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Discriminatory pricing of over-the-counter derivatives

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Abstract

New regulatory data reveal extensive discriminatory pricing in the foreign exchange derivatives market, in which dealer-banks and their non-financial clients trade over-the-counter. After controlling for contract characteristics, dealer fixed effects, and market conditions, we find that the client at the 75th percentile of the spread distribution pays an average of 30 pips over the market mid-price, compared to competitive spreads of less than 2.5 pips paid by the bottom 25% of clients. Higher spreads are paid by less sophisticated clients. However, trades on multi-dealer request-for-quote platforms exhibit competitive spreads regardless of client sophistication, thereby eliminating discriminatory pricing.

JEL Codes: G14, G18, D4

Keywords: dealer spreads, information rents, RFQ platforms, corporate hedging

1 Introduction

At the G20 summit in Pittsburgh in 2009, governments agreed that all standardized over-the-counter (OTC) derivatives contracts should be centrally cleared and traded on exchanges or electronic trading platforms. Yet this international agreement has been only partially implemented (Financial Stability Board, 2016). Relative to interest rate and credit derivatives, reform of the market for foreign exchange (FX) derivatives has fallen particularly short of the Pittsburgh agenda (Duffie, 2011). This paper evaluates the implications of the current OTC market structure for non-financial firms. We document extensive discriminatory pricing by dealers with respect to their non-financial clients, analyze the determinants of price discrimination, and quantify the effect of request-for-quote (RFQ) multi-dealer electronic trading platforms on lowering spreads. Our analysis can inform future regulatory reform of FX derivatives markets, which have hitherto been subject to little academic inquiry, despite their large size and importance for both the financial sector and the real economy.

The FX derivatives market provides a rich setting in which to study discriminatory pricing. This market features significant participation by non-financial firms; unlike participants in other OTC markets, these firms are heterogeneous in their financial sophistication, ranging from large multinational corporations to small import-export firms. Anecdotal evidence from the industry suggests that some clients simply do not know whether the spreads they pay are competitive—an information deficit that dealers could exploit to their advantage.[1] At the same time, participation in the FX derivatives market is important for firms' risk management. 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).[2]

Our analysis draws on new data available under the European Market Infrastructure Regulation (EMIR), which forms the largest transaction-level dataset on derivatives available globally. In this dataset, we observe the identity of both counterparties to each trade, as well as the contract characteristics. Focusing on EUR/USD forward contracts executed between April 1, 2016

[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.

[2] In a media interview following Monarch's bankruptcy, the newly appointed administrator referred to the "very material impact" arising from the exchange rate movement of sterling against the US dollar (see "Monarch Airlines goes bust", Reuters, October 2, 2017, available at: https://goo.gl/YR7Q7P).

and March 31, 2017, we analyze approximately half a million trades between 204 dealers and 10,062 of their non-financial clients. For each transaction, we compute the spread as the difference between the contractual forward rate and the mid-price from Thomson Reuters Tick History (TRTH). This allows us to compare execution quality across clients, conditional on contract characteristics.

We obtain four main findings. First, transaction spreads across clients are highly heterogeneous. Conditional on contract characteristics, dealer fixed effects, and market conditions, the client at the 75th percentile of the spread distribution pays an average of 30 pips over the market mid-price. This compares to competitive spreads of less than 2.5 pips paid by the bottom 25% of clients.

What accounts for this high dispersion in spreads? Our second finding is that less sophisticated clients— those with fewer counterparties, lower annual trading volumes, and fewer FX and non-FX contracts—pay substantially higher average spreads for the same contracts than more sophisticated clients. These proxies of client sophistication account for approximately 20% of the variation in average client spreads spanned by client fixed effects. The existing OTC market structure therefore subjects unsophisticated clients to substantial rent extraction by their dealers. This is consistent with search models such as Duffie, Gârleanu & Pedersen (2005), which predict that transaction costs decrease with client sophistication.

Third, we explore the effect of multi-dealer RFQ platforms. These platforms allow clients to request quotes from multiple dealers simultaneously. We find that trades which are executed via RFQ platforms feature competitive spreads, regardless of the sophistication of the client operating on the platform. This finding suggests that the use of more centralized electronic trading can eliminate the discriminatory pricing that exists in the current market structure.

Fourth, we find evidence that dealers are able to extract information rents. The OTC FX derivatives market is opaque, since there is no centralized dissemination of transaction prices. Consequently, dealers' superior information on prices puts them at an advantage relative to clients, for which information collection is more costly. Dealers exploit this information advantage by not passing on recent changes in the mid-price that would otherwise be to the benefit of the client. Interestingly, these information rents are not observed for trades on multi-dealer RFQ platforms.

We explore three further hypotheses that could account for variation in average client spreads. First, the *Relationship Hypothesis* posits that trades between clients and dealers with established relationships occur at more favorable forward rates. Yet we find no evidence that client-dealer relationships are associated with lower spreads; instead, we find some evidence for higher spreads. Second, the *Credit Risk Hypothesis* predicts that less creditworthy clients pay higher spreads. Changes in the market value of FX forwards can lead to counterparty credit risk. However, we find no evidence that client credit risk affects the pricing of FX forwards. Finally, the *Customization Hypothesis* suggests that non-standard contracts should trade at higher spreads. We measure customization as the distance in days between contracted maturity and the closest standard maturity, and indeed find that more non-standard maturities command higher spreads.

Related Literature

Our work contributes to the literature on OTC markets. In these markets, prospective counterparties must search for trading opportunities (Duffie et al., 2005).[3] Moreover, OTC markets are typically opaque as price information is not disseminated publicly, either before or after trade execution (Duffie, 2012). These frictions—namely search costs and opacity—give rise to imperfect competition. If these frictions are heterogeneous across OTC market participants, discriminatory pricing emerges as an equilibrium outcome.

Previous empirical studies provide some evidence regarding price variation in other OTC markets. Early contributions document that spreads are decreasing with trade size (see, for example, Schultz (2001), Harris & Piwowar (2006) and Green, Hollifield & Schürhoff (2007) for evidence on bond markets). More recently, O'Hara, Wang & Zhou (2018) examine the spreads paid by insurance companies trading corporate bonds, and find that more active insurance companies receive better prices for corporate bonds compared to less active insurers. In the FX spot market, Osler, Bjonnes & Kathitziotis (2016) use transaction data from a single bank to show that non-financial firms pay larger spreads than institutional investors. By contrast, the focus of our analysis is on heterogeneous execution quality within the group of non-financial firms.

The transaction data used in prior empirical studies typically do not identify counterparties, which limits inference about the determinants of price discrimination. In addition, most OTC markets, notably the bond market, are dominated by institutional investors, where even

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

relatively small market participants are reasonably sophisticated investors, whose primary expertise relates to the market in which they operate. In contrast, many of the clients trading FX derivatives are financially unsophisticated. This renders them susceptible to price discrimination.

Another strand of the literature uses event studies to examine the effect of OTC bond market 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. Public transaction records allow clients to verify the execution quality of their trades, thereby mitigating information asymmetries.

In spite of their considerable size, derivatives markets have been subject to little empirical analysis. A notable exception is Loon & Zhong (2014, 2016), who examine the effect of centralized clearing and enhanced post-trade transparency in the CDS market, and find positive effects on market liquidity In addition, Benos, Payne & Vasios (2016) analyze interest rate swap transactions recorded by the London Clearing House (LCH). They find that pre-trade transparency due to mandatory execution in Swap Execution Facilities (SEFs) increased market liquidity and lowered transaction costs. However, their data do not allow for the identification of individual market participants, and thus cannot shed light on the relationship between counterparty characteristics and price discrimination. Also related to our paper, Du, Gadgil, Gordy & Vega (2016) examine counterparty risk in CDS and show that it is priced, although the economic magnitude is small.

Our paper also relates to the literature on corporate hedging. Nance, Smith & Smithson (1993) argue that larger clients are more likely to hedge their currency risk because they benefit from scale economies of market participation. Yet the source of these scale economies is not elucidated. Guay & Kothari (2003) also show that larger clients engage more in derivatives activities, but that the magnitude of their positions tends to be small. Our analysis sheds light on these results: we document that more sophisticated clients with superior scale economies generally pay lower spreads.

2 Hypotheses

In this section, we articulate six hypotheses about the determinants of spreads on FX derivatives. Our first hypothesis relates to the theoretical literature on OTC markets. Duffie et al. (2005) show that dealers charge lower mark-ups to more sophisticated clients. In their model, clients with better (or faster) access to alternative dealers pay lower transaction costs. Intuitively, the ability to turn quickly to another counterparty exposes dealers to "sequential competition", inducing them to offer more competitive spreads. In addition, some clients have more bargaining power than others, resulting in better terms of trade. For example, larger trades are more profitable to dealers and can therefore results in price concessions. Also, some clients can devote more resources to eliminating the informational advantage of dealers, for example by purchasing real-time data feeds. We summarize these arguments in the following hypothesis.

Hypothesis 1: Client Sophistication

More sophisticated clients trade at lower spreads.

Besides client sophistication, the trading mechanism can matter for execution quality. Traditionally, most FX forwards were negotiated bilaterally, elevating search costs for all prospective clients. More recently, the advent of electronic trading has given rise to platforms on which clients can request quotes from multiple dealers simultaneously. Evidence from other markets suggests that such RFQ platforms reduce search costs, forcing dealers to compete with each other (Flood, Huisman, Koedijk & Mahieu, 1999; Hendershott & Madhavan, 2015). We therefore expect that the use of RFQ platforms is associated with a reduction in spreads. In addition, we expect that the least sophisticated clients see the largest decrease in spreads, as they have the most to gain from a more competitive trading environment. This gives rise to our second hypothesis:

Hypothesis 2: RFQ Platforms

Trades executed via RFQ platforms exhibit lower spreads. The spread reduction is larger for less sophisticated clients.

