Discriminatory Pricing of Over-the-Counter Derivatives

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Abstract

For the first time, new regulatory data allow precise measurement of price discrimination against non-financial clients in the FX derivatives market. Consistent with the theoretical literature, transaction costs vary systematically with measures of client sophistication. The median client pays 10.9 pips more than blue-chip companies due to its lower level of sophistication, which compares with a sample average effective spread of 6.9 pips. However, price discrimination is fully eliminated when clients trade electronically on multi-dealer platforms. We also document that less sophisticated clients incur additional costs when trading with their relationship bank and in fast-moving markets, but only for bilaterally negotiated contracts.

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1 Introduction

Many financial markets are decentralized, with trading taking place over-the-counter (OTC). Unlike in centralized markets, prices are typically negotiated bilaterally, which gives rise to frictions. In 2009, G20 leaders committed to reform the OTC market for financial derivatives. Yet many policies designed to improve the quality of derivatives markets are opposed by the industry. In currency markets, banks have brandished efforts to enhance post-trade transparency as "cumbersome" and "of little value" amid lobbying efforts to stymie reform.[1]

Our paper informs this high-stakes debate by exploiting new regulatory data that cover all derivatives trades involving at least one European Union (EU) counterparty.[2] Our analysis is motivated by a theoretical literature that predicts how bilateral transaction prices in OTC markets vary with the degree of customer sophistication (Duffie, Gârleanu & Pedersen, 2005). The ability to observe the identity of market participants enables us to quantify the extent of such price discrimination. We thereby make an evidence-based contribution to a debate frequently dominated by anecdotes and special interests.

The FX derivatives market provides a useful laboratory. Unlike other derivatives markets, it encompasses a wide spectrum of client sophistication. In our sample, 204 banks (henceforth "dealers") trade over half a million forward contracts with 10,087 non-financial firms ("clients"), which range from large multinationals to small import-export companies. Survey evidence suggests that small and medium sized enterprises lack financial expertise, which renders them susceptible to price discrimination by dealers.[3]

[1]See "Big banks to fight Mifid push for extra transparency in FX markets", *Financial Times*, May 16, 2019, available at `https://www.ft.com/content/f02cbc1a-7335-11e9-bbfb-5c68069fbd15`.

[2]Since our analysis pre-dates Brexit, we capture the large fraction of trades by UK-based entities. Consequently, our analysis spans the largest global segment of the FX derivatives market.

[3]See "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`.

We find that transaction costs—measured by the effective spread (henceforth "spread") of contractual forward rates relative to mid-quotes in the inter-dealer market—are highly heterogeneous across clients. To identify price discrimination, we estimate panel regressions with dealer-date fixed effects. We thus compare spreads across clients that trade with the *same* dealer on the *same* day. Our framework therefore controls for observed and unobserved time-varying dealer characteristics (e.g. dealer efficiency and balance sheet constraints).

We obtain robust evidence that transaction costs vary systematically with proxies for client sophistication.[4] Using a composite measure, we find that a one standard deviation decrease in client sophistication is associated with a 2.7 pip increase in spreads.[5] Our regression estimates imply that the median client incurs an additional markup of 10.9 pips relative to the largest blue-chip companies due to price discrimination based on sophistication. Given an average spread of 6.9 pips, these effects are economically large.

Our analysis sheds light on the economics of OTC markets along three additional dimensions. First, we examine trades on multi-dealer electronic trading platforms (henceforth "platforms"), which enable clients to request quotes from multiple dealers simultaneously rather than individual dealers sequentially. We show that platform trades exhibit significantly tighter spreads than comparable bilateral trades. Moreover, we find that the inverse relationship between spreads and client sophistication is absent for platform trades. This suggests that enforcing competition across dealers fully eliminates price discrimination based on sophistication.

Second, we use firm-bank linkages in the credit market to assess the role of dealer-client relationships in execution quality. Our novel methodology identifies relationships from firm-

[4] These proxies are: 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. Through the lens of Duffie et al. (2005), these proxies capture the terms ρ (the intensity with which clients encounter dealers) and $1-z$ (clients' bargaining power in bilateral negotiations).

