients' bargaining power in bilateral negotiations) in Duffie et al. (2005).

The extent to which dealers price-discriminate based on sophistication is quantitatively large. Relative to listed blue-chips, represented by the average firm in the EURO STOXX 50 index, the client at the median of the sophistication distribution pays an excess spread of 11 pips for the same contract executed at a similar time with the same dealer. Aggregating over all clients whose sophistication is lower than the average EURO STOXX 50 firm, we estimate that price discrimination based on client sophistication implies an aggregate dealer rent of approximately €638 million annually in the EUR/USD segment of the FX forward market.

Our analysis sheds additional light on the economics of OTC markets along three dimensions. First, we examine trades on request-for-quote (RFQ) platforms, which allow clients to query multiple dealers simultaneously rather than individual dealers sequentially. We find that RFQ platform trades exhibit significantly lower spreads than bilateral trades executed at a similar time and with the same dealer and contract characteristics. Moreover, the inverse relationship between spreads and client sophistication is absent for platform trades, suggesting that lower search costs and enhanced dealer competition eliminate price discrimination. To control for a potential selection bias due to unobserved client heterogeneity, we estimate regressions with client fixed effects and confirm that platform use is associated with significantly lower spreads. Hence, our results cannot be attributed to clients with inherently low search costs self-selecting onto platforms.

Second, we explore the role of bilateral dealer-client relationships in execution quality. In contrast to the existing literature, we measure relationships by the existence of firm-bank linkages in the credit market, which is more robust to potential concerns regarding the endogeneity

[2] In FX markets, a pip is the smallest measurable difference in an exchange rate. By convention, the EUR/USD cross is priced to four decimal places, so 1 pip refers to a 0.0001 difference.

of transaction costs and firm-bank relationships in the FX market. While most papers find that relationship trading is associated with a discount, we obtain a more nuanced result. For very sophisticated clients, we confirm the existence of a relationship discount. However, clients in the bottom 80% of the sophistication distribution pay a premium when trading with their relationship bank. The latter finding supports the interpretation that captive clients with no alternative trading opportunities are subject to additional rent extraction by dealers. Settings focused on sophisticated clients overlook this phenomenon, which is empirically important in the FX market.

Third, we identify and quantify the role of information rents resulting from the opacity of market price changes. In the absence of centralized dissemination of quotes or transaction prices in real time, dealers generally enjoy an information advantage. We find evidence that dealers exploit this advantage through asymmetric price adjustment. In particular, dealers only partially pass on recent changes in the market mid-price when the change is in the opposite direction to the client order. The extent of asymmetric adjustment declines with the level of client sophistication and is absent for RFQ platform trades. Quantitatively, however, information rents from asymmetric price adjustment are small, since they only accrue when mid-price movements are both large and in the opposite direction to the client order. This suggests that search frictions are more important in explaining dealer rents in OTC markets.

Our findings can inform policy. At the G20 summit in Pittsburgh in 2009, governments agreed that standardized OTC derivatives should trade through exchanges or electronic trading platforms. However, implementation of this pledge has been limited to interest rate swaps and index credit default swaps (Financial Stability Board, 2017a). In the FX market, a further expansion in platform trading could improve execution quality. Even without mandatory platform trading, enhanced disclosure of quotes and prices could promote a more efficient market structure. In our sample, nearly 90% of clients never use an RFQ platform—despite pricing being considerably more competitive. Since firms can join RFQ platforms at negligible cost, this begs the question of how such widespread non-participation can be an equilibrium. One explanation is that clients do not observe the potential gains from RFQ platform trading in the absence of pre- and post-trade price transparency. Enhanced disclosure would enable clients to make more informed choices about trading venues and more competitive pricing, possibly inducing additional hedging activity by firms which currently find it too expensive, causing them to bear exposure to currency risks.[3]

Related Literature

Our work contributes to the literature on OTC markets. Participants in these markets engage in a costly search for trading opportunities (Duffie et al., 2005).[4] In addition, OTC markets are characterized by opacity: price information is typically not disseminated publicly, either pre- or post-trade (Duffie, 2012). These search and information frictions both give rise to imperfect competition, allowing dealers to extract rents. Moreover, when clients are heterogeneous, the OTC market structure subjects them to price discrimination in equilibrium.

Existing empirical studies provide evidence of price dispersion in OTC markets. Early contributions document that transaction costs are decreasing in trade size (Schultz, 2001; Harris & Piwowar, 2006; Green, Hollifield & Schürhoff, 2007). But evidence on price dispersion does not constitute direct evidence of price discrimination in the cross-section of clients. More recently, Hendershott, Li, Livdan & Schürhoff (2017) and O'Hara, Wang & Zhou (2018) analyze the trading activity of insurance companies in the corporate bond market and find evidence of price discrimination, with larger and more active insurers paying lower spreads. The external validity of these findings to other markets is questionable, however, as insurance companies are professional investors with generally high levels of sophistication. In focusing on non-financial firms, we exploit a sample with lower average sophistication and considerably more heterogeneity.

Given that discriminatory pricing is a feature of bilateral bargaining, theory predicts that the venue of trading should matter for execution quality. Controlling for selection bias due to endogenous venue choice, Hendershott & Madhavan (2015) find that the average corporate bond trades at lower transaction costs on MarketAxess, a multi-dealer electronic platform, than via bilateral (voice) execution. They calculate that switching to electronic trading would save a total of US$2 billion per year in transaction costs. Qualitatively similar findings on execution

[3]The consequences of inadequate currency risk management were demonstrated recently by Monarch, a UK-based airline, which filed for bankruptcy in part owing to the depreciation of sterling (in which much of its revenues were denominated) against the US dollar (the invoice currency for expenses such as fuel and aircraft). See "Monarch Airlines goes bust", Reuters, October 2, 2017, available at: https://goo.gl/YR7Q7P.

[4]Extensions of this canonical search model include Duffie, Gârleanu & Pedersen (2007) and Lagos & Rocheteau (2007, 2009).

quality for platform trades have recently been obtained in markets for interest rate and index credit default swaps (Benos, Payne & Vasios, 2019; Riggs, Onur, Reiffen & Zhu, 2018). We advance this emerging literature on platform trading by studying the heterogeneous effects of venue choice in the cross-section of clients. Since unsophisticated clients face higher search costs, they have most to gain from requesting quotes through a multi-dealer platform rather than bilaterally. We find empirical support for this hypothesis, and discover that discriminatory pricing is entirely eliminated when clients trade through RFQ platforms.

Moreover, this paper speaks to the literature on relationship trading in OTC markets. In a variety of empirical settings, relationship trading is associated with lower transaction costs for clients (Bernhardt, Dvoracek, Hughson & Werner, 2004; Cocco, Gomes & Martins, 2009; Afonso, Kovner & Schoar, 2013; Hendershott et al., 2017; Di Maggio, Kermani & Song, 2017). We contribute to this literature in two ways. First, we propose a new measure of dealer-client relationships based on interactions in the credit market, which is less subject to endogeneity concerns than measures derived from bilateral trading data. Second, we allow the effect of relationships to vary with the level of client sophistication. We find that only very sophisticated clients obtain a relationship discount. For most clients, relationship trading is costly because it foregoes the benefits of dealer competition.

Another strand of literature on OTC markets uses event studies to examine the effect of enhanced transparency on execution quality. Bessembinder, Maxwell & Venkataraman (2006), Goldstein, Hotchkiss & Sirri (2006) and Edwards, Harris & Piwowar (2007) document that higher post-trade transparency in US corporate bond markets after the introduction of the Trade Reporting and Compliance Engine (TRACE) in 2002 generally reduced transaction costs and increased liquidity. Similar effects have been identified in the credit default swap market following provisions in the Dodd-Frank Act to promote post-trade transparency (Loon & Zhong, 2014, 2016). Public transaction records allow clients to verify the execution quality of their trades, thereby mitigating information asymmetries. In our setting, dealers are able to extract considerable information rents due to the absence of any public price dissemination. This suggests a role for policy intervention to enhance transparency in FX markets.

Finally, our analysis touches on the literature on corporate hedging. Nance, Smith & Smithson (1993) suggest that larger clients are more likely to hedge currency risk because they benefit from scale economies in market participation. Yet the source of these scale economies is not elucidated. Guay & Kothari (2003) show that larger corporate clients engage more in derivatives trading, even though the overall size of their positions tends to be small compared to financial investors. Our analysis sheds light on these results. We document that more sophisticated corporate clients generally pay lower spreads, which can induce greater market participation and more complete hedging of FX risks. Hedging reduces the probability of tail risk events and therefore bankruptcy, which in turn reduces funding costs (Smith & Stulz, 1985; Stulz, 1996) However, discriminatory pricing implies high transaction costs for unsophisticated firms, which may deter them from hedging FX risks despite the potential reduction in funding costs.

2 Hypotheses

In this section, we articulate four hypotheses about the determinants of spreads on FX forwards. Our first hypothesis derives from the theoretical literature on search frictions in OTC markets. Duffie et al. (2005) predicts that dealers charge lower mark-ups to more sophisticated clients with better (or faster) access to alternative dealers. Intuitively, the ability to turn (quickly) to another counterparty exposes dealers to sequential competition, inducing them to offer more competitive spreads. We thus adopt the following hypothesis:

Hypothesis 1: Client Sophistication

More sophisticated clients incur lower transaction costs.

While trading in OTC markets has long been dominated by bilateral voice trading, hybrid mechanisms such as RFQ platforms have begun to be used more widely in recent years. These systems allow clients to solicit quotes from multiple dealers simultaneously. Dealers observe the identity of the client and the fact that the quote is requested on the platform, but they do not observe the number of dealers from which the client requests a quote. Platforms therefore effectively replace sequential competition with simultaneous concealed bidding. Evidence from the corporate bond market suggests that RFQ platforms reduce search costs and induce greater dealer competition (Hendershott & Madhavan, 2015), in line with predictions from laboratory experiments (Flood, Huisman, Koedijk & Mahieu, 1999). We thus expect trades executed on RFQ platforms to exhibit lower spreads. Moreover, based on Hypothesis 1, the least sophisticated clients have most to gain from a more competitive trading environment and should thus experience a more pronounced improvement in execution quality when trading through RFQ platforms.

Hypothesis 2: RFQ Platforms

Trades on RFQ platforms incur lower transaction costs. The effect is stronger for less sophisticated clients.

Empirical research on OTC markets documents that real-world trading networks tend to be sparse: most market participants interact repeatedly with relatively few counterparties. Empirically, such relationship trading has often been associated with better trading terms (relative to "spot" trading), for example because of intertemporal competition (Bernhardt et al., 2004), co-insurance motives (Cocco et al., 2009; Afonso et al., 2013) and discounts for repeat business (Hendershott et al., 2017). Di Maggio et al. (2017) show that these relationship discounts increase with financial market volatility. On the other hand, Ferreira & Matos (2012) show that there can also be a "dark side" of relationship trading: board overlap between two counterparties is associated with higher financing costs in the syndicated loan market. Nevertheless, in line with most of the literature, we formulate the following hypothesis:

Hypothesis 3: Dealer-Client Relationships

Dealer-client relationships are associated with lower spreads.