OTC markets are opaque, and sometimes referred to as "dark markets" (Duffie, 2012). Unlike in centralized markets, there is typically no obligation for dealers to disclose prices or quotes publicly. Freely available real-time mid-prices are not available for FX forwards. This gives rise to an information asymmetry between dealers and clients. While dealers can infer price information from their frequent interactions in inter-dealer and dealer-to-client markets, clients are generally less well informed about the prevailing mid-price, particularly after sudden price movements.[4] Therefore, we expect dealers to earn information rents around mid-price changes through an asymmetric price adjustment. Consider for example a dealer that is approached by a client just after the EUR/USD forward rate has increased. For a client buy order, the dealer will base its quote on the updated market price. However, for a client sell order, the dealer has an incentive to offer a quote based on the outdated lower price. 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). Taken together, 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 is common 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). Moreover, we can test whether these information rents are reduced or even eliminated through enhanced competition on RFQ platforms.

Hypothesis 3: Information Rents

Dealers earn information rents through asymmetric price adjustment. Client orders in the opposite direction of recent price changes incur higher spreads than trades in the same direction. Multi-dealer RFQ platforms reduce these information rents.

Empirical research on trading networks highlights that most market participants concentrate their trading in relatively few counterparties.[5] Consistent with preferential treatment, Cocco et al. (2009) document relationship discounts in the Portuguese interbank market. In a similar vein, Hendershott et al. (2016) develop and test a model where dealers grant better prices to relationship clients to retain future business. Di Maggio et al. (2017) study a large dealer in the US corporate bond market and show that existing relationships are not easily substitutable. These insights motivate our fourth hypothesis.

[4]One way to reduce information frictions is to publish benchmark prices, which are available for a number of OTC markets. Duffie, Dworczak & Zhu (2017) show how the use of such benchmarks can raise welfare.

[5]See Cocco, Gomes & Martins (2009) and Afonso, Kovner & Schoar (2013) for evidence regarding the overnight interbank market; Hendershott, Li, Livdan & Schürhoff (2016) and Di Maggio, Kermani & Song (2017) for the corporate bond market; and Abad, Aldasoro, Aymanns, D'Errico, Rousova, Hoffmann, Langfield, Neychev & Roukny (2016) for three different derivatives markets, including FX.

Hypothesis 4: Client-Dealer Relationships

Client-dealer relationships are associated with lower spreads.

Next, we consider the role of counterparty credit risk in the pricing of FX derivatives. The bilateral nature of these transactions exposes counterparties to counterparty credit risk. However, in CDS markets, Arora, Gandhi & Longstaff (2012) and Du et al. (2016) find that the role of counterparty risk in the pricing of contracts is extremely low. Despite this, the exemption of FX derivatives from central clearing requirements can imply that there remains a role for counterparty credit risk in these markets (Duffie, 2017). The absence of central clearing from FX derivatives markets provides the foundation for our fifth hypothesis:

Hypothesis 5: Client Counterparty Risk

Clients with higher counterparty credit risk incur higher spreads.

The International Swap and Derivatives Association (ISDA) has defended the OTC market structure of derivatives markets as a way of providing customized contracts that are tailored to clients' needs (see, for example, ISDA (2010) and Duffie, Li & Lubke (2010)). One dimension along which FX forwards can be customized is their maturity. By contrast, exchange-traded futures only provide specific maturities, so they can expose risk managers to undesirable basis risk. Accordingly, clients can be willing to incur larger spreads for customized contracts. Further, non-standard tenors render price comparisons with published benchmark rates more difficult, which may allow dealers to earn larger information rents. This gives rise to our final hypothesis:

Hypothesis 6: Contract Customization

Forward contracts with more customized maturities trade at higher spreads.

3 Data and Measurement

3.1 Data Sources

At the Pittsburgh summit in September 2009, G20 leaders determined that OTC derivatives contracts should be reported to regulators. In the European Union (EU), this commitment is implemented in the European Markets Infrastructure Regulation (EMIR). Since February 2014, all counterparties resident in the EU have been required to report the contractual details of new and outstanding derivatives transactions to trade repositories, which share the data with authorities according to their jurisdiction. Two institutions, namely the European Systemic Risk Board (ESRB) and European Securities and Markets Authority (ESMA), have access to the full EU-wide transaction-level dataset, which is described in detail by Abad et al. (2016).

We obtain transaction-level data on all OTC FX derivatives transactions involving at least one EU counterparty. We focus on forwards referenced on EUR/USD, which constitute the obligation to buy or sell a given quantity of euro against dollar at a predetermined rate of exchange at some future date.[6] Our data cover both outright forwards and the forward leg of an FX swap. According to the Bank for International Settlements, these contract types account for approximately 85% of all FX derivatives, and EUR/USD is the currency cross with the largest notional outstanding (BIS, 2017).

Starting with the raw data obtained from trade repositories, we retain all trades marked as FX forwards in the EUR/USD currency pair with a maturity up to one year. Our sample period covers trades executed between April 1, 2016 and March 31, 2017. The transaction records provide a unique legal entity identifier for all counterparties, which allows us to match the transactions data to Bureau van Dijk's Orbis dataset. From Orbis, we retrieve information on counterparties' sector classification. Given our focus on discriminatory pricing, we retain trades in which one counterparty is classified as a non-financial firm and the other as a dealer (including both broker-dealers and banks). The final transaction-level dataset comprises 556,297 trades between 10,062 clients and 204 dealers. Summary statistics are reported in Table 1.

3.2 Measuring Transaction Spreads

We assess transaction costs by computing the effective spread (henceforth "spread")—that is, we compare the forward rates of executed trades to the competitive market mid-price at the corresponding tenor. For the latter, we use Thomson Reuters Tick History (TRTH) data, which combine two-sided intraday quotes from multiple dealers. These high-frequency quote data are available for forward rates at standard maturities of 1 day, 1 week, 2 weeks, 3 weeks, 1 month, 2 months, 3 months, 6 months, and 1 year. For each of these maturities, we compute the market

[6]For example, a client which sells a 3-month EUR/USD forward with a notional of €1 million and a forward rate of 1.2 agrees to transfer €1 million to a dealer in three months' time in exchange for $1.2 million, regardless of the spot rate prevailing on the settlement date.

mid-price from the best inside quotes of the participating dealers. To avoid using stale quotes, we assume that indicative quotes are valid for a maximum of 30 seconds. As our derivatives data are time-stamped to the full second, the mid-price is calculated from all valid quotes in the same second.

OTC trading allows for contract customization. Consequently, tenors vary significantly across the 556,297 trades in our dataset, as shown in Figure 1. To match contractual forward rates at non-standard maturities to the nine standard maturities for which we have mid-price data, we linearly interpolate across the nine standard maturity dates. 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.

To assess the quality of the mid-prices, we compare for each full trading hour the forward rates of all inter-dealer trades (on which EMIR also provides full information) to their corresponding contemporaneous mid-prices at the same matched maturity. The mean (median) difference between these variables is just 0.138 pips (−0.01 pips), with a standard deviation of 5.27 pips. This suggests that the calculated mid-prices approximate inter-dealer trades very closely, and thus constitute a reliable benchmark price.

The spread for each client-dealer trade is measured relative to the mid-price at the corresponding maturity. Let d_τ denote the direction of client orders, so $d_\tau = 1$ for client long positions in a EUR/USD forward ("client buys euro"), and $d_\tau = -1$ for short positions ("client sells euro"). The spread (expressed in pips) for transaction τ is defined as

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

where f_τ is the contractual forward rate, and m_τ the contemporaneous mid-price, interpolated linearly from the mid-prices of standard maturities. 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. To further illustrate this spread calculation, Figure 2 plots contractual forward rates against the mid-price for 1-month forwards executed on a given trading day.

3.3 Variables for Hypothesis Testing

The first hypothesis concerns client sophistication. Empirically, we measure sophistication in five ways. First, we define *Log#Counterparties* as the natural logarithm of the number of dealers with which a client trades over one year. This variable relates to the parameter ρ in Duffie et al. (2005), which denotes the intensity with which investors meet dealers. Clients with a high ρ, as proxied by a high $Log\#Counterparties$, meet dealers more frequently, exposing them to "sequential competition". We alternatively capture the size of a client's set of counterparties via the Herfindahl-Hirschman index (denoted HHI) of its trading volume across different dealers. This measure is expected to be inversely related to $Log\#Counterparties$, as higher dealer concentration implies that a client has 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 are more likely to spend resources in searching for competitive spreads. In addition, their larger trading volumes make them more attractive clients for dealers. Both effects improve the bargaining power of clients in bilateral negotiations, as captured by the parameter z in Duffie et al. (2005). Similarly, we define $Log\#TradesFX$ as the log of the number of EUR/USD forwards traded by a client in our one-year sample period. Finally, $Log\#TradesNonFX$ is 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 is not directly related to the spreads paid by clients in FX forwards. In our later analysis, it is useful to collapse these five measures of client sophistication into a single variable. To do this, we define *Sophistication* as the first principal component of these variables. We obtain qualitatively and quantitatively similar results if we instead calculate a linear combination of the respective regression fits of these variables.

The second hypothesis concerns the role of multi-dealer RFQ platforms. Our transaction-level data allow us to identify trades that were conducted via one of the four major multi-dealer RFQ platforms in the European FX market, namely 360t, FXall, Bloomberg, and Currenex. Accordingly, we define a dummy variable, $RFQPlatform$, that is equal to one for trades executed via these platforms, and zero otherwise. In later regressions, we interact the $RFQPlatform$ dummy with the aforementioned summary measure of client sophistication, i.e. *Sophistication*, to identify how the effect of platform trading on transaction spreads varies across clients.

Hypothesis 3 relates to dealer information rents. In order to identify whether dealers adjust prices asymmetrically following changes in the mid-price, we define $|\Delta m_\tau^{-d}|$ ($|\Delta m_\tau^{d}|$) as 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 than the client order, and zero otherwise. More formally,

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

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 $|\Delta m_\tau^{-d}|$ is positive, while the coefficient of $|\Delta m_\tau^{+d}|$ is expected to be zero. Interacting both variables with the $RFQPlatform$ dummy reveals how the use of RFQ platforms affects dealers' information rents.