[5] In FX markets, a pip is the smallest measurable difference in an exchange rate. By convention, EUR/USD is priced to four decimal places, so 1 pip refers to a 0.0001 point difference. In our sample, the EUR/USD exchange rate was close to 1, so pips are close to basis points.

bank linkages in the credit market instead of transaction data, which mitigates concerns about reverse causality. We find a nuanced role of relationships that varies with the level of client sophistication. While highly sophisticated clients obtain a relationship discount, most pay higher spreads when trading with their relationship bank, consistent with the idea that they are captive.

Third, we identify and quantify the role of price opacity. We find evidence that clients incur additional costs in fast-moving markets because dealers adjust prices asymmetrically when trading bilaterally with less sophisticated clients. However, their overall economic magnitude is small because they arise only when mid-quote movements are both large and in the opposite direction to the client order.

Finally, we perform three robustness tests. First, we show that our results are not driven by differences in counterparty risk. Second, we provide evidence that financial clients are also subject to price discrimination, but the economic magnitude is approximately 1/10th of that found for non-financial clients. Third, our results are robust to a sample split into platform users and non-users.

Our findings can inform policy. In our sample, nearly 90% of clients never trade on a platform. Some of this non-adoption can be explained by small trading needs and setup costs. However, we estimate that increased platform trading could generate aggregate client savings of approximately €168 million per year in EUR/USD. The fact that clients do not realize these gains suggests that they do not observe the benefits of platform trading. Better price disclosure would enable clients to make informed choices about trading venues, and the resulting improvements in execution quality could spur additional hedging activity and reduce firms' exposure to currency risk.

Related Literature

Our work contributes to the literature on decentralized OTC markets. These markets are characterized by search frictions (Duffie et al., 2005) and opacity (Duffie, 2012). The resulting imperfect competition enables dealers to engage in price discrimination and generates heterogeneous transaction costs for clients. While early empirical studies provide evidence of price dispersion in fixed-income OTC markets (Schultz, 2001; Harris & Piwowar, 2006; Green, Hollifield & Schürhoff, 2007), this does not necessarily imply discrimination in the absence of client identifiers.

Our work is closely related to O'Hara, Wang & Zhou (2018) and Hendershott, Li, Livdan & Schürhoff (2020), who study trading activity in the corporate bond market. By drawing on counterparty identifiers, they find evidence of price discrimination, with larger and more active clients paying tighter spreads. However, their samples are restricted to insurance companies, which are generally sophisticated market participants. In contrast, our focus on non-financial firms allows us to assess price discrimination in a richer setting with a diverse range of clients. In a robustness test, we show that price discrimination with respect to financial clients exists, but to a much lesser extent than for non-financial clients. This suggests that studies restricted to sophisticated clients underestimate economic magnitudes.

Our analysis is also related to the work of Osler, Bjonnes & Kathitziotis (2016), who study the markups set by a single FX dealer. The EU-wide coverage of our dataset allows gives rise to a number of advantages, including the use of dealer-time fixed effects and the identification of dealer-client relationships through outside data sources.

This paper also contributes to the literature on electronic platform trading in OTC markets.[6] We advance this literature by studying how the benefits of platform trading vary across market participants. We show that platform trading completely eliminates price discrimination based on sophistication, which benefits less sophisticated clients most. Against this background, the fact that most firms in our sample never trade on a platform may appear puzzling. However, it can largely be explained by the presence of fixed costs and the relatively low trading activity of smaller clients. Nevertheless, we find that some active firms forego substantial benefits by sticking to bilateral trading, which amount to approximately €168 million on aggregate.

Moreover, we speak to the literature on relationship trading in OTC markets. In various empirical settings, relationship trading is associated with lower transaction costs.[7] 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 trading data. Second, we allow the effect of relationships to vary with client sophistication.

Our results on asymmetric price adjustment are related to the literature on price transparency and execution quality.[8] More generally, our analysis touches on the topic of corporate hedging. Nance, Smith & Smithson (1993) and Guay & Kothari (2003) show that larger firms hedge more. We find that sophisticated clients generally face tighter spreads, which may induce them to participate more actively in this market.

[6]See, e.g., Hendershott & Madhavan (2015), Benos, Payne & Vasios (2020), Riggs, Onur, Reiffen & Zhu (2020), and Collin-Dufresne, Junge & Trolle (2020).

[7]See Bernhardt, Dvoracek, Hughson & Werner (2004), Cocco, Gomes & Martins (2009), Afonso, Kovner & Schoar (2013), Di Maggio, Kermani & Song (2017), and Hendershott et al. (2020).