Due to their opacity, OTC markets are sometimes referred to as "dark markets" (Duffie, 2012). Unlike in centralized exchanges, there is often no obligation for dealers to disclose prices or quotes publicly. In the FX forwards market, transaction prices are not publicly available in real-time or even post-execution, and interdealer quotes are only available with a considerable time lag. This gives rise to an information asymmetry between dealers and clients. While dealers can infer the market price from their frequent interactions in inter-dealer and dealer-to-client markets, clients are generally less well informed about market conditions.[5] The information asymmetry between a dealer and a client may matter most when price movements are large, since dealers can exploit their information advantage by adjusting prices asymmetrically in response to recent changes in the market mid-price. Consider for example a dealer that receives a quote request just after the EUR/USD forward rate has increased. For a client buy order, the dealer has an incentive to update its quote to fully reflect the new market price. However, for a client sell order, the dealer prefers to offer a quote closer to the outdated lower

[5] One way to reduce information frictions is to publish benchmark prices, as is done in several other OTC markets. Duffie, Dworczak & Zhu (2017) show how such benchmarks can raise welfare.

price.[6] More generally, client orders in the opposite direction of recent price changes are predicted to incur higher spreads compared to trades in the same direction. Such asymmetric price adjustment—sometimes known as the "rockets and feathers" phenomenon—has been observed in retail markets (see, e.g., Peltzman, 2000), and has also been documented for smaller trades in the US municipal bond market (Green, Li & Schürhoff, 2010). We predict that dealers' ability to extract information rents through asymmetric price adjustment decreases when search frictions are reduced.

> **Hypothesis 4: Information Rents from Asymmetric Price Adjustment**
> Client orders in the opposite direction of recent price changes incur higher transaction costs than trades in the same direction. This effect declines with client sophistication and when clients trade through RFQ platforms.

3 Data and Measurement

The European Market Infrastructure Regulation (EMIR) requires that all counterparties resident in the European Union (EU) report the contractual details of derivatives transactions to trade repositories. These repositories share the data with authorities according to their jurisdiction. Two authorities, namely the European Systemic Risk Board (ESRB) and European Securities and Markets Authority (ESMA), have access to the full EU-wide transaction-level dataset.[7] From the three largest trade repositories—namely DTCC, REGIS and UnaVista—we collect information on FX derivatives contracts executed over a one year period between April 1, 2016 and March 31, 2017. We restrict the dataset to plain vanilla FX forwards, which account for approximately 85% of all FX derivatives (BIS, 2017). These contracts, which include both outright forwards and forward legs of FX swaps, generate an obligation to exchange a given quantity of one currency against another at a predetermined exchange rate at some future date.[8] We restrict the dataset to FX forwards referenced to EUR/USD, which is the

[6] The opposite is true for trades following price decreases (i.e. the dealer will be tempted to quote based on the outdated higher price in case of a client buy order).

[7] The dataset is described in detail by Abad, Aldasoro, Aymanns, D'Errico, Rousova, Hoffmann, Langfield, Neychev & Roukny (2016).

[8] For example, a client selling a 3-month EUR/USD forward with a notional of €1 million and a forward rate of 1.10 commits to transfer €1 million to the dealer in three months' time in exchange for US$1.1 million, regardless of the spot rate prevailing at the delivery date.

currency cross with the largest notional outstanding according to the Bank for International Settlements.

The transaction records provide a unique legal entity identifier for all counterparties. Importantly, this allows us to identify the counterparties and collect additional information on them. We match the transaction-level data with firm-level data from Bureau van Dijk's Orbis dataset, which includes information on counterparties' location at the parent level and their sector classification. We retain all trades in which one counterparty is classified as a non-financial firm (the "client") and the other as a bank (the "dealer"). In our one-year sample, we have 10,087 clients and 204 dealers.

We implement various filters and checks on data quality. The raw dataset comprises dual-sided reporting whenever both trade counterparties are EU-domiciled. We check the consistency of dual reports and discard approximately 25,000 trades which feature discrepancies, for example with different execution timestamps. Trade reports without dual reporting are only retained if they come from dealers, which are subject to more stringent oversight. Consequently, all dealers in our dataset are resident in the EU, but the non-financial firms can reside in any country. Our final transaction-level dataset comprises 548,298 trades with a total notional of over €5 trillion. The summary statistics are discussed Section 4.

3.1 Transaction Costs

We use the effective spread (henceforth "spread") to measure transaction costs. The spread (expressed in pips) for transaction τ is defined as

$$Spread_\tau = d_\tau \times (f_\tau - m_\tau) \times 10^4, \tag{3.1}$$

where f_τ is the contractual forward rate, m_τ the contemporaneous mid-price, and d_τ is a trade direction indicator (equal to $d_\tau = 1$ for client long positions in EUR/USD and $d_\tau = -1$ for short positions).[9]

The contemporaneous mid-price m_τ is based on indicative quotes posted by dealers, which we obtain from Thomson Reuters Tick History (TRTH). These quotes are available for forward rates at the standard maturities of 1 day, 1 week, 2 weeks, 3 weeks, 1 month, 2 months, 3

[9] A long (short) position in EUR/USD constitutes the obligation to buy (sell) EUR against USD at the contractual forward rate. For example, if a client buys euro at 1.0500, but the prevailing mid-price is 1.0450, the spread paid by the client is 50 pips.

months, 6 months, and 1 year. For each of these maturities, we compute the mid-price from the best inside quotes of the participating dealers. To avoid using stale quotes, we assume that quotes are valid for a maximum of 30 seconds. We calculate mid-prices for non-standard tenors by linearly interpolating across the nine standard maturities.[10] Figure 1 illustrates client buy and sell trades (in blue and red, respectively) relative to the mid-price for 30-day EUR/USD forward contracts traded on a single day.

3.2 Explanatory Variables

Next, we define the explanatory variables used to test the four hypotheses. These include measures of sophistication, identifiers for platform and relationship trades, variables capturing asymmetric price adjustment, as well as a set of contract characteristics that serve as control variables.

Client Sophistication

We propose five different measures of client sophistication. $Log\#Counterparties$ denotes the natural logarithm of the number of dealers with which a client trades during our one year sample period. This variable aims to capture the parameter ρ in Duffie et al. (2005), which represents the intensity with which clients encounter dealers. Alternatively, we compute the Herfindahl-Hirschman index (HHI) based on the share of a client's trades with each of its dealers. This measure is inversely related to $Log\#Counterparties$ as higher dealer concentration typically comes with fewer counterparties. Further, we calculate $LogTotalNotional$ as the log of total notional (in euros) of all EUR/USD forwards traded by a client in our one year sample period. Clients with higher trading volumes have a greater incentive to spend resources on search for competitive spreads. In addition, larger trading volumes are more attractive for dealers, which increases clients' bargaining power in bilateral negotiations, as captured by $1-z$ in Duffie et al. (2005). Finally, we define $Log\#TradesFX$ as the log of the number of EUR/USD forwards traded by a client in our one year sample period, and $Log\#TradesNonFX$ as the log of one plus the total number of a client's outstanding positions in interest rate, credit, and commodity derivatives at the start of our sample period on April 1, 2016. Trading experience in other derivatives contracts proxies for client sophistication in a similar way to $Log\#TradesFX$, but

[10] For example, the mid-price for a 10-day forward is calculated as the weighted average of the 1-week and 2-week mid-prices, where the weights are 3/7 and 4/7, respectively.

is not directly related to the spreads paid by clients in FX forwards. We also collapse these five measures of client sophistication into a single variable by defining *Sophistication* as the demeaned first principal component of these five variables.[11]

RFQ Platform Use

The second hypothesis concerns the role of multi-dealer RFQ platforms. Our transaction-level data allow us to identify trades executed through a major multi-dealer RFQ platform, which includes 360t, FXall, Bloomberg, and Currenex. Accordingly, we define a dummy variable, $RFQPlatform$, that is equal to one for trades on these platforms, and zero otherwise.

Dealer-Client Relationships

Research in market microstructure has studied the effect of trading relationships on the terms of trade. In this literature, relationships are typically measured based on trading data, which is subject to endogeneity with respect to the variables of interest, notably transaction costs. Consequently, the econometrician cannot exclude that firms simply trade more with banks that offer lower spreads. We avoid this problem by retrieving information on firms' credit relationships outside the FX market. We obtain the identities of firms' main relationship (lending) banks from Orbis, which are listed under a variable called "banker". We then create a dummy variable, *Relationship*, that takes the value of one for trades where the client has a pre-existing credit relationship with the dealer, and zero otherwise.[12]

Information Rents from Asymmetric Price Adjustment

To identify whether dealers adjust prices asymmetrically following changes in the mid-price, we denote by $|\Delta m_\tau^{-d}|$ ($|\Delta m_\tau^{d}|$) the absolute value of the change in the mid-market forward rate over the preceding 30 seconds (in pips) if the price change was in the opposite (same) direction

[11] We obtain qualitatively and quantitatively similar results if we instead define *Sophistication* as a fitted linear combination of these five variables.

[12] In the Online Appendix (Table A.4), we alternatively use a more standard measure of relationships defined as the notional traded between client i and dealer d relative to client i's total notional traded. We obtain qualitatively similar results when using this alternative measure.

as the client order, and zero otherwise. More formally, we define

$$|\Delta m_\tau^{-d}| = \begin{cases} |\Delta m_\tau| & \text{if } sign(d_\tau) \neq sign(\Delta m_\tau) \\ 0 & \text{otherwise} \end{cases}, \tag{3.2}$$

$$|\Delta m_\tau^{+d}| = \begin{cases} |\Delta m_\tau| & \text{if } sign(d_\tau) = sign(\Delta m_\tau) \\ 0 & \text{otherwise} \end{cases}, \tag{3.3}$$

where Δm_τ denotes the market mid-price change in the 30-second interval prior to trade τ. Hypothesis 3 predicts that the coefficient of $|\Delta m_\tau^{-d}|$ on the transaction spread is positive whenever a client buy (sell) coincides with a recent mid-market price decrease (increase) in the EUR/USD exchange rate, while the coefficient of $|\Delta m_\tau^{+d}|$ on spreads is expected to be zero, provided that dealers quickly update their quoted prices.

Contract Characteristics

Finally, we define a set of variables to capture contract characteristics that may affect spreads. First, $Notional$ (in €mn) is the notional amount of the forward contract (in logs). Research on bond markets documents that spreads are decreasing with trade size, so we expect $Notional$ to be negatively associated with spreads. Second, $Tenor$ is a trade's original maturity (in days). We expect dealers to charge higher spreads for long maturity contracts in compensation for greater market risk. Third, $Customization$ is the difference in days between the tenor of a forward contract and its nearest standard tenor (i.e. 0, 1, 7, 30, 60, 90, 180, 270, or 360 days). We expect dealers to charge higher spreads for customized contracts, since these are more difficult to hedge in the interdealer market. Fourth, $Volatility$ is defined as the realized volatility of the FX spot rate over the preceding 30 minutes, based on one minute intervals. Spreads are expected to be higher in volatile market conditions to compensate dealers for the extra execution risk. Fifth, Buy is a dummy which equals one when a client forward-buys euro against dollar, and zero otherwise. This variable may affect spreads (either positively or negatively) insofar as there is a structural imbalance of buy or sell orders.