Fourth, we evaluate the effect of client-dealer relationships on spreads. We measure client-dealer relationships in two distinct ways. First, we define $Notional_{i,d}/Notional_i$ and $Notional_{i,d}/Notional_d$, which is the notional traded in EUR/USD forwards between client i and dealer d relative to their respective total notionals traded. Such measures are frequently used in the literature to test the effect of relationships on trading terms (Cocco et al., 2009). However, they are endogenous and specific to the data sample. Our second measure captures the existence of bilateral credit relationships outside the FX market, which is arguably unrelated to derivatives trading. To this end, we retrieve the identities of firms' main relationship banks from Orbis (via a variable called "banker"). We then create a dummy variable, *Relationship*, that takes the value of one for trades where the dealer is engaged in a pre-existing credit relationship with the client, and zero otherwise.

Fifth, to measure a client's credit risk, we use the modified Altman credit score (*ZScore*), which is computed as a linear combination of working capital, retained earnings, profits, and sales.[7] As an alternative measure of client credit risk we use the volatility of its cash flows (*CashFlowVol*). The underlying data are obtained from Orbis.

Our final hypothesis concerns contract customization. We define *LogCustomization* as the log of one plus *Customization*, which is the absolute value of the difference (in days) to the

[7]The formula to calculate the modified Altman *ZScore* is: $1.2 \times WorkingCapital + 1.4 \times RetainedEarnings + 3.3 \times EBITDA + 0.999 \times Sales$, where all variables are scaled by total assets.

nearest standard tenor published by WM/Reuters.[8] As customization represents an alternative explanation for the observed heterogeneity in spreads, we generally include it as a control variable in all specifications.

4 Descriptive Statistics

Table 1, Panel A provides summary statistics on the 10,062 clients trading with dealers in the EUR/USD FX forward market for the sample period 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 ($Av.ClientSpread$). The mean value of $Av.ClientSpread$ in the sample is 18.1 pips, with a large standard deviation of 26.6 pips. The distribution of this variable is positively skewed, and clients at high percentiles pay very considerable spreads. For example, the client at the 75th percentile pays an average spread of 33.9 pips, while the clients and the median and 25th percentile pay 14.3 pips and 2.0 pips, respectively. This is illustrated in Figure 3, which plots the cross-sectional distribution for the 10,062 average spreads at client level using a kernel estimator. The high dispersion in average client spreads is suggestive of substantial price discrimination.

Further, we observe that a large fraction of clients in the sample have only few counterparties. More than half of clients trade with just one dealer. Even the client at the 75th percentile of the $\#Counterparties$ distribution has just two counterparties. This counterparty concentration is also reflected in HHI, which measures the degree of concentration of a client's dealer trading relationships. Clients with a low HHI have diverse trading relationships; clients with a HHI of 1 have only one dealer as their counterparty. The average HHI is 0.8, with just over half of clients having a HHI of one.

On average, clients traded a total notional of €2.7mn over the one year sample period. However, the heterogeneity in trading volumes is very large, with clients at the 10th and 90th percentiles of the distribution trading approximately €100,000 and €120 million, respectively. A similar picture emerges from the variables $\#TradesFX$ and $\#TradesNonFX$, which respectively measure clients' trading frequency in FX and non-FX derivatives markets.

[8] The standard maturities are: O/N, T/N, 1W, 1M, 2M, 3M, 6M, 9M, 1Y. See https://financial.thomsonreuters.com/content/dam/openweb/documents/pdf/financial/wm-reuters-methodology.pdf for details.

Turning to client-dealer relationship variables, we aggregate *Relationship* at the client level and observe that on average clients trade about 60% of their FX forwards with their relationship bank(s). The summary statistics indicate a bimodal distribution of this variable: while at least 25% of clients never trade with their relationship bank(s), more than 50% exclusively trade with their relationship bank(s).

The final two variables reported in Table 1, Panel A measure clients' credit risk. $ZScore$ represents the modified Altman Z-Score. The lower the $ZScore$, the riskier the client.[9] On average, clients in our sample have a $ZScore$ of 2.9, which is above the average of 1.9 reported in Campello, Lin, Ma & Zou (2011). In addition to the $ZScore$, we consider clients' cash flow volatility ($CashFlowVol$), which we standardize to have a zero sample mean and unit sample variance.

Next, we turn to the number of trades executed by each client. While the median client trades 10 times during our sample period, the mean trade count is 61.7, driven by a small number of clients that trade very frequently. For example, the client at the 90th percentile of the distribution trades 103 times in our 12-month sample. In contrast, the client at the 25th percentile trades only three times. Thus, our sample of 10,062 clients is comprised of a large number of small entities that trade FX forwards infrequently, and a small number of very active traders.

Table 1, Panel B provides summary statistics at the transaction level for the $556,297$ EUR/USD forward trades. The distribution of spreads is much narrower compared to the one obtained at client level. The average spread over all trades is only 6.6 pips, compared to 18.1 pips across clients. The spread at the 90th percentile of the transaction-level distribution is 30.4 pips, compared to 52.6 pips at the client level. This suggests that more active traders obtain lower transaction costs on average. Moreover, we see that the spread at the 25th percentile of the transaction-level distribution is slightly negative, at -1.2 pips, compared with a positive average client spread at the same percentile. 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).

[9]According to Altman (1968), a client that has a $ZScore$ of greater than 2.9 is considered to be in the "safe" zone; clients with a $ZScore$ of greater than 1.23 and smaller than 2.9 are in the "gray zone"; and clients with a $ZScore$ of less than 1.23 are in the "distressed" zone.

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. On average, trades have a tenor that is approximately five days from the nearest standard tenor. Half of all transactions pertain to contracts with an original maturity of fewer than 35 days. The frequency of executed trades is decreasing as a function of the tenor of the contract, as shown in Figure 1.

The table also reports the distribution of *Buy*, which is a dummy equal to one when a client commits to buy euros against dollars (taking a long position in EUR/USD), and zero for sell-euro positions. In 40% of all trades in our sample, clients enter a long position, so that the value of the position is positive when the euro appreciates.

$RFQPlatform$ is a dummy equal to one if a transaction was executed via a multi-dealer RFQ platform, and zero otherwise. Approximately 40% of trades in our sample are executed through such trading platforms, which is broadly in line with existing survey evidence on the use of multi-dealer platforms (see BIS, 2016). Finally, we observe that the means of $|\Delta m_\tau^{-d}|$ and $|\Delta m_\tau^{+d}|$ are both 0.5 pips, indicating that the average price change preceding client orders in the preceding 30 seconds is very small.

5 Analysis

To analyze the determinants of transaction spreads, we estimate a linear model for the 556,297 client-dealer trades in our sample. The baseline specification takes the form:

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

where X_i represents client characteristics, and Z_τ a set of contract characteristics. Additionally, we include dealer fixed effects (δ_d) in all specifications to control for time-invariant dealer-specific 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. Omitted variables at the dealer level therefore do not affect our inference. To control for time-varying market conditions, we include date (γ_t) and minute-of-day (γ_m) fixed effects. The contract characteristics comprise the following transaction controls:

$$Z_\tau = \{LogNotional_\tau, LogTenor_\tau, LogCustomization_\tau, Volatility_\tau, Buy_\tau\},$$

where $LogNotional_\tau$ is the log notional amount of the transaction, $LogTenor_\tau$ is the log tenor (in days) of a forward contract, $LogCustomization_\tau$ is a measure of contract customization given by one plus the absolute difference (in logs) between the tenor of a forward contract and its nearest standard tenor, $Volatility_\tau$ is the 30-minute realized volatility of the FX spot rate (based on one-minute intervals), and Buy is a dummy that takes the value of one when a client commits to buy euros (in exchange for dollars) and zero otherwise.

5.1 Conditional Average Client Spreads

To assess the scope of discriminatory pricing in the OTC FX derivatives market, we first compare the unconditional distribution of the average spread to its conditional distribution. The conditional distribution is given by the distribution of client fixed effects μ_i in the linear regression:

$$Spread_{i,b,\tau} = \mu_i + Z_\tau \beta_2 + \delta_d + \gamma_t + \gamma_m + \epsilon_\tau,$$

which controls for the contract characteristics Z_τ of each trade τ, the identity of each dealer through the fixed effect δ_d, and additional fixed effects for the time-varying market conditions γ_t and γ_m. By contrast, the unconditional distribution of average spreads is obtained if we drop the control terms Z_τ, δ_d, γ_t, and γ_m from the regression.

Both the unconditional and conditional distributions of the average spread μ_i are depicted as histograms in Figure 4. The two distributions are strikingly similar. This implies that differences in average spreads across clients cannot be attributed to differences in contract characteristics, dealer efficiency or market timing. Instead, they are inherent to the client identity, which defines discriminatory pricing. Moreover, the degree of discriminatory pricing is economically large: the client at the 75th percentile pays an average spread of 30.1 pips—2.5 times that of the median client, which transacts at a spread of only 12.1 pips, and 12 times that of the client at the 25th percentile, which transacts at a competitive spread of 2.5 pips. In the next section, we explore the determinants of this large degree of discriminatory pricing.

5.2 Client Sophistication

To explore the relationship between discriminatory pricing and client characteristics, we use the following set of proxy variables for client sophistication:

$$X_i = \{Log\#Counterparties,\ HHI,\ LogTotalNotional,\ Log\#TradesFX,\ Log\#TradesNonFX\}.$$

Replacing the client fixed effects in the previous specification with these variables produces the regression estimates reported in Table 2. Columns (1) to (5) introduce each of the sophistication measures separately, while controlling for transaction characteristics and dealer, date, and minute-of-day fixed effects. Column (1) indicates that clients with more counterparties pay lower spreads on average, consistent with Hypothesis 1. Similarly, Column (2) indicates that clients with more concentrated counterparties pay higher spreads. In Columns (3) and (4), we find that more active clients, in terms of number of trades and the notional traded respectively, obtain lower spreads. Finally, Column (5) shows that clients with more outstanding derivatives contracts in other asset classes benefit from lower spreads on average. Column (6) synthesizes these results using a summary measure of sophistication based on the first principal component of the five individual sophistication measures. The estimated coefficient is -1.509 and statistically significant at the 1% level. This point estimate implies that a one standard deviation increase in client *Sophistication* is associated with an average spread reduction by 2.7 pips.