[8]Bessembinder, Maxwell & Venkataraman (2006), Goldstein, Hotchkiss & Sirri (2006) and Edwards, Harris & Piwowar (2007) document that the introduction of TRACE in the US corporate bond market led to lower transaction costs and increased liquidity. Similar effects have been identified in the CDS market following provisions in the Dodd-Frank Act to promote post-trade transparency (Loon & Zhong, 2014, 2016).

2 Hypotheses

We articulate four hypotheses about the determinants of transaction costs in the FX derivatives market. Our first hypothesis derives from the theoretical literature on OTC markets. In Duffie et al. (2005), clients with better (or faster) access to alternative dealers incur lower mark-ups because they expose dealers to sequential competition. Moreover, large or active clients have more bargaining power in bilateral negotiations with dealers compared to small and inactive ones. Since it is difficult to empirically differentiate clients' search technology and bargaining power, we subsume them under the term "sophistication".[9] 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 multi-dealer platforms have developed recently, allowing clients to solicit quotes from multiple dealers simultaneously. Evidence from the corporate bond market suggests that platforms reduce search costs and enhance dealer competition (Hendershott & Madhavan, 2015), in line with predictions from laboratory experiments (Flood, Huisman, Koedijk & Mahieu, 1999). We thus expect platform trades to exhibit tighter spreads. Moreover, we predict that the least sophisticated clients have most to gain from such platforms.

Hypothesis 2: Platforms

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

[9] We adopt this label from Duffie et al. (2005), who show that clients with a higher dealer contact rate incur lower markups, holding bargaining power fixed. However, variation in bargaining power across clients has qualitatively similar cross-sectional implications. We therefore characterize both a high contact rate and high bargaining power as sophistication.

Empirical research on OTC markets documents that trading networks tend to be sparse: most participants interact with few counterparties. Relationship trading has been associated with better terms than "arm's length" trading, which can be rationalized by 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., 2020). However, financial intermediaries may also use relationships to charge higher prices to captive clients. 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 transaction costs.

OTC markets are sometimes referred to as "dark markets" (Duffie, 2012). Unlike in centralized structures, there is typically no obligation to disclose prices or quotes publicly. While dealers obtain information from their frequent interactions in inter-dealer and dealer-to-client markets, clients are generally less well informed about market conditions in the absence of benchmark prices (Duffie, Dworczak & Zhu, 2017). Dealers can exploit this information advantage by adjusting prices asymmetrically in response to market conditions.[10] Such behavior has been observed in the US municipal bond market (Green, Li & Schürhoff, 2010) and various goods markets (Peltzman, 2000). Consequently, we adopt the following hypothesis:

Hypothesis 4: Information Rents from Asymmetric Price Adjustment

Client orders in the opposite direction of recent market price changes incur higher transaction costs than trades in the same direction. This effect declines with client sophistication.

[10] To see this, consider for example a dealer that receives a quote request after the EUR/USD forward rate has increased. For a client buy order, the dealer has an incentive to update its quote to reflect the new market price. However, for a client sell order, the dealer prefers to offer a quote closer to the outdated lower price. The opposite is true for trades following price decreases, i.e. the dealer will prefer to quote based on the outdated higher price in case of a client buy order.

3 Institutional Details

Despite its size and importance for global capital flows, the FX derivatives market is arguably understudied relative to other financial markets.[11] Consequently, institutional details related to the FX derivatives market are perhaps less commonly known. To fill this gap and to contextualize the analysis in the paper, this section provides an overview of the key institutional features of the FX derivatives market.

According to the BIS Triennial Central Bank Survey, daily transaction volumes in FX markets grew from US$1.5 trillion in 1998 to US$6.6 trillion in 2019. At 64%, swaps and forwards represent the largest share of this market, with most of the remainder comprising spot transactions.[12] The US dollar is one leg of a transaction in 88% of the volume, followed by the euro (32%) and the yen (17%).[13] While the market is dominated by financial institutions, trading by non-financial firms accounts for nearly 7% of the activity in FX derivatives globally. Many non-financial firms face currency mismatches, typically because their revenues are denominated in domestic currency while their expenses are in foreign currency.[14] A forward contract can be used to hedge this exchange rate risk by locking in the future domestic currency value of foreign currency expenses.