4 Descriptive Statistics

Table 1, Panel A provides summary statistics on the 10,087 clients trading with 204 dealers in the EUR/USD forwards market between April 1, 2016 and March 31, 2017. A key variable of interest is the average spread paid by a client over all its trades ($AvClientSpread$). The average $AvClientSpread$ is 18.1 pips, with a large standard deviation of 26.6 pips. The distribution of this variable is positively skewed; clients at high percentiles pay considerable spreads. For example, the client at the 75th percentile pays an average spread of 33.9 pips, whereas clients at the 50th and 25th percentiles pay only 14.3 pips and 2.1 pips, respectively. Figure 2 plots the cross-sectional distribution of average spreads at the client level. The high dispersion in average client spreads is suggestive of substantial price discrimination.

The distribution of clients' counterparties is similarly skewed. More than half of clients trade with just one dealer. Even the client at the 75th percentile has just two counterparties. This is reflected in HHI, whose average of 0.8 is close to perfect concentration. Only in the very high percentiles do $\#Counterparties$ and HHI reach large values: clients in the top 1%, for example, have between 11 and 29 dealers and a HHI of less than 0.006.

On average, clients traded a total notional of €515mn over the one year sample period. However, heterogeneity in trading volumes is very large: clients at the 10th and 90th percentiles of the distribution trade an annual total notional of approximately €$100,000$ and €114 mn, respectively. A similar picture emerges from the variables $\#TradesFX$ and $\#TradesNonFX$. While the median client trades eight times during our sample period, the mean trade count is 54 and driven by a small number of clients that trade very frequently. For example, the client at the 90th percentile of the distribution trades 86 times in one year. By contrast, the client at the 25th percentile trades only three times. Moreover, more than three quarters of 10,087 clients never trade any non-FX derivatives.

The aforementioned variables are summarized in $Sophistication$, which represents the first principal component. Nearly two-thirds of the 10,087 clients display a negative value of $Sophistication$, indicating a positive skewness. The $Relationship$ dummy shows an almost bimodal distribution at the client level: while one third of clients never trade with their relationship bank(s), just over one half exclusively trade with their relationship bank(s).

Table 1, Panel B provides summary statistics at the transaction level for the 548,298 EUR/USD forward contracts. The distribution of spreads is much narrower than at the client level. The average spread over all trades is only 6.9 pips compared to 18.1 pips when averaging by client. The spread at the 90th percentile of the transaction-level distribution is 31 pips, compared to 52 pips at the client level. This implies that more active traders obtain lower spreads on average. Moreover, we see that the spread at the 25th percentile of the transaction-level distribution is slightly negative at −1.1 pips compared with a positive average client spread at the same percentile.[13]

Most contracts have an underlying notional value of less than €1 million; just under 10% of contracts have a notional in excess of €15 million. Half of all transactions pertain to contracts with an original maturity of fewer than 35 days. The frequency of executed FX forward trades is a decreasing function of the contract tenor (i.e. maturity), as shown in Figure 3. Table 1, Panel B also reveals that clients enter long positions in around 40% of trades. Moreover, just under 40% of all trades are executed through RFQ platforms, in line with existing survey evidence on the use of multi-dealer platforms (BIS, 2016). Finally, the distributions of $|\Delta m_\tau^{-d}|$ and $|\Delta m_\tau^{+d}|$ show that mid-price movements over the 30 seconds preceding a trade average 0.5 pips in both directions, and large mid-price changes are rare.

In the Online Appendix (Table A.1), we provide additional summary statistics at client and transaction level. We do so by cutting the data in two ways. First, clients are sorted into terciles of low, medium and high sophistication. Second, clients are split according to whether they use an RFQ platform at least once. These sorts indicate a negative correlation between transaction costs and sophistication and suggest that platform use is associated with lower spreads. Moreover, Table A.2 provides a breakdown of clients according to their geographical location and industry sector. Consistent with derivatives trading being motivated by hedging needs, most firms are involved in trade or production, which is naturally exposed to currency risk. For example, purchases of foreign goods may be invoiced in USD, requiring a currency hedge until the invoice is settled (Gopinath & Rigobon, 2008). Likewise, firms are primarily domiciled in export-oriented economies, such as Germany.

[13] The existence of negative spreads is consistent with evidence from dealer-client segments in other OTC markets, such as the sovereign bond market (Dunne, Hau & Moore, 2015). Transactions with a negative spread can occur when dealers engage in price shading in order to rebalance their inventories (Garman, 1976; Amihud & Mendelson, 1980).

5 Analysis

To characterize the determinants of spreads, we estimate a linear model for the 548,298 dealer-client trades in our sample. The baseline specification takes the form

$$Spread_{i,d,\tau} = X_i\beta_1 + Z_\tau\beta_2 + \delta_d + \gamma_t + \gamma_m + \epsilon_\tau, \tag{5.1}$$

where X_i represents a set of proxies for client sophistication and Z_τ is a vector of control variables describing the five contract characteristics defined in Subsection 3.2. To control for time-varying market conditions, we include date (γ_t) and minute-of-day (γ_m) fixed effects. We also include dealer fixed effects (δ_d) to control for time-invariant dealer characteristics. In this way, we compare the spread that a dealer charges to one client with the spread that the same dealer charges to another client.

5.1 Client Sophistication

Figure 4 provides an insightful univariate view of the relationship between transaction costs and client sophistication. It plots the average spread across all trades by clients with a given number of dealers ($\#Counterparties$). The size of each dot is proportional to the notional share for each group of clients. While clients with only one dealer only account for only 2% of the notional, they represent 68% of all firms. On average, they pay a spread of 17.4 pips. Access to more dealers is associated with substantially lower spreads, but this effect declines in magnitude as the number of dealers increases. The average spread for clients trading with five or more dealers is 1.2 pips. While this group represents only 6% of all clients, their aggregate notional accounts for 88% of the total.

We proceed with formal tests of Hypothesis 1, which concerns price discrimination based on client sophistication. We estimate Equation 5.1 separately for each of the five proxies of client sophistication discussed in Subsection 3.2 as well the composite measure. The resulting coefficient estimates, with standard errors clustered at the client level, are reported in Table 2. We find that all five sophistication measures have the expected directional effect implied by Hypothesis 1, and the coefficient estimates are statistically significant at the 1% level. More specifically, Column (1) shows that clients with more counterparties pay lower spreads on average. Similarly, Column (2) indicates that clients with more concentrated counterparties pay higher spreads. In Columns (3) and (4), we find that more active clients, either in terms of number of trades or notional traded, incur lower spreads. Finally, Column (5) reveals that clients with more outstanding derivatives contracts in other asset classes benefit from lower spreads on average. Column (6) synthesizes these results using the composite measure of sophistication calculated as the first principal component of the five individual measures. The estimated coefficient is -1.518 and statistically significant at the 1% level. Accordingly, an increase in client sophistication of one standard deviation is associated with a decrease in spreads of 2.7 pips.

As noted in Section 4, the cross-sectional distribution is highly right-skewed for all sophistication measures, meaning that our sample consists of a few very sophisticated firms and many less sophisticated firms. Therefore, it is meaningful to compare clients to a benchmark group of very sophisticated clients who are likely to trade at competitive prices. We screen our sample of clients for the constituent firms of EURO STOXX 50, a pan-European blue chip index comprising the largest listed firms. We identify 38 index members.[14] The average level of *Sophistication* of these firms is 6.65, which lies above the 99th percentile of our cross-sectional distribution. By contrast, median *Sophistication* in our full sample is -0.5. According to the estimated coefficients of *Sophistication* in Table 2, Column (6), the median firm pays an excess spread of 10.9 pips due to its lower level of sophistication than the average EURO STOXX 50 firm.

To gauge economic magnitudes, we compute the aggregate rent that accrues to dealers due to price discrimination based on sophistication by summing over all excess spreads relative to the average EURO STOXX 50 firm. Formally, we define

$$TotalRent = \sum_{\tau} \widehat{\beta}_1 (Sophistication_{\tau} - 6.65) \times Notional_{\tau}, \tag{5.2}$$

where $\widehat{\beta}_1$ denotes the coefficient estimate for the effect of client sophistication on spreads in Table 2, Column (6); $Sophistication_{\tau}$ represents the sophistication of the client involved in trade τ; and $Notional_{\tau}$ captures the total notional value of trade τ to which the excess spread applies. For clients with a sophistication below the EURO STOXX 50 average of 6.65, we find that price discrimination generates aggregate dealer rents from corporate clients of €638

[14] 10 index members are banks or insurance companies, and thus are not included in our sample of non-financial firms. Hence our coverage of the EURO STOXX 50 index is almost complete.

million annually in the EUR/USD cross alone. Hence, dealers extract significant rents from search frictions even in the most liquid segment of the FX market.

We briefly comment on the control variables. A larger notional amount commands lower spreads, consistent with evidence from the corporate bond market (Schultz, 2001; Harris & Piwowar, 2006; Green et al., 2007). This size discount is obtained even after controlling for client sophistication, which incorporates variation in counterparty size (e.g., via $LogTotalNotional$). Given that dealer revenue scales linearly with the notional value traded (i.e., the spread is per unit), a negative coefficient is likely to reflect a fixed cost component of trading. Moreover, we find that longer contract maturity ($LogTenor$) is associated with larger spreads, potentially reflecting higher counterparty risk associated with long-term contracts.[15] The coefficient of $Volatility$ has the expected positive sign but is statistically insignificant. The inclusion of date and minute-of-day fixed effects already captures a large fraction of the time-series variation in this variable. The coefficient on the Buy dummy is statistically significant, suggesting that dealers demand a premium for providing funding in USD. This is consistent with the continued failure of the covered interest parity since the financial crisis (Du, Tepper & Verdelhan, 2018). Finally, we find that trades with a tenor that differs from a standard maturity command higher transaction costs. An increase in the customization measure by one standard deviation is associated with a spread increase of approximately 1 pip, which is economically relatively small.

5.2 RFQ Platforms

In this section, we explore the effects of RFQ platforms on transaction costs. These platforms allow clients to query multiple dealers at the same time, thus curbing their ability to exert market power. As detailed in Table 1, around 39% of all trades are executed through RFQ platforms. These trades are executed by 1,218 clients (i.e. 12.1%). The majority of clients therefore never use an RFQ platform to trade FX forwards.