Overall, the results reported in Table 2 provide strong support for Hypothesis 1. All proxies of client sophistication have the expected sign, and are highly statistically significant. Not reported here are regression results for other proxies of client sophistication, such as their (log) asset size, which shows that smaller clients tend to pay higher spreads. Yet, most of our sophistication measures tend to be correlated with each other so that their marginal explanatory power decreases. A variance decomposition shows that client fixed effects account for 40% of the total spread variation across all trades. By comparison, the client sophistication proxies X_i together account for 8% of the total spread variation, which explains 20% of the discriminatory pricing embodied in the client fixed effects. Imperfect measurement of client sophistication implies that 20% represents a lower bound on the share of discriminatory pricing that can be attributed to variation in client sophistication.

A more intuitive way of illustrating the economic significance of client sophistication for price discrimination is provided in Figure 5, which plots the average spread of all clients with the same number of dealer counterparties against the number of counterparties ($\#Counterparties$). The size of the symbol represents the notional share for each group of clients. Clients with only one dealer counterparty account for 2% of the notional and 68% of the 10,062 clients engaged in risk hedging; these less sophisticated clients trade at an average spread of 17.5 pips. With each additional dealer counterparty, the average spread falls substantially, and reaches 5 pips when clients have four counterparties. For the groups of clients trading with five or more dealers, the average spread is around 2 pips or less, which can be considered a benchmark for the competitive spread. While this group represents only 6% of all clients, their aggregate notional accounts for 89% of the total.

5.3 Contract Characteristics

The regression results reported in Table 2 control for a variety of contractual features. The role of these features in determining spreads is also of interest. We find that contracts with a larger $LogNotional$ generally exhibit lower spreads. This finding is consistent with evidence from other OTC markets, notably the bond market (Schultz, 2001; Green, Hollifield & Schürhoff, 2006). This trade size discount is robust to controlling for sophistication, which includes the effects of counterparty size (e.g., via $LogTotalNotional$). But given that dealer revenue scales linearly in the notional value of each trade (as the spread is computed per unit), a negative coefficient is likely to reflect a fixed cost component of the transaction cost of a trade.

Moreover, we find that longer contract maturity ($LogTenor$) is associated with larger spreads, perhaps because forwards of longer duration expose dealers to greater market risk. The coefficient of $Volatility$ has the expected positive sign, but is statistically insignificant. This low level of statistical significance is due to the inclusion of date and minute-of-day fixed effects, which absorb most of the variation in volatility. Further, the dummy variable for Buy trades is statistically significant. The observed aggregate demand imbalance between long and short positions in the European market segment can explain these more favorable spreads for buy than for sell trades.

Finally, we cannot reject Hypothesis 6. Trades with a tenor that differs from a standard maturity do indeed command a spread premium. However, the economic magnitude of this effect is relatively modest. An increase in the customizing measure by one standard deviation is associated with a spread increase of approximately 1 pip.

5.4 Multi-Dealer Request-for-Quote Platforms

As centralized exchange trading is often proposed as a remedy for monopolistic pricing practices in OTC markets, it is insightful to explore whether the use of multi-dealer RFQ platforms is associated with spread compression. As discussed previously, the ability to simultaneously query multiple dealers on RFQ platforms allows clients to put dealers into competition with each other for a particular trade, similar to a privately organized batch auction. In our one-year sample, 40.9% of the 556,297 EUR/USD forwards are executed via a multi-dealer RFQ platform. These trades are executed by just 1,219 clients (i.e. 12.2% of our full sample), which means that the vast majority of clients never use an RFQ platform to trade FX forwards.

According to Hypothesis 2, clients using RFQ platforms are expected to enjoy lower spreads. Figure 6 suggests that this is indeed the case. It plots the average spread for the 10,062 clients as a function of their sophistication. Lower client sophistication implies a much larger dispersion of the average spread. This is partly explained by larger sampling errors, as sophistication correlates negatively with the number of trades used for calculating average spreads. But the more important feature of the figure is the marked difference in the average transaction spread of RFQ platform trades (marked by red crosses) and non-platform trades (marked by blue dots) represented by a dashed and solid black line, respectively. While the average spreads are extremely low and mostly invariant to client sophistication for platform trades, bilateral trades feature a steep cost increase as client sophistication declines. Visually, price discrimination based on sophistication disappears almost entirely if a client uses an RFQ platform for its trade execution.

In Table 3, we investigate the effect of platform use on spreads by conditioning on contract characteristics, counterparty identities, and market conditions. Column (1) indicates that trading through a platform is associated with an average spread reduction of 7.2 pips. However, this specification does not control for client sophistication, which represents an important conditioning variable for the benefits of platform use. By including the *Sophistication* variable and its interaction with the $RFQPlatform$ dummy in Column (3), we can gauge how platform use improves execution quality for clients with different levels of sophistication. As sophisticated clients already obtain low spreads, the incremental spread compression should be largest for the least sophisticated, as predicted by Hypothesis 2.

The estimated coefficients reported in Column (3) confirm this intuition. The point estimate of -1.925 for *Sophistication* indicates an economically strong negative relationship between spreads and sophistication. Yet, this relationship is completely eliminated for RFQ platform users, as indicated by the positive coefficient of 1.964 for the interaction term $RFQPlatform$ $\times$ *Sophistication*; adding the relevant coefficients together implies a zero net effect for sophistication. This conditional analysis implies that the discriminatory spread mark-up for less sophisticated clients vanishes on RFQ platforms. More broadly, it confirms the visual impression given by Figure 6: The lower the level of client sophistication, the greater the benefit of platform use in improving trade execution quality.

The economic magnitude of the spread compression on multi-dealer RFQ platforms may be surprising. Non-anonymity of counterparties is a necessary feature of such trading 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.

In unreported results, we find that the benefits of trading via RFQ platforms are present even if a client always executes its trades with the same dealer. To obtain this finding, we repeat the specifications estimated in Table 3 using only the subsample of clients which only ever trade with one dealer in our data sample. The coefficients of the $RFQPlatform$ variable are negative and significant even when estimated on this restricted sample. At first glance, this result might seem surprising, since dealers know the identity of the client when submitting a quote, and can therefore discriminate based on that client's sophistication. However, on RFQ platforms, dealers do not know the number of dealers from which a client simultaneously requests quotes. Hence, clients can benefit from this information asymmetry as platform-based requests for quotes signal outside trading options with other dealers even if these are either not available or not used in equilibrium.

5.5 Information Rents and Asymmetric Price Adjustment

OTC derivatives markets generally lack price transparency. Is this an important source of dealers' market power? Hypothesis 3 suggests that dealers derive profits from better access to real-time price data. We can test for the existence of such information rents around changes in the market mid-price. If clients are not aware of recent changes in the mid-price, they are more likely to accept outdated ("stale") transaction prices, thus generating information rents for the dealer. Importantly, dealers can only exploit recent price changes when they occur in the opposite direction of the client's trading intention. This gives rise to an asymmetric price adjustment.

In Table 4, Columns (1) reports the coefficient estimates of a regression of spreads on $|\Delta m_\tau^{-d}|$ and $|\Delta m_\tau^{+d}|$ as well as *Sophistication* and the usual set of control variables, namely contract characteristics and dealer, date, and minute-of-day fixed effects. For robustness, columns (3) and (6) additionally report the estimates for mid-price changes in the last 60 and 90 second intervals prior to the transaction, respectively.

For the 30-second interval, the coefficient of $|\Delta m_\tau^{-d}|$ is 0.391 and statistically significant at the 1% level. This indicates that dealers do indeed charge higher spreads when a trade is preceded by a price change in the opposite direction from the client order, as compared to a static mid-price. However, the coefficient of $|\Delta m_\tau^{+d}|$ is negative and also statistically significant at -0.229; hence, clients enjoy lower spreads when their trade is preceded by a mid-price change in the same direction of the trade compared to a static mid-price. This implies that dealers update their price offers only in a sluggish manner, even if this squeezes their spreads. However, the sum of both coefficients is statistically different from zero for pre-trade intervals of 30 and 90 seconds. This is consistent with the existence of information rents earned through asymmetric price adjustment following changes in the mid-price.

As seen in subsection 5.4, trading on multi-dealer RFQ platforms helps clients to reduce dealers' market power and eliminate discriminatory pricing. Hypothesis 3 suggests that RFQ platforms should also reduce information rents. Accordingly, we expect the observed asymmetry in price adjustment to be particularly prevalent for bilateral trades, and absent for platform trades. To examine this, we add the $RFQPlatform$ dummy and its interactions with $|\Delta m_\tau^{-d}|$ and $|\Delta m_\tau^{+d}|$ to the regression specification. The results in Columns (2), (4) and (6) are consistent with the prediction. For off-platform trades, the asymmetry in price adjustment at the 30-second interval becomes larger with point estimates of 0.581 and -0.256 for $|\Delta m_\tau^{-d}|$ and $|\Delta m_\tau^{+d}|$, respectively. However, platform trades do not share in this asymmetric price adjustment. For example, the point estimates of -0.515 for the interaction term $|\Delta m_\tau^{-d}| \times RFQPlatform$ in Column (2) cancels the contribution of the baseline coefficient of

0.581 of $|\Delta m_{\tau}^{-d}|$. This indicates that RFQ platform trading greatly reduces the information rents earned by dealers.

To summarize, OTC market opacity is a source of market power for dealers. This finding is consistent with prior evidence of asymmetric price adjustments in the US municipal bond market (Green et al., 2010). Moreover, we show that these information rents vanish once dealers compete on RFQ platforms.

5.6 Client-Dealer Relationships

Hypothesis 4 predicts that the existence of client-dealer relationships lowers spreads. Different from the existing literature, we not only rely on observed trading relationships, but also make use of the existence of client-dealer ties in credit markets, thus alleviating possible endogeneity concerns.

Table 5, Columns (1) and (2) show the regression results for the first set of relationship variables based on the respective bilateral volume share of activity for the client i and the dealer d. In Column (1), we observe that clients pay higher spreads when trading with their relationship bank(s). An increase in a client's trading share with a dealer by 10 percentage points of its total notional increases its average spread by about 1 pip. Clients that are important to their dealers receive discounts of a similar magnitude.