Like other OTC markets, the FX derivatives market is split into inter-dealer (D2D) and dealer-to-customer (D2C) segments. The D2D segment is approximately evenly split into voice and electronic trading, with the latter fragmented across many different trading venues

[11] As one indicator of relative paucity, a Google Scholar search of "FX derivatives market" returns just 188 papers (as of April 27, 2020). By contrast, "corporate bond market" is associated with 16,500 papers.

[12] An outright forward contract constitutes the obligation to exchange one currency for another at a pre-specified date and exchange rate. In an FX swap, two currencies are exchanged at contract initiation together with the obligation to reverse the exchange at a future date. Accordingly, they are equivalent to a combined spot and outright forward.

[13] For information on the Triennial Survey, see www.bis.org/statistics/rpfx19.htm.

[14] For example, Monarch, a UK-based airline, 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.

(Schrimpf & Sushko, 2019). In the D2C segment, trades have traditionally been negotiated by phone. However, trading has become increasingly electronic, with several multi-dealer platforms (e.g., 360T, FXall, Bloomberg, and Currenex) offering alternatives to traditional voice execution.[15] They enable clients to solicit quotes from multiple dealers simultaneously by indicating the desired currency pair, tenor, amount, and trade direction (sometimes optional). Dealers can respond either with a static quote or a quote stream that updates in real time as market conditions change. Importantly, dealers observe the client's identity and are thus able to tailor their quote or quote stream accordingly. They also observe whether they compete with other dealers, but not with how many. Once a client accepts a quote, dealers retain a "last look" on whether the trade is executed.

To counteract these competitive pressures, dealers have improved offerings on their own single-dealer platforms (Barclays BARX, Deutsche Bank Autobahn, UBS Neo, etc). These trading venues are geared towards more active clients, enable faster execution, and provide additional features such as access to execution algorithms. However, single-dealer platforms may hinder competitive pricing.

Regulatory reform of FX derivatives has lagged behind that of other asset classes. Most interest rate swaps and index CDS are subject to mandatory central clearing in the EU. However, these rules do not apply to FX derivatives. In addition, physically settled FX swaps and forwards are exempt from initial margin rules pertaining to non-centrally cleared derivatives. A variation margin must be posted by financial clients and for non-financial clients that trade above a threshold, but these rules were fully phased-in only by 2018, after our sample ends.[16]

[15] For a list of active trading venues, see https://www.marketfactory.com/venues/.

[16] See the official text of EU Regulation 2016/2251, available at https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32016R2251&from=EN.

Consequently, most trades in our sample do not involve any exchange of variation margin, potentially giving rise to counterparty risk (see Subsection 7.1).

4 Data and Measurement

The European Market Infrastructure Regulation (EMIR) requires that all counterparties resident in the EU report the contractual details of derivatives transactions to trade repositories, which share data with authorities by jurisdiction. Two authorities—the European Systemic Risk Board (ESRB) and the European Securities and Markets Authority (ESMA)—have access to the full EU-wide transaction-level dataset.[17]

From the three largest trade repositories—namely DTCC, REGIS and UnaVista—we collect information on FX derivatives contracts executed between April 1, 2016 and March 31, 2017. We restrict coverage to FX forward contracts, which generate an obligation to exchange a given quantity of one currency against another at a predetermined exchange rate at some future date. This includes both outright forwards as well as the forward legs of FX swaps. We further limit the sample to contracts referenced to EUR/USD, which is the currency pair with the largest notional outstanding according to the Bank for International Settlements (BIS, 2017).

The transaction records provide a legal entity identifier for all counterparties. We therefore 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").

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

We implement various filters and checks on data quality. The raw dataset comprises dual-sided reporting whenever both counterparties to a trade are EU-domiciled. We check the consistency of dual reports and discard approximately 25,000 observations which feature discrepancies, such as different execution timestamps. Reports without dual reporting are retained only if they come from dealers, which are subject to more stringent oversight. Consequently, in our dataset all dealers are resident in the EU, but clients can reside anywhere. The final dataset used for our main analysis comprises 548,298 trades between 10,087 clients and 204 dealers, with a total notional traded of over €5 trillion.