Hypothesis 2 predicts that trades on RFQ platforms incur lower spreads. As indicative evidence, Figure 5 plots the average spreads paid by the 10,087 clients as a function of their sophistication. Blue dots correspond to clients that trade only bilaterally, while red dots rep-

[15] In the Online Appendix (Table A.5), we additionally investigate the role of clients' credit quality, as proxied by $ZScore$ and cash flow volatility. We find no consistent evidence for counterparty risk affecting transaction costs. However, it is important to note that we do not have reliable information on collateralization, which prevents a more detailed analysis.

resent firms that execute at least one of their trades through a platform. Consistent with Hypothesis 2, platform users incur lower average spreads than firms with a similar level of sophistication that negotiate only bilaterally. Moreover, the negative relationship between transaction costs and client sophistication holds only for non-users. All platform users obtain competitive prices irrespective of their level of sophistication. Table 3 reports OLS regressions with the transaction spread as the dependent variable and controls for contract characteristics as well as dealer, day and minute-of-day fixed effects. In Column (1), we obtain a negative coefficient of the $RFQPlatform$ dummy: platform trading is associated with a statistically significant average spread reduction of 7.3 pips. This effect diminishes to 3.8 pips when controlling for *Sophistication* in Column (2), but remains statistically significant. In Column (3), we add the interaction of *Sophistication* and $RFQPlatform$ and obtain a positive coefficient of 1.95. This implies that the benefits of RFQ platform trading are larger for less sophisticated firms. Moreover, this effect completely offsets the negative baseline effect of *Sophistication*. Accordingly, RFQ platform trading fully eliminates discriminatory pricing based on client sophistication. Platform trading is therefore a powerful tool that allows even less sophisticated clients to obtain competitive spreads.

One potential concern with this analysis is the possibility that unobserved client characteristics correlate with platform usage. For example, firms with high levels of unobserved sophistication might self-select to be platform users, thus introducing a selection bias. To address this issue, we include client fixed effects in an augmented specification. This allows us to compare spreads for the same client on- and off-platform by saturating with fixed effects all discriminatory pricing across clients which do not change their trading practice during the sample period. The coefficients in Table 3, Columns (4) and (5), show some attenuation in the effect of platform use, consistent with a selection effect. Yet the baseline and interaction effects are still economically and statistically significant. In Column (4), platform trading implies an average spread reduction of approximately 1.5 pips. The regression result reported in Column (5) implies that the median firm (with *Sophistication* $= -0.5$) saves around 4.8 pips when trading through a platform, whereas this spread reduction is only around 1 pip (and statistically insignificant) for the average EURO STOXX 50 firm. Thus, we confirm that the benefits of platform trading are larger for less sophisticated clients. In the Online Appendix (Table A.3), we report the same regressions estimated on the subsample of 6,816 clients that trade with only one dealer. In this restricted sample, we find that RFQ platform use reduces transaction costs even if a client executes all trades with the same dealer. At first glance, this seems surprising, as dealers always know the identity of anyone requesting a quote; they can still price discriminate based on client sophistication. However, dealers do not know the number of other dealers from which a client simultaneously requests quotes through an RFQ platform. Clients can thus signal outside trading options to their dealer through the platform even if they have no access to other dealers. The signaling power of platform use is present regardless of client sophistication. Overall, the economic magnitude of the spread compression on platforms is impressive. Non-anonymity of counterparties is a necessary feature of such systems, because trades are not centrally cleared and thus carry counterparty credit risk. Discriminatory pricing based on client sophistication is therefore still feasible. Yet, the lack of client anonymity does not impair the considerable improvement in execution quality obtained through these platforms by forcing competition on dealers.

5.3 Dealer-Client Relationships

Next, we examine the effects of relationship trading on transaction costs. In contrast to the existing literature, we identify dealer-client relationships based on their interactions in credit markets. We use the firm identities and matched corporate data from Orbis to identify the main credit relationship(s) of 6,638 clients in our sample. By relying on external credit relationships, we mitigate potential endogeneity issues that arise when identifying relationships from the structure of the trading network. In particular, our measure avoids the issue of reverse causality that can arise because clients trade more with dealers that offer tighter spreads.

We start by regressing spreads on a relationship dummy as well as the standard set of contract characteristics and dealer and time fixed effects. Table 4, Column (1) shows that the coefficient of *Relationship* is positive and statistically significant, with an average premium of 2.9 pips per relationship trade. By contrast, the existing literature typically finds that relationship trading is associated with a discount, albeit usually using trades of financially sophisticated clients such as insurance companies, hedge funds and banks.

Unlike prior research on bond markets, our focus on the FX market incorporates a wide range of client types, from large multinationals to small import-export companies. This provides a richer empirical setting in which to study the effect of dealer-client relationships according to client sophistication. When we include *Sophistication* in Column (2), the premium for relationship trades is no longer statistically significant. To explore the client type dependence of the relationship premium, Column (3) interacts the *Relationship* dummy with *Sophistication*. The point coefficient estimate of -1.097 is statistically significant at the 1% level, as is the coefficient for *Relationship* at 3.594. Accordingly, the median client pays a relationship premium of approximately 7.8 pips relative to the average firm in the EURO STOXX 50 index. These results suggest that unsophisticated clients are captive to dealers with which they have a relationship. When such clients have few outside trading opportunities, dealers can charge higher spreads. In contrast, sophisticated clients are not subject to relationship premia because they can subject dealers to competition. In fact, for clients in the top 6% of the sophistication distribution, relationship dealers offer small concessions in return for repeated business.

While these findings are different from those of Hendershott et al. (2017), they are not contradictory. Our sample features mostly non-financial firms of low financial sophistication, whereas theirs is based on insurance companies, which are more likely to resemble financially sophisticated firms such as those in the EURO STOXX 50 index. Our finding of a relationship discount for highly sophisticated clients therefore matches the results in Hendershott et al. (2017). The additional evidence on a relationship premium for clients of low sophistication adds a new element to the literature on relationships in trading networks.

Columns (4) and (5) additionally control for $RFQPlatform$. As in previous specifications, we find that trading through a platform is associated with an economically large compression in transaction costs, particularly for low sophistication firms. The size of this effect dominates the relationship premium. For example, Column (5) implies that the median client pays an average premium of 2.5 pips to trade with its relationship dealer, whereas it earns a discount of 16.1 pips when trading through a platform. Interestingly, however, platform use does not mitigate the marginal effect of relationship trading, as it does entirely for sophistication. Clients trading through a platform therefore still face a relationship premium. The explanation for this finding may lie in the fact that relationship banks typically acquire information about their clients, which could extend to knowledge about their FX trading counterparties. Hence, using a platform cannot play the same signaling role for relationship trades as it does for non-relationship trades.

Ideally, we would control for unobserved client heterogeneity with client fixed effects to compare the cost of relationship trades to that of non-relationship trades for the same client. In our empirical setting, however, most clients conduct either all or none of their trades with a relationship dealer. Only 895 clients engage in both types of trades. These clients are generally more sophisticated than others, with an average *Sophistication* of 2.38, roughly corresponding to the 90th percentile of the cross-sectional distribution. Client fixed effects therefore absorb a significant amount of the variation in relationship trading. For the subset of clients that engage in both relationship and non-relationship trading, there is no difference in transaction costs, regardless of the level of client sophistication.

As an alternative to measuring relationships with respect to credit market interactions, we can also capture dealer-client relationships within the FX market. In particular, we compute the notional traded between client i and dealer d relative to client i's total notional traded. Regression results using this alternative measure of relationships are reported in the Online Appendix (Table A.4). Our findings are qualitatively consistent with those based on credit market interactions. Hence, our results cannot be attributed to the novelty of the main relationship measure.

In sum, our results paint a nuanced picture of the effects of relationship trading on transaction costs. In contrast to earlier research, we find that most clients pay a premium for trading with their relationship dealer. We attribute this finding to the predominance of low sophistication clients in our empirical setting. These clients are captive to their dealer, which extracts rents from the relationship, even when clients trade through a platform. Only highly sophisticated clients are able to extract discounts from their relationship dealers.

5.4 Information Rents from Asymmetric Price Adjustment

OTC derivatives markets generally lack price transparency. Consequently, there is an asymmetry between dealers and clients in their knowledge of the true mid-market price in real time. In line with Hypothesis 4, this can generate additional dealer rents though asymmetric price adjustment. The quantitative implications of asymmetric price adjustment for transaction costs should be greater in fast moving markets with elevated price volatility.

We test for the existence of such information rents immediately after changes in the market mid-price. If clients are not aware of such changes, they are more likely to accept outdated ("stale") quotes. Importantly, dealers can only exploit recent price changes when they occur in the opposite direction of the client's trading intention (i.e. when the mid-price movement benefits the client). This gives rise to asymmetric price adjustment. Using the definitions given in Equation 3.2 and Equation 3.3 for the alignment of recent mid-price changes and a client's trade direction, we estimate the following linear regression:

$$Spread_{i,d,\tau} = \beta_1 |\Delta m_\tau^{-d}| + \beta_2 |\Delta m_\tau^{+d}| + \beta_Z Z_\tau + \delta_d + \gamma_t + \gamma_m + \epsilon_\tau, \tag{5.3}$$

where the sum $\beta_1 + \beta_2$ represents dealers' rent under asymmetric price adjustment. The sum is zero in a frictionless market but positive under Hypothesis 4. Table 5, Column (1) shows that β_1 is indeed positive and statistically significant, indicating that dealers charge higher spreads when a trade is preceded by a price change in the opposite direction of the client order, compared to the case of no change in the mid-price in the preceding 30 seconds. However, we also find that β_2 is negative and statistically significant. This implies that clients typically enjoy lower spreads when their trade is preceded by a mid-price change in the same direction of the trade (as compared to a static mid-price). The latter finding suggests that stale quotes get "picked off" by clients, either deliberately or inadvertently. Importantly, however, the sum $\beta_1 + \beta_2 = 0.167$ is positive and significant at the 10% level. Hence, quote adjustment is asymmetric on average in a manner that generates positive dealer rents in fast moving OTC markets.

In Column (2), we control for client sophistication, which does not change our results qualitatively. Next, we test whether dealers' ability to extract information rents from asymmetric price adjustment varies with client sophistication. To this end, we interact $|\Delta m_\tau^{d}|$ and $|\Delta m_\tau^{-d}|$ with *Sophistication* in Column (3). The sum of the coefficients of these interaction terms is equal to -0.097 and is statistically significant at the 1% level. Hence, dealers' information rents from asymmetric price adjustment decrease in client sophistication. When trading with a client of average sophistication, dealers extract an average of 57.1% of the recent price change to their advantage. This drops to a statistically insignificant -8.9% when dealers trade with an average EURO STOXX 50 firm.

While our findings are consistent with dealers extracting additional information rents in fast moving markets, the economic magnitude of this rent is small. Price movements in the 30-second interval preceding trades rarely exceed 1 pip. Even though dealers earn a significant fraction of such price movements as rent when trading with unsophisticated clients, the dollar value of these rents is limited by market volatility. Consequently, time variations in information rents from asymmetric price adjustment are small relative to the static rents from price discrimination based on client sophistication.

It is also interesting to explore how platform trading alters information rents related to market volatility. We add the $RFQPlatform$ dummy in Column (4) and also interact it with $|\Delta m_\tau^d|$ and $|\Delta m_\tau^{-d}|$ in Column (5). Platform trading mitigates the average effect of asymmetric price adjustment. This highlights how RFQ platforms force dealers to compete away the rents that they earn under bilateral negotiation.