In Column (2), we also control for client sophistication. Less sophisticated clients tend to have more concentrated trading relationships with particular dealers, but due to their smaller size matter less to their main dealer. After including client sophistication in the specification, the magnitude of both of the aforementioned coefficients diminishes substantially. However, we still observe that clients pay higher spreads by around 0.3 pips if their notional share with a particular dealer increases by 10 percentage points. In contrast, dealers seem not to discriminate across clients of different relative importance once we control for *Sophistication*.

Alternatively, we measure client-dealer relationships through the existence of bilateral ties in the credit market. The dummy variable *Relationship* marks all client-dealer trades for which there exists an additional credit relationship outside the derivatives market. We find that clients tend to pay higher spreads to their relationship dealers even after controlling for *Sophistication*. Overall, these findings are at odds with models in which relationships procure transactional benefits (Hendershott et al., 2016).

5.7 Client Credit Risk

The absence of central clearing or widespread collateralization in the FX derivatives market creates credit risk. Hypothesis 5 posits that client credit risk is compensated by higher spreads. To test this hypothesis, we augment the baseline regression with two alternative proxies for client credit risk, namely $ZScore$ and $CashFlowVol$. The results are presented in Table 6, Columns (1) and (2), respectively. Columns (3) and (4) add *Sophistication* as an additional control variable.

The positive and statistically significant coefficient of $ZScore$ in Column (1) suggests that low-risk clients (with a high $ZScore$) pay higher spreads. This is at odds with Hypothesis 5, which predicts that dealers charge higher spreads to riskier clients in compensation for credit risk. $CashFlowVol$, the second measure of client risk in Column (2), is not associated with higher spreads. After controlling for client *Sophistication* in Columns (3) and (4), neither of the coefficients for the two risk measures is statistically significant.

While our finding that credit risk is not priced may be surprising, it is broadly consistent with existing evidence. Arora et al. (2012) and Du et al. (2016) examine the role of counterparty risk in the CDS market. While they find the effect of credit risk on prices to be statistically significant, the economic magnitude is extremely small.

6 Conclusion

New regulatory derivatives data with counterparty identities allow for the first time a comprehensive analysis of spreads for non-financial clients in the highly liquid segment of EUR/USD FX forwards. We highlight four findings:

First, clients trade at very heterogeneous spreads, even after controlling for contract characteristics, dealer fixed effects, and market conditions. We find that the client at the 75th percentile of the conditional spread distribution pays 30 pips on average over the market midprice. This compares to competitive spreads of less than 2.5 pips paid by clients in the bottom 25% of the distribution.

Second, various proxies of client sophistication are strongly correlated with the degree of discriminatory pricing a client experiences. These proxies include a client's number of dealers, concentration of trading across dealers, the aggregate notional traded, and the total number of trades in FX and non-FX derivatives. Extensive discriminatory pricing in the OTC market occurs largely at the expense of unsophisticated clients.

Third, we document that the use of multi-dealer RFQ platforms removes the market power of dealers and compresses average spreads to a competitive level. The largest benefits accrue to the least sophisticated clients, because RFQ platform trading fully eliminates discriminatory pricing based on client sophistication. This occurs despite of the fact that dealers know the identity of their clients in RFQ platforms, unlike in an anonymous limit order book.

Fourth, we document that dealers benefit from opacity in the OTC market by exploiting recent prices movement to their advantage. In particular, changes in the mid-price are shown to trigger an asymmetric price adjustment whereby dealers do not pass on changes in the mid-price that would otherwise be to the benefit of the client. However, RFQ platform trades do not exhibit such a pattern, suggesting that they curtail information rents.

Overall, these results suggest that the current OTC market structure for FX derivatives can be improved. Multi-dealer platforms appear effective at reducing dealers' market power and the associated price discrimination against less sophisticated clients. However, more than half of clients' trades (conducted by almost 90% of clients) continue to be conducted bilaterally. Accordingly, mandating trading on organized platforms would benefit less sophisticated clients and possibly induce additional firms with latent exchange rate exposure to participate in the market.

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Table 1: Summary Statistics

Panel A: Client Data	Obs.	Mean	St.Dev	p10	p25	p50	p75	p90
$AvClientSpread$	10062	18.1	26.6	-3	2.0	14.3	33.9	52.6
$\#Counterparties$	10062	1.8	2	1	1	1	2	3
HHI	10062	0.8	0.3	0.1	0.6	1	1	1
$TotalNotional$ (in €mn)	10062	539.1	7480.2	0.1	0.4	1.8	11.2	116.1
$\#TradesFX$	10062	55.3	411.4	1	3	8	24	85
$\#TradesNonFX$	10062	14.7	232.7	0	0	0	0	3
$Sophistication$	10062	0	1.8	-1.7	-1.2	-0.5	0.7	2.4
$Notional_{i,d}/Notional_i$	10062	0.9	0.2	0.5	0.9	1	1	1
$Notional_{i,d}/Notional_d$	10062	0.01	0.08	0.000001	0.000005	0.00005	0.0008	0.010
$Relationship$	6621	0.6	0.5	0	0	1	1	1
$ZScore$	6173	2.9	1.8	1.0	1.8	2.7	3.8	5.1
$CashFlowVol$	6793	0	1	-0.3	-0.2	-0.1	0.1	0.6
Panel B: Transaction Data	**Obs.**	**Mean**	**St.Dev**	**p10**	**p25**	**p50**	**p75**	**p90**
$Spread$	556297	6.6	19.2	-4.9	-1.2	1.9	10.7	30.4
$Notional$ (in €mn)	556297	9.8	53.1	0.02	0.06	0.3	1.9	15
$Tenor$	556297	68.5	80.2	2	9	35	96	188
$Customization$	556297	10.6	16.7	1	2	3	12	33
$Volatility$	556297	0.007	0.004	0.004	0.005	0.006	0.008	0.01
Buy	556297	0.4	0.5	0	0	0	1	1
$RFQPlatform$	556297	0.4	0.5	0	0	0	1	1
$\lvert\Delta m_{\tau}^{-d}\rvert$	554357	0.5	1	0	0	0	1	1.5
$\lvert\Delta m_{\tau}^{+d}\rvert$	554357	0.5	0.9	0	0	0	1	1.5

Note: Panel A shows client-level data for the 10,062 non-financial clients that trade at least one EUR/USD forward with a dealer between April 2016 and March 2017, and Panel B shows transaction-level data for 556,297 EUR/USD forward trades. In Panel A, *Av.ClientSpread* 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 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 $Log\#TradesNonFX$. $Notional_{i,d}/Notional_i$ and $Notional_{i,d}/Notional_d$ quantify the notional traded in EUR/USD forwards between a client and dealer relative to the total EUR/USD notional traded by a client and dealer, respectively. *Relationship* is the share of forwards that a client trades with its relationship bank(s). $ZScore$ 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 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 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. $RFQPlatform$ is a dummy equal to one when a trade is executed via a multi-dealer electronic trading platform, and zero otherwise. $|\Delta m_{\tau}^{-d}|$ ($|\Delta m_{\tau}^{+d}|$) 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: Client Sophistication (Hypothesis 1)

	(1)	(2)	(3)	(4)	(5)	(6)
Sophistication measures:						
$Log\#Counterparties$	-3.887***					
	(0.216)					
HHI		8.997***				
		(0.710)				
$LogTotalNotional$			-1.541***			
			(0.069)			
$Log\#TradesFX$				-1.777***		
				(0.098)		
$Log\#TradesNonFX$					-0.994***	
					(0.101)	
$Sophistication$						-1.509***
						(0.073)
Transaction controls:						
$LogNotional$	-0.602***	-0.462***	-0.293***	-1.079***	-0.785***	-0.588***
	(0.078)	(0.103)	(0.088)	(0.096)	(0.100)	(0.081)
$LogTenor$	1.118***	1.158***	0.916***	1.082***	1.180***	1.056***
	(0.092)	(0.094)	(0.088)	(0.090)	(0.094)	(0.090)
$LogCustomization$	0.941***	1.127***	0.868***	0.872***	1.007***	0.925***
	(0.102)	(0.122)	(0.100)	(0.103)	(0.115)	(0.103)
$Volatility$	6.465	5.536	2.965	3.634	9.661	4.221
	(15.833)	(15.717)	(15.956)	(15.572)	(15.703)	(15.710)
Buy	-6.449***	-6.678***	-6.164***	-6.368***	-6.600***	-6.341***
	(0.302)	(0.311)	(0.293)	(0.301)	(0.332)	(0.297)
R-squared	0.276	0.270	0.288	0.273	0.259	0.282
Obs.	556297	556297	556297	556297	556297	556297
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 transaction spread on measures of client sophistication. The sophistication measures and transaction controls are defined in the footnote 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: Request-for-Quote Multi-Dealer Platform Trades (Hypothesis 2)

	(1)	(2)	(3)
$RFQPlatform$	-7.219***	-3.766***	-13.25***
	(0.459)	(0.427)	(0.604)
$Sophistication$		-1.189***	-1.925***
		(0.084)	(0.079)
$RFQPlatform \times Sophistication$			1.964***
			(0.124)
R-squared	0.269	0.287	0.299
Obs.	556297	556297	556297
Dealer FE	Yes	Yes	Yes
Date FE	Yes	Yes	Yes
Minute of day FE	Yes	Yes	Yes
Transaction controls	Yes	Yes	Yes

Note: This table reports OLS regression estimations of transaction spreads on $RFQPlatform$, which is a dummy equal to one when a transaction was executed via a request-for-quote multi-dealer electronic trading platform, and zero otherwise. In addition, in Column (3), we interact $RFQPlatform$ with $Sophistication$. The latter variable is the first principal component of $Log\#Counterparties$, HHI, $LogTotalNotional$, $Log\#TradesFX$, and $Log\#TradesNonFX$. In addition, each specification controls for transaction 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 4: Asymmetric Price Adjustment (Hypothesis 3)

	Mid-price move in the preceding:					
	30 Seconds		60 Seconds		90 Seconds	
	(1)	(2)	(3)	(4)	(5)	(6)
$\lvert\Delta m_\tau^{-d}\rvert$	0.391***	0.581***	0.334***	0.497***	0.333***	0.481***
	(0.054)	(0.063)	(0.037)	(0.047)	(0.034)	(0.042)
$\lvert\Delta m_\tau^{+d}\rvert$	-0.229***	-0.256***	-0.293***	-0.364***	-0.232***	-0.285***
	(0.051)	(0.072)	(0.037)	(0.054)	(0.033)	(0.047)
$RFQPlatform$		-3.543***		-3.570***		-3.521***
		(0.432)		(0.431)		(0.433)
$\lvert\Delta m_\tau^{-d}\rvert \times RFQPlatform$		-0.515***		-0.448***		-0.413***
		(0.069)		(0.051)		(0.046)
$\lvert\Delta m_\tau^{+d}\rvert \times RFQPlatform$		0.0661		0.173***		0.129**
		(0.080)		(0.058)		(0.051)
$Sophistication$	-1.509***	-1.189***	-1.509***	-1.190***	-1.509***	-1.190***
	(0.074)	(0.084)	(0.074)	(0.084)	(0.074)	(0.085)
R-squared	0.283	0.289	0.284	0.289	0.284	0.290
Obs.	554356	554356	554356	554356	554356	554356
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
Transaction controls	Yes	Yes	Yes	Yes	Yes	Yes
P-value 1	0.0646	0.0024	0.5013	0.1037	0.0563	0.0048
P-value 2		0.0001		0.0014		0.0001
P-value 3		0.0362		0.0644		0.0046
P-value 4		0.0002		0.0000		0.0000
P-value 5		0.0775		0.0000		0.0004

Note: This table reports OLS regression estimations of transaction spreads on measures of price staleness. $|\Delta m_\tau^{-d}|$ ($|\Delta m_\tau^{+d}|$) is the absolute value of the change in the mid-price over the preceding 30, 60 or 90 seconds (in pips) if the price change was in the opposite (same) direction of the client order, and zero otherwise. In Columns (2), (4) and (6), these variables are interacted with $RFQPlatform$, which is a dummy equal to one when a transaction was executed via a multi-dealer electronic trading platform, and zero otherwise. $Sophistication$ is the first principal component of $Log\#Counterparties$, HHI, $LogTotalNotional$, $Log\#TradesFX$, and $Log\#TradesNonFX$. In addition, each specification controls for transaction characteristics (i.e. $LogNotional$, $LogTenor$, $LogCustomization$, $Volatility$, and Buy). P-values 1-5 refer to the following hypothesis tests. P-value 1: $|\Delta m_\tau^{-d}|=-|\Delta m_\tau^{+d}|$. P-value 2: $|\Delta m_\tau^{-d}| \times RFQPlatform=-|\Delta m_\tau^{+d}| \times RFQPlatform$. P-value 3: $|\Delta m_\tau^{+d}| + |\Delta m_\tau^{+d}| \times RFQPlatform = 0$. P-value 4: $|\Delta m_\tau^{-d}| + |\Delta m_\tau^{-d}| \times RFQPlatform = 0$. P-value 5: $|\Delta m_\tau^{-d}| + |\Delta m_\tau^{-d}| \times RFQPlatform=-|\Delta m_\tau^{+d}| - |\Delta m_\tau^{+d}| \times RFQPlatform$. 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: Client-Dealer Relationships (Hypothesis 4)

	(1)	(2)	(3)	(4)
$Notional_{i,d}/Notional_i$	9.899***	3.038***		
	(0.630)	(0.876)		
$Notional_{i,d}/Notional_d$	-10.11***	0.206		
	(3.103)	(3.052)		
Relationship			3.568***	1.274**
			(0.736)	(0.650)
Sophistication		-1.191***		-1.459***
		(0.115)		(0.083)
R-squared	0.274	0.283	0.249	0.282
Obs.	556297	556297	556297	556297
Dealer FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Minute of day FE	Yes	Yes	Yes	Yes
Transaction controls	Yes	Yes	Yes	Yes

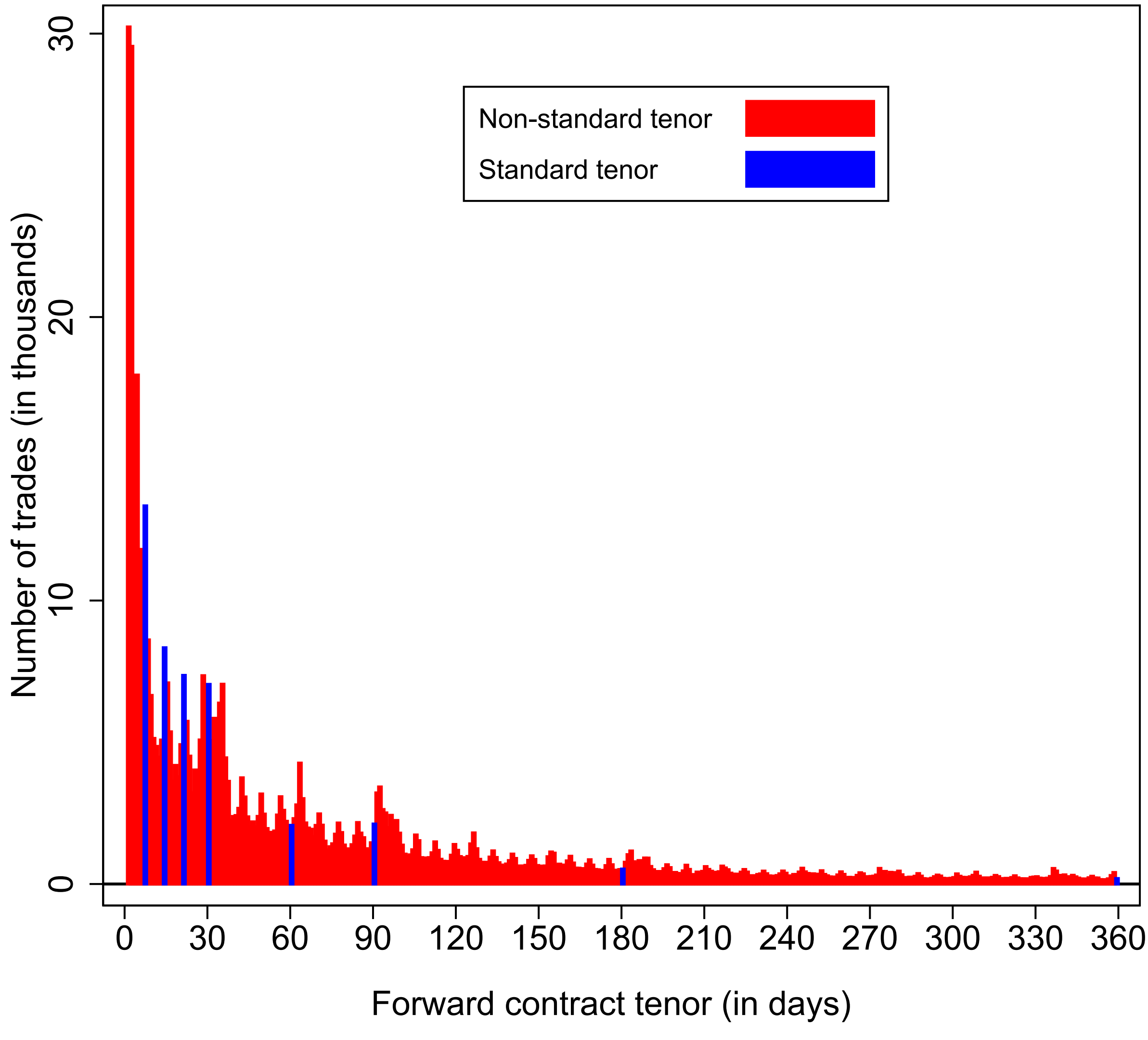
Note: This table reports OLS regression estimations of transaction spreads on measures of client-dealer relationships. First, $Notional_{i,d}/Notional_i$ and $Notional_{i,d}/Notional_d$ quantify the notional traded in EUR/USD forwards between a client and dealer relative to the total EUR/USD notional traded by a client and dealer respectively. Second, *Relationship* is a transaction-level dummy that takes the value of one when a client trades a forward with its relationship bank(s), and zero otherwise. In Columns (3) and (4), we replace missing observations on *Relationship* with an arbitrary constant value; to account for this, we include in the regressions a dummy which equals one when the observation on *Relationship* was originally missing, and zero otherwise. In Columns (2) and (4), we also include *Sophistication*, which is the first principal component of $Log\#Counterparties$, HHI, $LogTotalNotional$, $Log\#TradesFX$, and $Log\#TradesNonFX$. In addition, each specification controls for transaction 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 6: Client Credit Risk (Hypothesis 5)

	(1)	(2)	(3)	(4)
ZScore	0.534***		-0.00359	
	(0.159)		(0.137)	
CashFlowVol		0.0839		-0.233
		(0.247)		(0.211)
Sophistication			-1.515***	-1.510***
			(0.073)	(0.074)
R-squared	0.245	0.244	0.282	0.282
Obs.	556297	556297	556297	556297
Dealer FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Minute of day FE	Yes	Yes	Yes	Yes
Transaction controls	Yes	Yes	Yes	Yes