In sum, we find support for Hypothesis 4. Dealers extract additional information rents under elevated market price volatility, but only when trading bilaterally with unsophisticated clients. However, the economic magnitude of these rents is small compared to steady state price discrimination against unsophisticated clients.

6 Conclusion

For the first time, new regulatory derivatives data with counterparty identities allow a comprehensive analysis of transaction costs for non-financial clients in the FX derivatives market. Against the background of a global policy agenda on derivatives markets, careful measurement of market quality and the scale of price discrimination is currently scarce. We fill this gap and obtain four new findings.

First, OTC clients trade at very heterogeneous spreads. The corporate client at the 90th percentile of the spread distribution pays 52 pips over the competitive market mid-price. By contrast, one quarter of clients pay less than 2 pips. To identify price discrimination, we control for contract characteristics and dealer and time fixed effects. We find that spreads vary systematically with measures of client sophistication, as predicted by search models of OTC markets.

Second, the use of multi-dealer RFQ platforms eliminates price discrimination by forcing dealers to compete with each other. The largest benefits of platform use accrue to the least sophisticated clients. This occurs despite the fact that dealers know the identity of their clients when trading through RFQ platforms, unlike in an anonymous limit order book.

Third, we find that the effects of relationship trading vary with client sophistication. Less sophisticated clients pay a premium when using a relationship bank in their OTC trades, consistent with the idea that they are captive. By contrast, very sophisticated clients obtain a discount from their relationship bank compared to trades with other dealers.

Fourth, we document that dealers earn additional information rents in fast moving markets. In particular, changes in the mid-price trigger an asymmetric price adjustment whereby dealers do not fully pass on changes in the mid-price that should benefit the client. This asymmetric adjustment declines in client sophistication. In aggregate, however, these rents are small compared to those earned from discriminatory pricing against less sophisticated clients.

Overall, these findings suggest that the current OTC market structure can be made more efficient. While RFQ platforms appear effective at reducing dealers' market power, more than half of trades (conducted by almost 90% of clients) continue to be executed bilaterally. Accordingly, a move to mandatory platform trading would benefit less sophisticated clients and possibly induce additional firms with latent exchange rate exposure to participate in the market. Alternatively, enhanced post-trade transparency could raise client awareness about discriminatory OTC pricing and spur the adoption of RFQ platform trading.

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Table 1: Summary Statistics at Client and Transaction Level

Panel A: Client Data	Observations	Mean	St.Dev	p10	p25	p50	p75	p90
$AvClientSpread$	10,087	18.1	26.5	−2.9	2.1	14.3	33.9	52.4
$\#Counterparties$	10,087	1.8	2.0	1	1	1	2	3
HHI	10,087	0.8	0.3	0.1	0.6	1	1	1
$TotalNotional$ (in €mn)	10,087	515	7396	0.1	0.4	1.8	11.4	114
$\#TradesFX$	10,087	54	417	1	3	8	24	86
$\#TradesNonFX$	10,087	15	232	0	0	0	0	3
$Sophistication$	10,087	0	1.8	−1.7	−1.2	−0.5	0.7	2.4
$Relationship$	6,638	0.6	0.5	0	0	1	1	1
Panel B: Transaction Data	**Observations**	**Mean**	**St.Dev**	**p10**	**p25**	**p50**	**p75**	**p90**
$Spread$	548,298	6.9	19.4	−4.9	−1.1	2.0	11.3	31.0
$Notional$ (in €mn)	548,298	9.5	53.6	0.02	0.06	0.2	1.8	14
$Customization$	548,298	10.6	16.7	1	2	3	12	33
$Tenor$	548,298	69	80	2	9	35	96	188
$Volatility$	548,298	0.007	0.004	0.004	0.005	0.006	0.008	0.01
Buy	548,298	0.4	0.5	0	0	0	1	1
$RFQPlatform$	548,298	0.4	0.5	0	0	0	1	1
$\lvert\Delta m_\tau^{-d}\rvert$	548,298	0.5	1	0	0	0	1	1.5
$\lvert\Delta m_\tau^{+d}\rvert$	548,298	0.5	0.9	0	0	0	1	1.5

Note: Panel A shows client-level data for the 10,087 non-financial clients that trade at least one EUR/USD forward contract between April 2016 and March 2017, and Panel B shows transaction-level data for 548,298 EUR/USD individual trades. In Panel A, *AvClientSpread* is the average spread that a client pays on its trades. $\#Counterparties$ is the number of dealers with which a client interacts. HHI is the Herfindahl-Hirschman index of the degree of concentration of a client's counterparty relationships with dealers. $TotalNotional$ (in €mn) is the total notional traded by a client during the sample period. $\#TradesFX$ is the number of forward contracts traded by a client. $\#TradesNonFX$ is the total number of a client's outstanding interest rate, credit and commodity derivatives positions at the beginning of our sample period. *Sophistication* is the first principal component of *Log#Counterparties*, HHI, $LogTotalNotional$, $Log\#TradesFX$, and $Log\#TradesNonFX$. *Relationship* is the share of forwards that a client trades with its relationship bank(s). In Panel B, *Spread* is the difference (in pips) between the contractual forward rate and the mid-price. $Notional$ (in €mn) is the notional of each forward contract. $Tenor$ is the original maturity (in days). $Customization$ is the difference in days between the tenor of a forward contract and its nearest standard tenor (i.e. 0, 1, 7, 30, 60, 90, 180, 270, or 360 days). $Volatility$ is defined as the realized volatility of the FX spot rate over the preceding 30 minutes, based on one minute intervals. *Buy* is a dummy which equals one when a client forward-buys euro against dollar, and 0 otherwise. $RFQPlatform$ is a dummy equal to one when a trade occurs on an RFQ platform, and zero otherwise. $\lvert\Delta m_\tau^{-d}\rvert$ ($\lvert\Delta m_\tau^{+d}\rvert$) is the absolute value of the change in the mid-price over the preceding 30 seconds (in pips) if the price change was in the opposite (same) direction of the client order, and zero otherwise.

Table 2: Spreads and Client Sophistication (Hypothesis 1)

	(1)	(2)	(3)	(4)	(5)	(6)
Sophistication measures:						
Log#Counterparties	−3.872***					
	(0.225)					
HHI		8.798***				
		(0.681)				
LogTotalNotional			−1.556***			
			(0.074)			
Log#TradesFX				−1.783***		
				(0.099)		
Log#TradesNonFX					−1.011***	
					(0.105)	
Sophistication						−1.518***
						(0.079)
Contract characteristics:						
LogNotional	−0.620***	−0.481***	−0.303***	−1.101***	−0.789***	−0.608***
	(0.080)	(0.102)	(0.090)	(0.099)	(0.102)	(0.082)
LogTenor	1.144***	1.193***	0.947***	1.142***	1.224***	1.089***
	(0.094)	(0.096)	(0.090)	(0.091)	(0.095)	(0.091)
LogCustomization	0.991***	1.168***	0.900***	0.893***	1.048***	0.965***
	(0.107)	(0.128)	(0.104)	(0.107)	(0.119)	(0.108)
Volatility	7.592	6.185	4.138	3.756	9.966	5.219
	(16.401)	(16.344)	(16.516)	(16.141)	(16.252)	(16.277)
Buy	−6.500***	−6.764***	−6.187***	−6.388***	−6.644***	−6.393***
	(0.313)	(0.319)	(0.302)	(0.309)	(0.343)	(0.306)
R-squared	0.276	0.270	0.289	0.274	0.260	0.282
Observations	548,298	548,298	548,298	548,298	548,298	548,298
Dealer FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Minute of day FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports OLS regressions of the spread on measures of client sophistication. The sophistication measures and transaction controls are defined in the note to Table 1. One, two and three asterisks represent statistical significance at 10%, 5% and 1% respectively. Standard errors clustered at client level are reported in parentheses.

Table 3: Spreads and RFQ Platform Use (Hypothesis 2)

	(1)	(2)	(3)	(4)	(5)
$RFQPlatform$	−7.290***	−3.815***	−13.11***	−1.475***	−4.530***
	(0.472)	(0.433)	(0.634)	(0.272)	(0.923)
$Sophistication$		−1.202***	−1.926***		
		(0.089)	(0.080)		
$RFQPlatform \times Sophistication$			1.951***		0.505***
			(0.139)		(0.130)
R-squared	0.270	0.288	0.300	0.513	0.513
Observations	548,298	548,298	548,298	546,796	546,796
Client FE	No	No	No	Yes	Yes
Dealer FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Minute of day FE	Yes	Yes	Yes	Yes	Yes
Contract characteristics	Yes	Yes	Yes	Yes	Yes

Note: This table reports OLS regression estimations of spreads on $RFQPlatform$, which is a dummy equal to one for platform trades and zero otherwise. Each specification controls for dealer fixed effects, date and minute of day fixed effects, and contract characteristics (i.e. $LogNotional$, $LogTenor$, $LogCustomization$, $Volatility$, and Buy). In addition, Columns (4) and (5) control for client fixed effects. $Sophistication$ is the first principal component of $Log\#Counterparties$, HHI, $LogTotalNotional$, $Log\#TradesFX$, and $Log\#TradesNonFX$, which are defined in the note to Table 1. One, two and three asterisks represent statistical significance at 10%, 5% and 1% respectively. Standard errors clustered at client level are reported in parentheses.

Table 4: Spreads and Dealer-Client Relationships (Hypothesis 3)

	(1)	(2)	(3)	(4)	(5)
Relationship	2.939***	0.700	3.594***	3.439***	2.186***
	(0.656)	(0.606)	(0.821)	(0.805)	(0.829)
Sophistication		−1.730***	−1.340***	−0.896***	−1.764***
		(0.172)	(0.143)	(0.141)	(0.146)
Relationship × *Sophistication*			−1.097***	−1.070***	−0.666***
			(0.204)	(0.201)	(0.243)
$RFQPlatform$				−4.925***	−15.000***
				(0.514)	(1.019)
Relationship × $RFQPlatform$					0.473
					(1.025)
Sophistication × $RFQPlatform$					2.253***
					(0.185)
R-squared	0.285	0.311	0.314	0.320	0.328
Observations	278,491	278,491	278,491	278,491	278,491
Dealer FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Minute of day FE	Yes	Yes	Yes	Yes	Yes
Contract characteristics	Yes	Yes	Yes	Yes	Yes

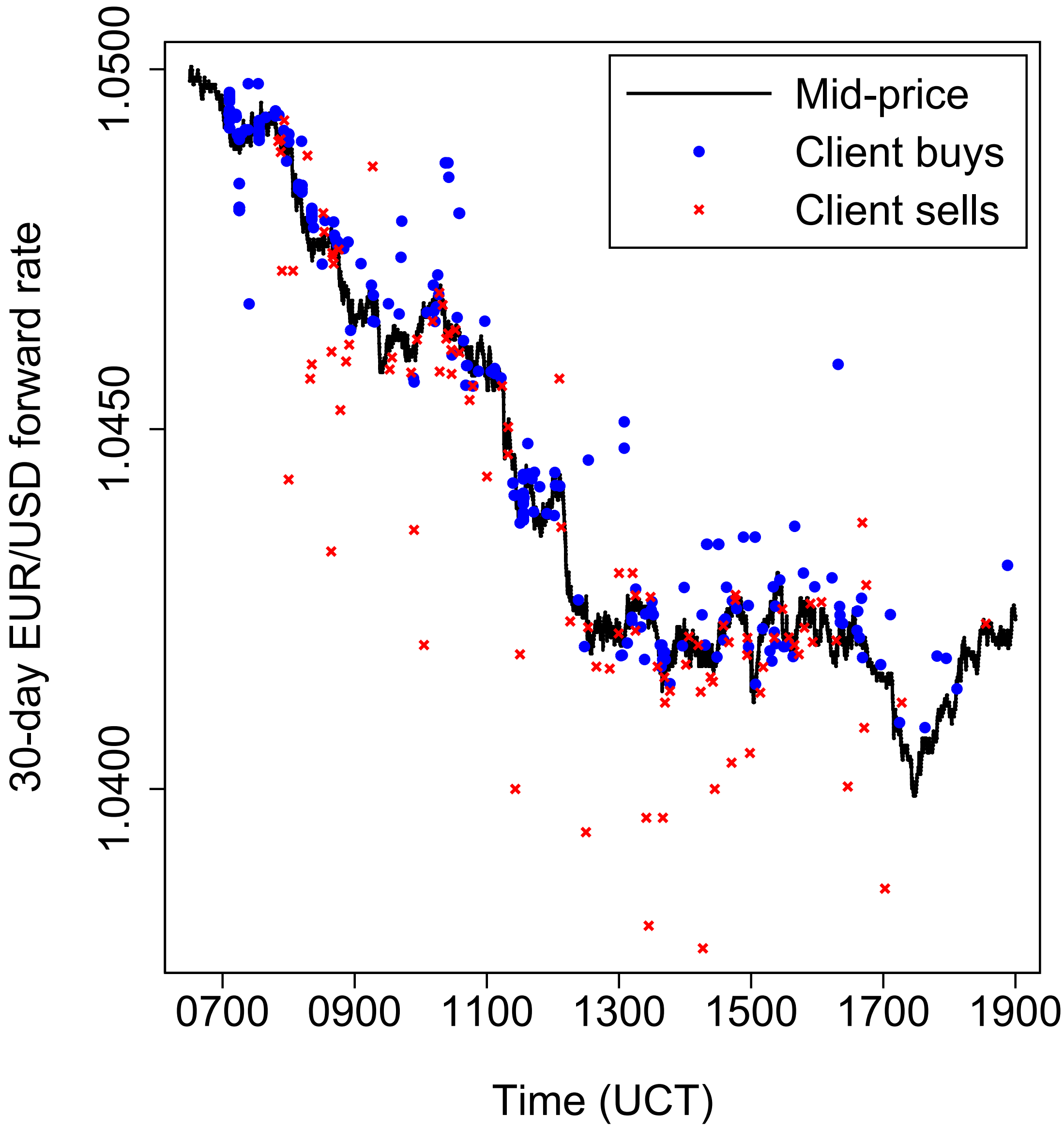
Note: This table reports OLS regression estimations of spreads on dealer-client relationships, defined as a transaction-level dummy that takes the value of one when a client trades with its relationship bank(s), and zero otherwise. In Columns (3)-(5), we interact this measure with *Sophistication*, which is the first principal component of *Log#Counterparties*, HHI, $LogTotalNotional$, $Log\#TradesFX$, and $Log\#TradesNonFX$. Column (5) adds interactions with $RFQPlatform$. Each specification controls for dealer fixed effects, date and minute of day fixed effects, and contract characteristics (i.e. $LogNotional$, $LogTenor$, *LogCustomization*, $Volatility$, and *Buy*). One, two and three asterisks represent statistical significance at 10%, 5% and 1% respectively. Standard errors clustered at client level are reported in parentheses.

Table 5: Information Rents from Asymmetric Price Adjustment (Hypothesis 4)

	(1)	(2)	(3)	(4)	(5)
$\lvert\Delta m_\tau^{-d}\rvert$	0.409***	0.410***	0.658***	0.660***	0.647***
	(0.050)	(0.054)	(0.075)	(0.075)	(0.074)
$\lvert\Delta m_\tau^{d}\rvert$	−0.243***	−0.236***	−0.100	−0.093	−0.142*
	(0.052)	(0.052)	(0.083)	(0.083)	(0.084)
Sophistication		−1.518***	−1.470***	−1.152***	−1.896***
		(0.079)	(0.084)	(0.094)	(0.082)
$\lvert\Delta m_\tau^{-d}\rvert \times$ *Sophistication*			−0.062***	−0.065***	−0.012
			(0.016)	(0.015)	(0.016)
$\lvert\Delta m_\tau^{d}\rvert \times$ *Sophistication*			−0.035**	−0.037**	−0.051**
			(0.016)	(0.015)	(0.021)
$RFQPlatform$				−3.810***	−12.960***
				(0.434)	(0.623)
$\lvert\Delta m_\tau^{-d}\rvert \times RFQPlatform$					−0.530***
					(0.084)
$\lvert\Delta m_\tau^{d}\rvert \times RFQPlatform$					0.246**
					(0.104)
Sophistication $\times RFQPlatform$					1.952***
					(0.139)
R-squared	0.246	0.283	0.283	0.288	0.300
Observations	548,298	548,298	548,298	548,298	548,298
Dealer FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Minute of day FE	Yes	Yes	Yes	Yes	Yes
Contract characteristics	Yes	Yes	Yes	Yes	Yes

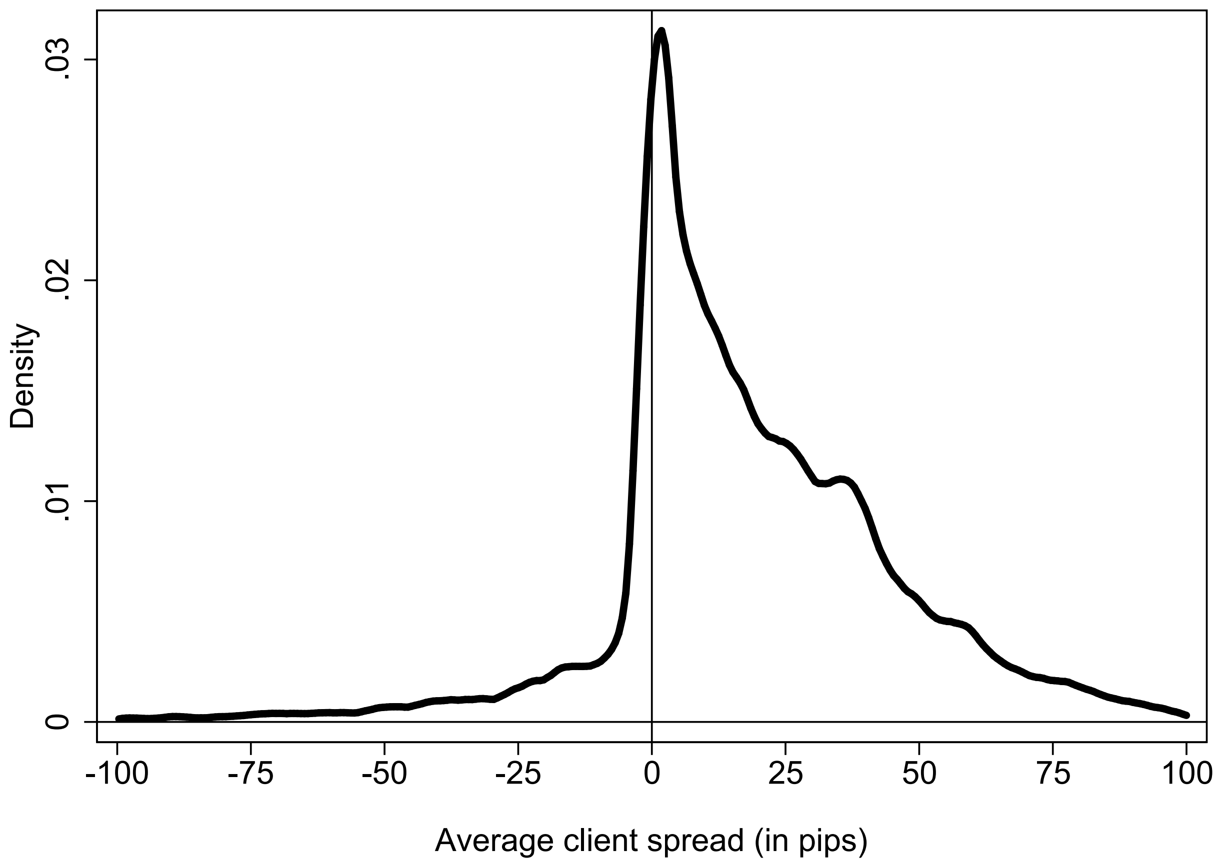
Note: This table reports OLS regression estimations of spreads on measures of price staleness. $\lvert\Delta m_\tau^{-d}\rvert$ ($\lvert\Delta m_\tau^{+d}\rvert$) is the absolute value of the change in the mid-price over the preceding 30 seconds (in pips) if the price change was in the opposite (same) direction of the client order, and zero otherwise. Each specification controls for dealer fixed effects, date and minute of day fixed effects, and contract characteristics (i.e. $LogNotional$, $LogTenor$, $LogCustomization$, $Volatility$, and *Buy*). In addition, Columns (2)-(5) control for *Sophistication*, which is the first principal component of $Log\#Counterparties$, HHI, $LogTotalNotional$, $Log\#TradesFX$, and $Log\#TradesNonFX$. Columns (4) and (5) control for $RFQPlatform$, which is a dummy equal to one when a transaction was requested on an RFQ platform, and zero otherwise. One, two and three asterisks represent statistical significance at 10%, 5% and 1% respectively. Standard errors clustered at client level are reported in parentheses.