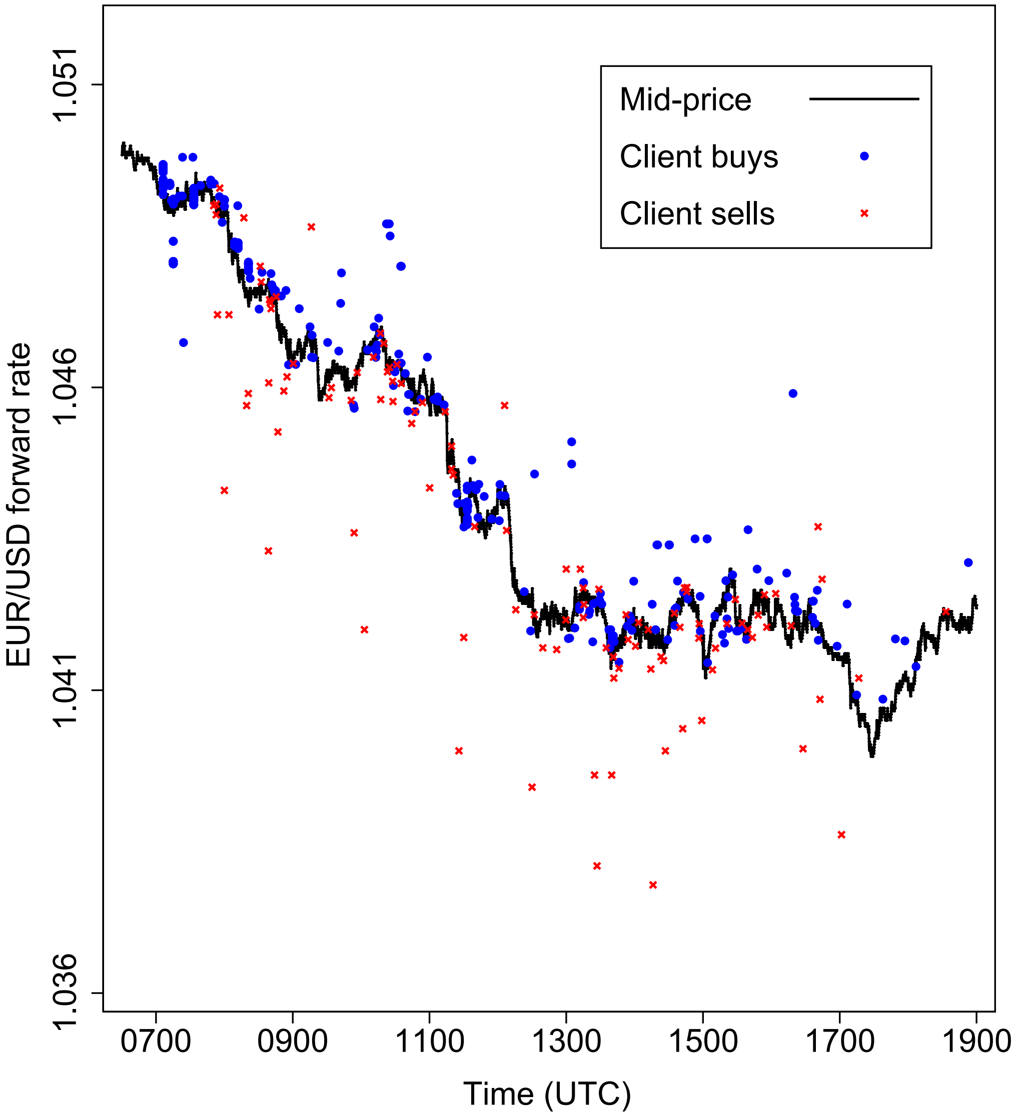
Note: This table reports OLS regression estimations of transaction spreads on measures of client risk. *ZScore* is a client's modified Altman Z-score, calculated as the linear combination of working capital, retained earnings, profits, and sales. *CashFlowVol* is a client's standardized coefficient of variation of cash flows. We replace missing observations on *ZScore* and *CashFlowVol* with an arbitrary constant value; to account for this, we include in the regressions a dummy which equals one when the observation on *ZScore* and *CashFlowVol* was originally missing, and zero otherwise. In Columns (3) and (4), we also include *Sophistication*, which is the first principal component of *Log#Counterparties*, *HHI*, *LogTotalNotional*, *Log#TradesFX*, and *Log#TradesNonFX*. In addition, each specification controls for transaction 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.

Figure 1: Trade Distribution by Maturity Date



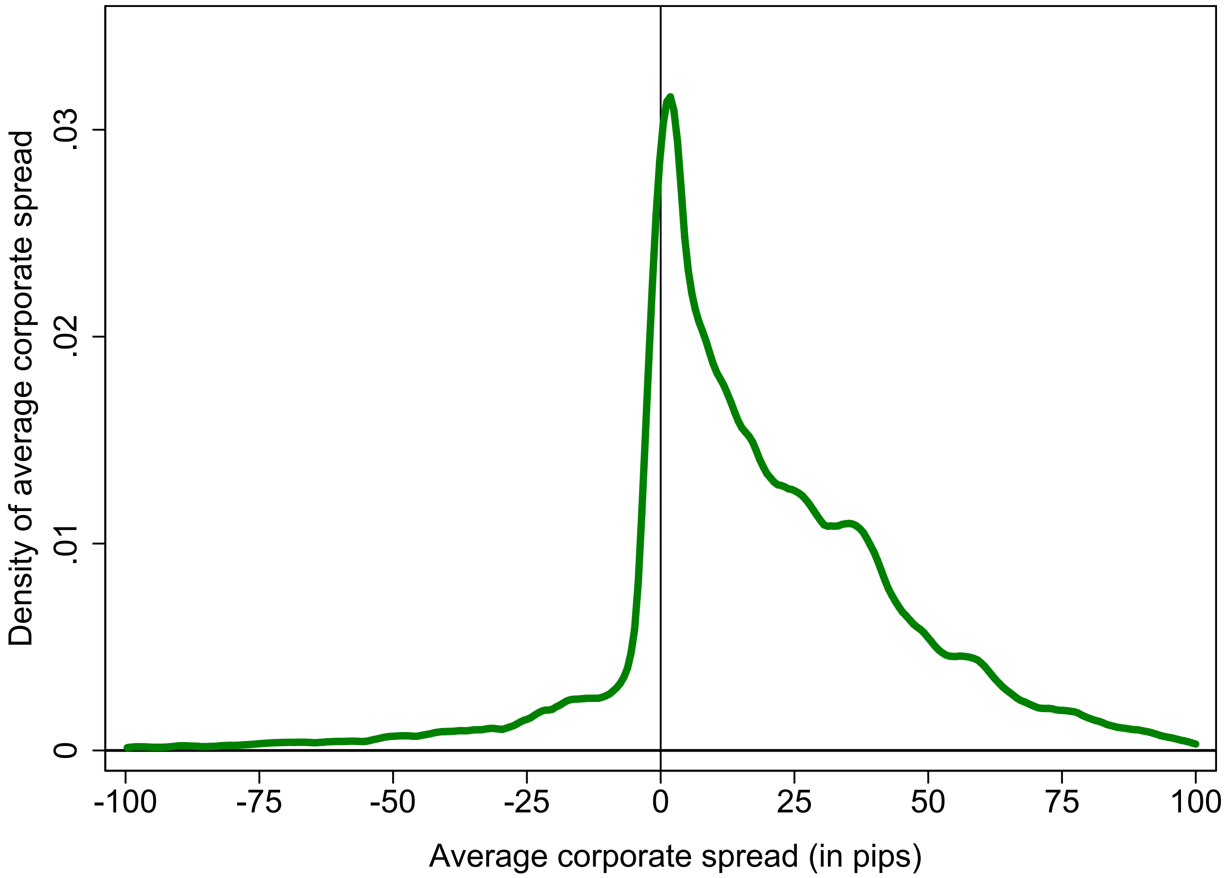
Note: This figure plots the distribution of contract tenors (in days) for all 556,297 EUR/USD forwards traded between dealers and clients over April 1, 2016 to March 31, 2017. Blue bars denote trades at standard tenors, i.e. 7, 14, 21, 30, 60, 90, 180, and 360 days, and red bars denote trades at non-standard tenors.

Figure 2: Contracted Forward Rates versus the Mid-Market Rate



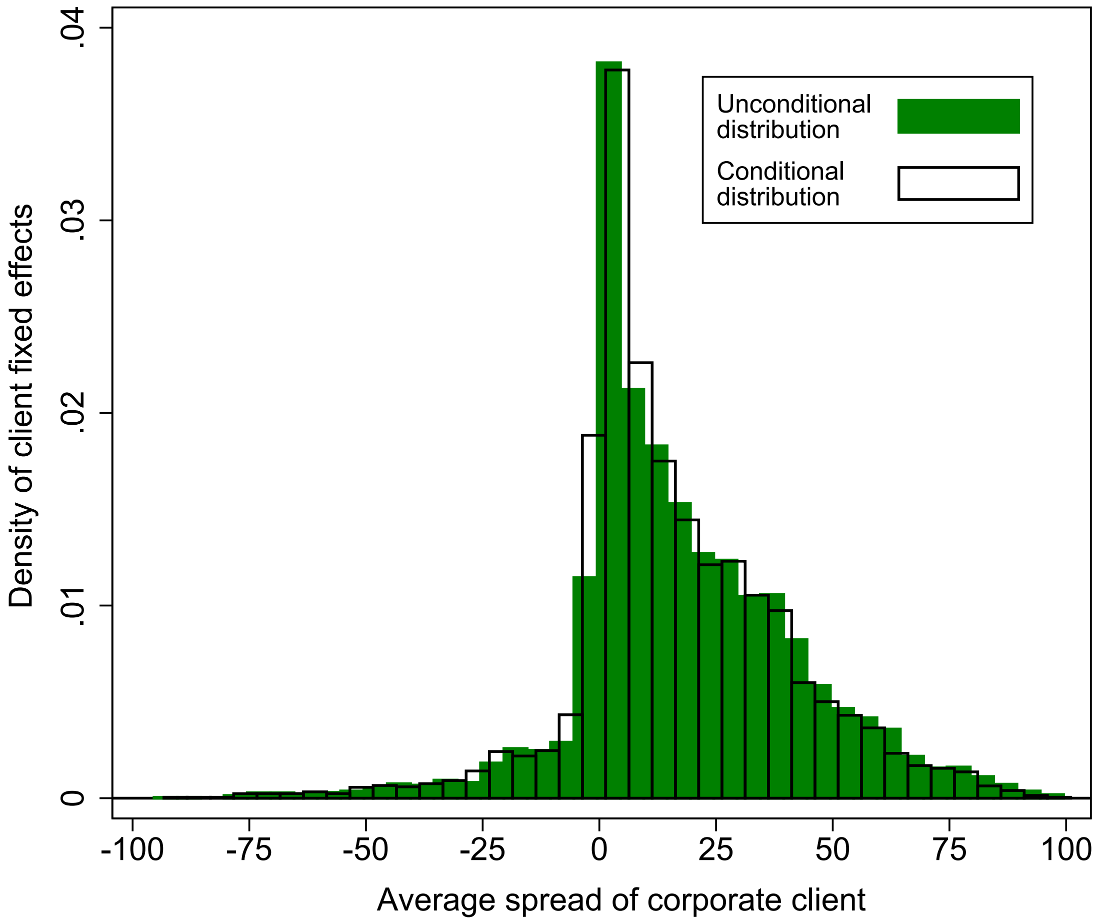
Note: This figure plots contractual forward rates versus the mid-price on a given day (28 December 2016). The mid-price is shown by the solid black line, which tracks intraday mid-prices for one month EUR/USD forwards (as constructed from Thomson Reuters quote data). The contractual forward rates are shown by blue dots (for forwards in which the client buys euro against dollar) and red crosses (for forwards in which the client sells euro against dollar). For the latter, we only include forwards with an original maturity of between 25 and 35 days (to match the one month tenor of the mid-price). Blue dots (red crosses) above (below) the solid black line imply positive spreads for the client.