Figure 1: Contracted Forward Rates versus the Mid-Price



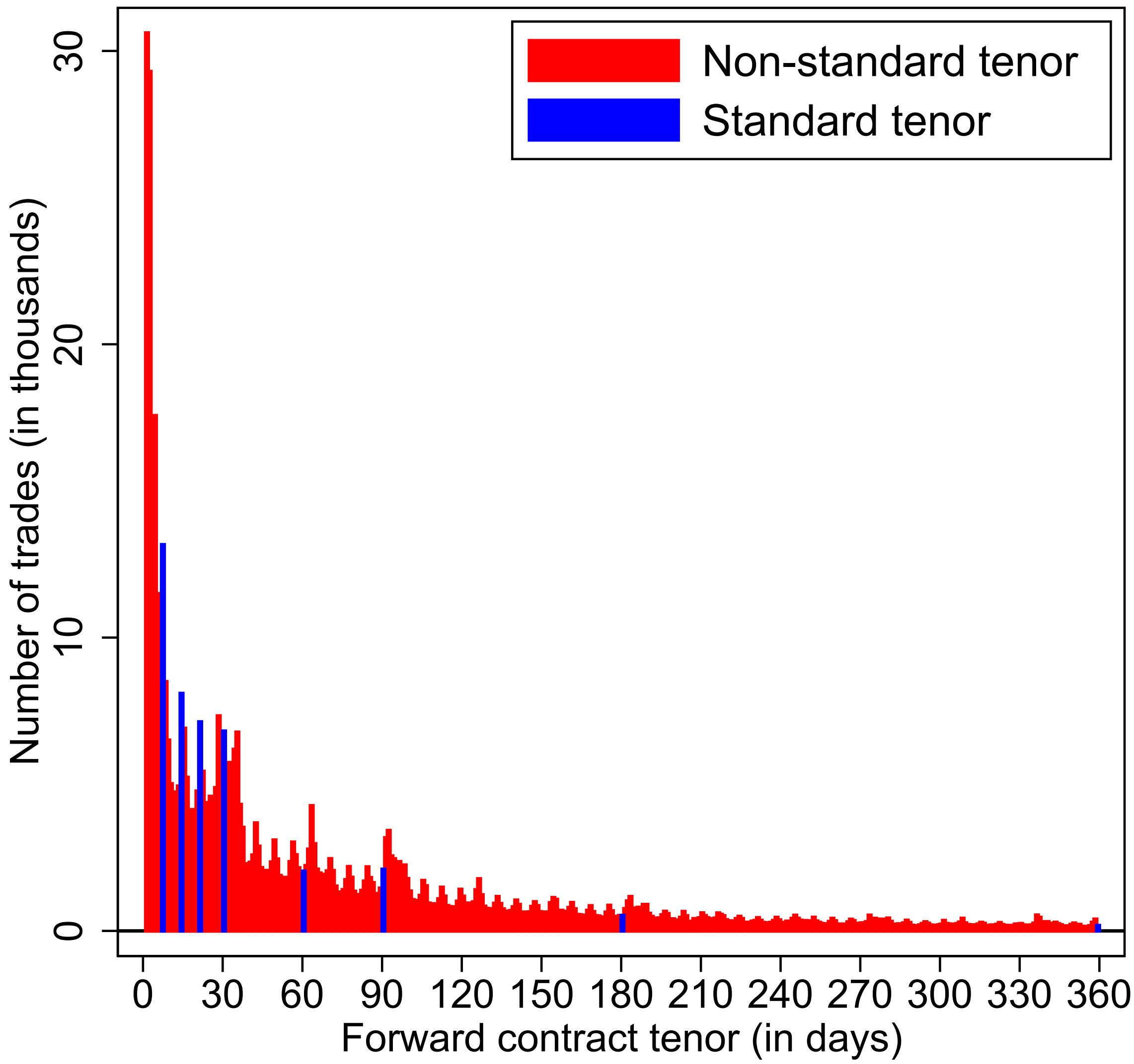
Note: This figure plots contractual forward rates versus the mid-price on a single day (28 December 2016). The mid-price is shown by the solid black line, which tracks intraday mid-prices for 30-day EUR/USD forward contracts (constructed from Thomson Reuters interdealer quote data). To approximately match this 30-day mid-price, we only depict contracts with an original maturity of between 25 and 35 days. Client long and short positions are indicated by blue dots and red crosses, respectively. Blue dots (red crosses) above (below) the solid black line imply that the client pays a positive spread.

Figure 2: Distribution of Average Client Spread



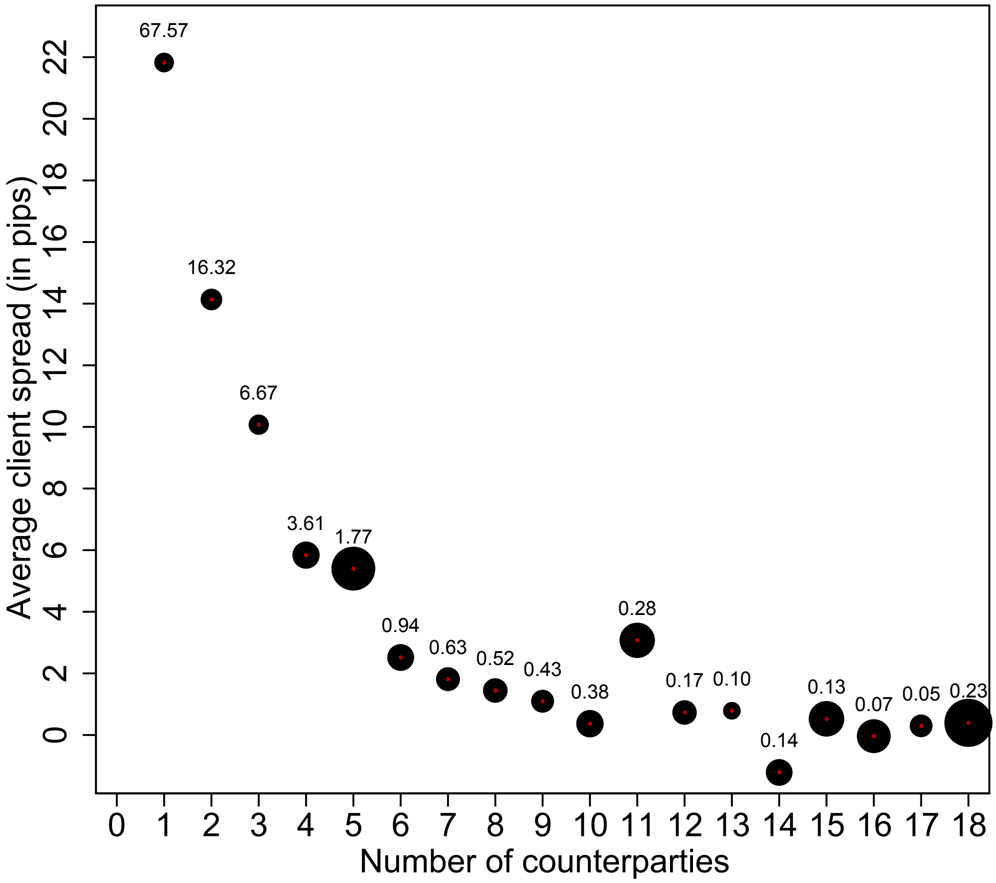
Note: This figure plots the cross-sectional distribution of average client spreads, based on 548,298 EUR/USD forward transactions between 10,087 clients and 204 dealers. The sample period is April 1, 2016 to March 31, 2017. Positive spreads are costly to the client and advantageous to the dealer.

Figure 3: Trade Distribution by Tenor



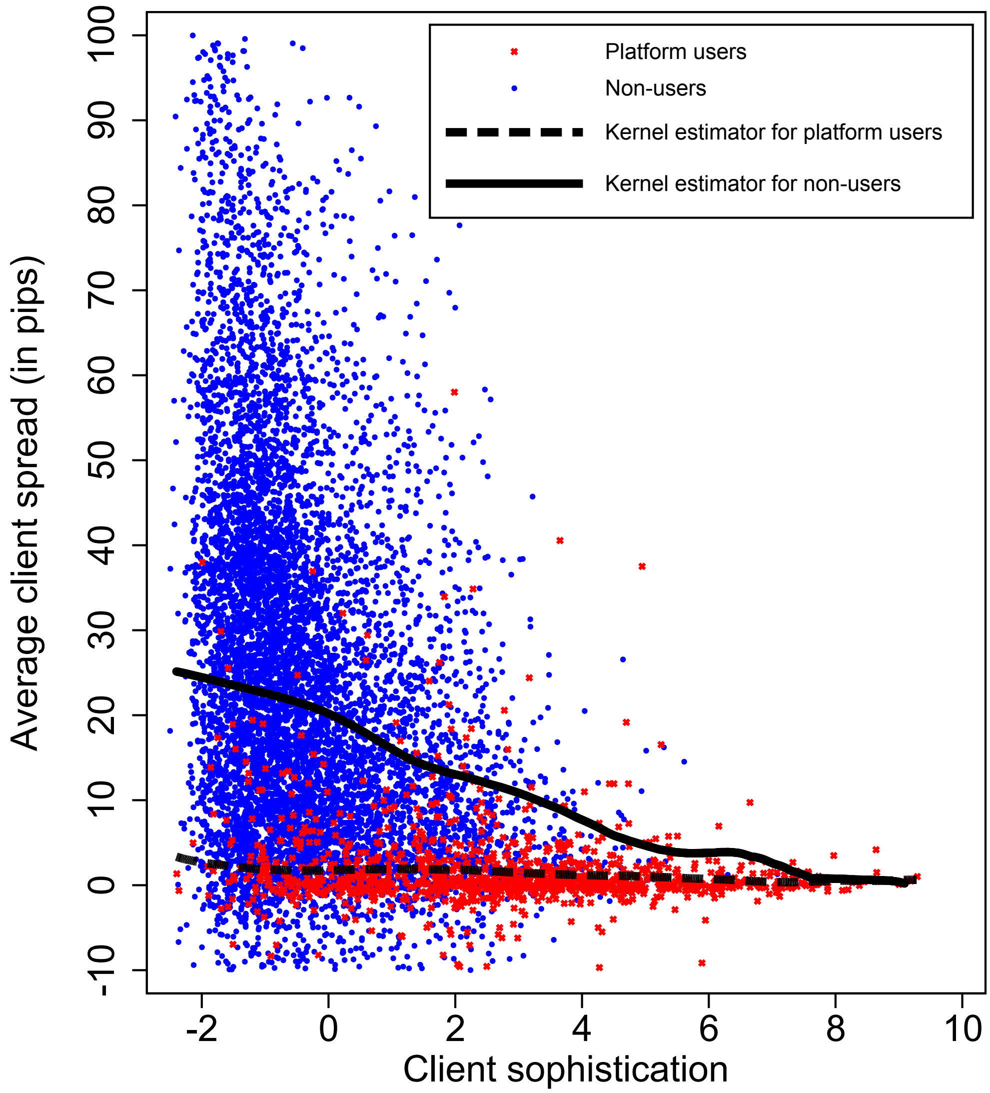
Note: This figure plots the distribution of contract tenors (in days) for all 548,298 EUR/USD forwards traded between dealers and clients over April 1, 2016 to March 31, 2017. Blue bars denote trades at standard tenors, i.e. 7, 14, 21, 30, 60, 90, 180, and 360 days, and red bars denote trades at non-standard tenors.

Figure 4: Average Client Spread by Number of Dealer Counterparties



Note: This figure plots the average spread paid by clients with a given number of dealer counterparties in the EUR/USD forwards market. Marker size is proportional to aggregate notional traded. Marker labels indicate the percentage of clients with a given number of dealer counterparties. For readability, the 18 counterparty group aggregates all clients with 18 or more counterparties.

Figure 5: Average Client Spread by Sophistication and Platform Use



Note: This figure plots the average spread paid by each client (on the vertical axis) against *Sophistication* (on the horizontal axis). *Sophistication* is the first principal component of *Log#Counterparties*, *HHI*, *LogTotalNotional*, *Log#TradesFX*, and *Log#TradesNonFX*. Clients using an RFQ platform at least once in our sample period are colored red; clients that never use a platform are colored blue. The solid black line plots the estimated Kernel-weighted local polynomial regression of average client spread on *Sophistication* for the subset of clients that never trade through a platform. The dashed black line plots the same regression for the subset of clients that trade through a platform at least once during our sample period. For readability, the vertical axis is truncated at -10 pips.

Online Appendix

Table A.1: Client and Transaction Characteristics by Sophistication and Platform Use

	Low Sophistication			Medium Sophistication			High Sophistication		
RFQ Platform User	Yes	No	Diff	Yes	No	Diff	Yes	No	Diff
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Client Data									
AvClientSpread	4.2	25.6	21.4***	1.1	20.4	19.3***	1.4	13.1	11.7***
#Counterparties	1.0	1.0	0.0	1.0	1.1	0.1***	5.4	2.5	2.9***
HHI	1.0	1.0	0.0	1.0	0.9	0.1***	0.3	0.5	0.2***
TotalNotional (in €mn)	1.9	0.5	1.4***	37	7	30***	4704	147	4557***
#TradesFX	1.9	2.7	0.8***	10	17	7***	302	74	228***
#TradesNonFX	0.11	0.09	0.02	2.41	0.52	1.89	100	18	82***
Sophistication	−1.44	−1.48	0.04**	−0.44	−0.49	0.05**	3.4	1.4	2***
Observations	61	3,301		131	3,231		1,026	2,337	
Panel B: Transaction Data									
Spread	4.0	27.8	23.8***	−0.1	21.7	21.8***	1.2	11.3	10.1***
Notional (in €mn)	1.0	0.2	0.8***	3.6	0.4	3.2***	15.6	2.0	13.6***
Tenor	55	91	36***	56	96	40***	58	78	20***
Customization	8.1	13.8	5.7***	7.7	15.2	7.5***	8.9	12.1	3.2***
Volatility	0.007	0.007	0.0	0.0066	0.0073	0.0007***	0.0070	0.0071	0.0001***
Buy	0.5	0.3	0.2***	0.6	0.3	0.3***	0.5	0.4	0.1***
Observations	117	9,029		1,344	54,411		309,526	173,871	

Note: The table sorts clients into two groups. The first relates to client sophistication: low, medium and high sophistication clients are in the bottom, middle and top third of the distribution respectively. The second sort is on whether a client uses an RFQ platform at least once in our sample period. The table reports mean values for all variables. Columns (3), (6), and (9) report mean differences and mark their statistical significance using a non-parametric Wilcoxon test. In Panel A, which reports client-level data, *AvClientSpread* is the average spread that a client pays on its trades with dealers. *#Counterparties* is the number of dealers with which a client trades. HHI is the Herfindahl-Hirschman index of the degree of concentration of a client's counterparty relationships with dealers. $TotalNotional$ (in €mn) is the total notional traded by a client during the sample period. $\#TradesFX$ is the number of EUR/USD forwards traded by a client. $\#TradesNonFX$ is the total number of a client's outstanding interest rate, credit and commodity derivatives positions at the beginning of our sample period. *Sophistication* is the first principal component of $Log\#Counterparties$, HHI, $LogTotalNotional$, $Log\#TradesFX$, and $Log\#TradesNonFX$. In Panel B, which reports transaction-level data, *Spread* is the difference (in pips) between the contractual forward rate and the mid-price. $Notional$ (in €mn) is the notional of each forward contract. $Tenor$ is a trade's original maturity (in days). $Customization$ is the difference in days between the tenor of a forward contract and its nearest standard tenor (i.e. 0, 1, 7, 30, 60, 90, 180, 270, or 360 days). $Volatility$ is defined as the realized volatility of the FX spot rate over the preceding 30 minutes, based on one minute intervals. *Buy* is a dummy which equals one when a client forward-buys euro against dollar, and 0 otherwise.

Table A.2: Clients by Location and Sector

	Number of clients	Share (%)	Total notional (in €mn)	Share (%)	*Sophistication* (mean)	*Spread* (mean)
Panel A: Client Location						
Germany	3,501	42.4	761,291	17.3	−0.3	27.8
France	941	11.4	999,971	22.7	0.1	8.6
Netherlands	724	8.8	249,064	5.7	−0.1	19.5
Spain	538	6.5	56,985	1.3	0.1	1.4
Italy	459	5.6	135,086	3.1	−0.3	8.5
United States	321	3.9	1,127,073	25.6	1.7	3.4
Belgium	318	3.8	115,415	2.6	−0.1	15.5
United Kingdom	275	3.3	201,877	4.6	0.6	9.6
Austria	158	1.9	33,821	0.8	−0.1	22.1
Portugal	129	1.6	885	0.0	0.0	13.6
All other locations	899	10.9	723,763	16.4	0.4	15.1
Panel B: Client Sector						
Wholesale trade	3,324	40.2	196,281	4.5	−0.3	21.9
Machinery and equipment	408	4.9	414,578	9.4	0.1	15.8
Retail trade	328	4.0	41,992	1.0	−0.3	24.8
Head offices and consultancy	317	3.8	176,961	4.0	0.6	12.0
Food products	289	3.5	134,440	3.1	0.4	15.3
Computers, electronics, optics	226	2.7	294,441	6.7	0.4	15.3
Financial service activities	190	2.3	69,492	1.6	0.5	9.9
Metal products, except machinery	190	2.3	18,543	0.4	−0.3	22.1
Chemicals and chemical products	188	2.3	246,268	5.6	0.6	15.2
Travel agencies	170	2.1	11,800	0.3	−0.9	32.7
All other sectors	2,633	31.9	2,800,435	63.6	0.3	14.4

Note: The table reports summary statistics for clients by location and sector. In Panel A, clients are grouped according to their main location of operations at the parent level. In Panel B, clients are grouped by their sector according to the second (two-digit) level of NACE Rev 2, which is the statistical classification of economic activity in the European Community, based on standards set by the UN Statistical Commission (ISIC Rev 4). For each group, the table reports the number of clients (also as a share of the 8,263 clients for which we have country and sector information), the total notional (also as a share), and the group-level averages of *Sophistication* and *Spread*. Both panels report the 10 most populous categories, as well as an "other" category which aggregates all countries and sectors below the top 10.

Table A.3: Spreads and RFQ Platform Use (Alternative Sample)

	(1)	(2)	(3)	(4)	(5)
$RFQPlatform$	−9.031***	−8.261***	−9.370***	−9.551***	−13.320***
	(1.240)	(1.284)	(1.176)	(4.049)	(4.208)
$Sophistication$		−4.685***	−4.853***		
		(0.384)	(0.415)		
$RFQPlatform \times Sophistication$			1.957***		2.851***
			(1.025)		(1.218)
R-squared	0.319	0.335	0.335	0.595	0.596
Observations	122,968	122,968	122,968	121,637	121,637
Client FE	No	No	No	Yes	Yes
Dealer FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Minute of day FE	Yes	Yes	Yes	Yes	Yes
Contract characteristics	Yes	Yes	Yes	Yes	Yes

Note: This table reports OLS regression estimations of spreads on $RFQPlatform$, which is a dummy equal to one for platform trades and zero otherwise. Compared with Table 3, this table is restricted to the 6,816 clients that trade with only one dealer. Each specification controls for dealer fixed effects, date and minute of day fixed effects, and contract characteristics (i.e. $LogNotional$, $LogTenor$, $LogCustomization$, $Volatility$, and Buy). In addition, Columns (4) and (5) control for client fixed effects. $Sophistication$ is the first principal component of $Log\#Counterparties$, HHI, $LogTotalNotional$, $Log\#TradesFX$, and $Log\#TradesNonFX$, which are defined in the note to Table 1. One, two and three asterisks represent statistical significance at 10%, 5% and 1% respectively. Standard errors clustered at client level are reported in parentheses.

Table A.4: Spreads and Dealer-Client Relationships (Alternative Definition)

	(1)	(2)	(3)	(4)	(5)
Relationship	9.790***	2.724***	8.385***	7.763***	2.081*
	(0.662)	(0.884)	(0.947)	(0.948)	(1.196)
Sophistication		−1.232***	−0.463***	−0.218*	−1.485***
		(0.118)	(0.129)	(0.127)	(0.150)
Relationship × *Sophistication*			−1.926***	−1.942***	−0.997***
			(0.228)	(0.233)	(0.249)
$RFQPlatform$				−3.732***	−14.590***
				(0.422)	(1.453)
Relationship × $RFQPlatform$					4.040**
					(1.753)
Sophistication × $RFQPlatform$					1.933***
					(0.207)
R-squared	0.273	0.283	0.290	0.295	0.301
Observations	548,298	548,298	548,298	548,298	548,298
Dealer FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Minute of day FE	Yes	Yes	Yes	Yes	Yes
Contract characteristics	Yes	Yes	Yes	Yes	Yes

Note: This table reports OLS regression estimations of spreads on dealer-client relationships. Compared with Table 4, *Relationship* is defined as the notional traded in EUR/USD forwards between a client and dealer relative to the total EUR/USD notional traded by the same client. In Columns (3)-(5), we interact this measure with *Sophistication*, which is the first principal component of *Log#Counterparties*, HHI, $LogTotalNotional$, $Log\#TradesFX$, and $Log\#TradesNonFX$. Column (5) adds interactions with $RFQPlatform$. Each specification controls for dealer fixed effects, date and minute of day fixed effects, and contract characteristics (i.e. $LogNotional$, $LogTenor$, $LogCustomization$, $Volatility$, and *Buy*). One, two and three asterisks represent statistical significance at 10%, 5% and 1% respectively. Standard errors clustered at client level are reported in parentheses.

Table A.5: Spreads and Client Counterparty Credit Risk

	(1)	(2)	(3)	(4)
$Sophistication$	-1.467^{***}	-1.468^{***}	-1.560^{***}	-1.557^{***}
	(0.113)	(0.110)	(0.110)	(0.110)
$LogTenor$	0.936^{***}	-0.095	0.932^{***}	0.945^{***}
	(0.095)	(0.166)	(0.094)	(0.095)
$ZScore$	0.043	-1.521^{***}		
	(0.135)	(0.285)		
$ZScore \times LogTenor$		0.450^{***}		
		(0.080)		
$CashFlowVol$			-0.216	-0.644^{*}
			(0.212)	(0.340)
$CashFlowVol \times LogTenor$				0.151
				(0.138)
R-squared	0.246	0.250	0.255	0.256
Observations	331,388	331,388	359,443	359,443
Dealer FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Minute of day FE	Yes	Yes	Yes	Yes
Contract characteristics	Yes	Yes	Yes	Yes

Note: This table reports OLS regression estimations of spreads on measures of client risk. $ZScore$ is a client's modified Altman Z-score, calculated as the linear combination of working capital, retained earnings, profits, and sales. $CashFlowVol$ is a client's standardized coefficient of variation of cash flows. In Columns (2) and (4), we interact these measures with $LogTenor$, which denotes the natural logarithm of a contract's original maturity (in days). One, two and three asterisks represent statistical significance at 10%, 5% and 1% respectively. Standard errors clustered at client level are reported in parentheses.