Figure 3: Distribution of Average Client Spread



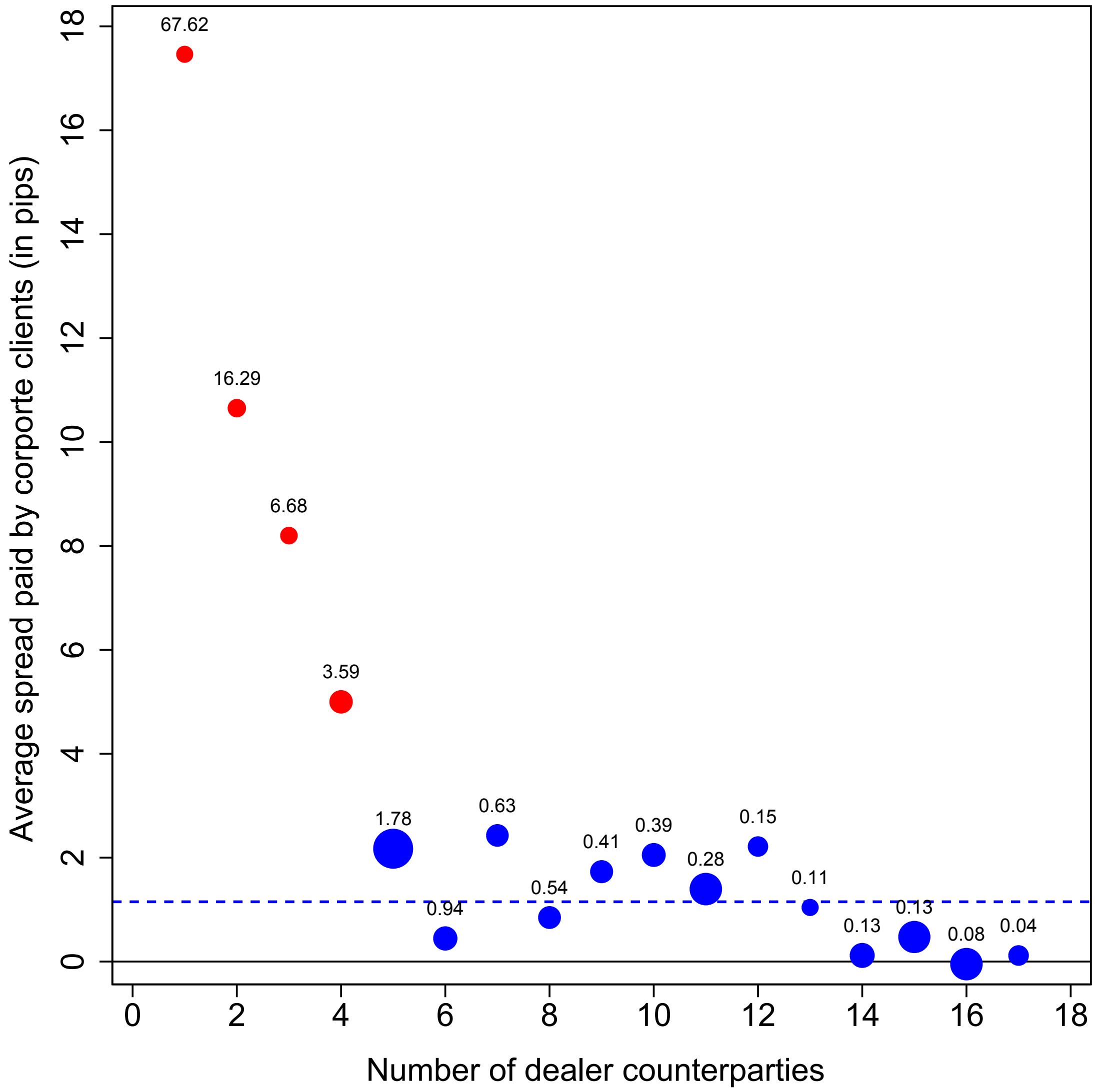
Note: This figure plots the distribution of average spreads paid by the 10,062 clients that engage in 556,297 forward transactions with 204 dealers between April 1, 2016, and March 31, 2017. Positive spreads are costly to the client and advantageous to the dealer, and vice versa for negative spreads.

Figure 4: Distributions of Conditional and Unconditional Average Client Spreads



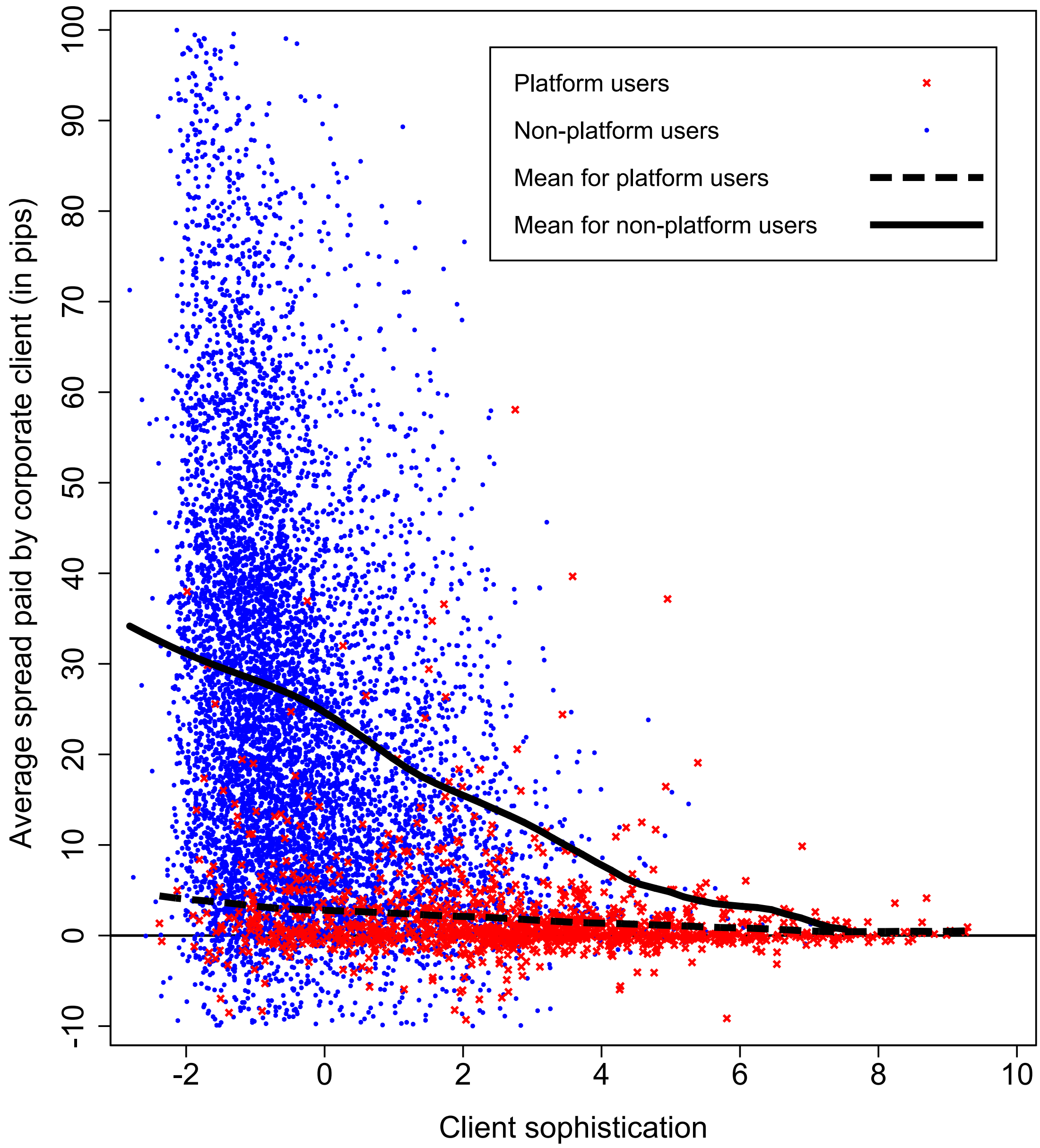
Note: This figure plots the distributions of conditional and unconditional average client spreads (in pips) for the 8,533 clients that traded more than one EUR/USD forward over April 1, 2016, to March 31, 2017. The unconditional distribution of average client spreads is calculated as in Figure 3. The distribution of conditional average client spreads controls for contract characteristics, dealer fixed effects, and market conditions.

Figure 5: 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 represents the aggregate notional traded (in logs). Marker labels indicate the percentage of the 10,062 clients with a given number of dealer counterparties. Client groups with five or more dealer counterparties are colored blue; groups with four or fewer counterparties are colored red. The horizontal line plots the average spread paid by the client groups colored blue (i.e. 1.2 pips).

Figure 6: Average Client Spread by Sophistication and Trade Execution Type



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 $Log\#TradesNonFX$. The solid black line plots the estimated Kernel-weighted local polynomial regression of average client spreads on *Sophistication*. The dashed black line plots the estimated Kernel-weighted local polynomial regression for the hypothetical case in which clients trade exclusively through request-for-quote multi-dealer electronic platforms, based on the estimates reported in Table 3, Column (3). For readability, the vertical axis is truncated at -10 pips.

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