4.1 Transaction Costs

We measure transaction costs by the effective spread (expressed in pips). For transaction τ, the spread is defined as

$$Spread_\tau = d_\tau \times (f_\tau - m_\tau) \times 10^4, \tag{4.1}$$

where f_τ is the contractual forward rate, m_τ is the contemporaneous mid-quote, 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).[18]

To construct the mid-quote m_τ, we obtain quote data for the EUR/USD spot exchange rate as well as “forward points” for standard maturities from Refinitiv Datascope (formerly Thomson Reuters Tick History).[19]. These quotes are indicative (i.e. non-executable) and collected in real-time from the inter-dealer market. The set of quoting dealers is determined by Refinitiv through proprietary data quality measures, including tolerance bands on the bid-ask spread and quote changes.

[18] A long (short) position in EUR/USD constitutes the obligation to buy (sell) EUR against USD at the contractual forward rate when the contract matures.

[19] These standard maturities are one day, one week, two weeks, three weeks, one month, two months, three months, six months, and one year.

We compute the mid-quote for each series as the midpoint of the best bid and ask across dealers at a given point in time. To avoid using stale quotes, we assume that quotes are valid for a maximum of 30 seconds, although most dealers provide updates at much higher frequency. The mid-quote for a given tenor is the sum of the mid-quotes of the spot exchange rate and the respective forward points. For non-standard maturities, we linearly interpolate the forward points across adjacent standard maturities.[20]

For illustration, Figure 1 plots intraday mid-quotes for 30-day forwards on an arbitrary trading day. The contractual forward rates of executed buy (sell) trades with comparable tenors are marked by blue dots (red crosses). Following Equation 4.1, *Spread* is calculated as the vertical distance between the contractual forward rate and the mid-quote, with buy (sell) trades above (below) the mid-quote implying positive spreads for the client.

4.2 Explanatory Variables

We now define the explanatory variables used to test the four hypotheses. These include measures of sophistication, identifiers for platform and relationship trades, and variables capturing asymmetric price adjustment. We also use a set of trade characteristics as control variables.

Client Sophistication

We propose five measures of client sophistication. $\#Counterparties$ denotes the number of dealers with which a client trades during our one year sample period. We also compute the Herfindahl-Hirschman index (HHI) of the share of a client's trades with each dealer. HHI is inversely related to $\#Counterparties$, since higher dealer concentration implies fewer counterparties. Both variables capture the meeting intensity parameter ρ in Duffie et al. (2005).

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

Further, we calculate $TotalNotional$ as the total notional (in euros) of EUR/USD forwards traded by a client in the one year sample period. Similarly, $\#TradesFX$ is the number of EUR/USD forwards traded by a client. Clients that trade larger volumes or at higher frequency are more attractive to dealers, improving their bargaining power in bilateral negotiations, represented by $1 - z$ in Duffie et al. (2005).

Finally, $\#TradesNonFX$ is 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. More trading experience in other derivatives contracts indicates a higher degree of sophistication, but is not directly related to the spreads paid in the FX derivatives market. This variable captures both more efficient search and greater bargaining power.

In regressions, we take the natural logarithms of these variables (except for HHI). All five variables are highly correlated in the cross-section, with absolute correlation coefficients ranging from 0.4 to 0.84 (see Online Appendix, Table A.1). Thus, for convenience, much of our analysis uses the first (demeaned) principal component of these five variables, which we label as $Sophistication$ (following the terminology of Duffie et al. (2005)).

Platforms

The second hypothesis concerns the role of platforms. Our transaction-level data identifies trades executed on a platform such as 360T, FXall, Bloomberg, or Currenex. Accordingly, we define a dummy variable, $Platform$, that is equal to one for trades on these platforms, and zero otherwise.

Dealer-Client Relationships

Research on market microstructure has studied the effect of 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 transaction costs. Consequently, the econometrician cannot exclude that firms tend to trade with banks that offer tighter spreads. We avoid this problem by retrieving information on firms' credit relationships outside the FX market. In particular, we obtain the identities of firms' main relationship (lending) bank(s) from Orbis. These data are available for a subset of 6,638 firms. We create a dummy variable, *Relationship*, that equals one for trades where the client has a credit relationship with the dealer, and zero otherwise.

Information Rents from Asymmetric Price Adjustment

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

$$|\Delta m_\tau^{-d}| = \begin{cases} |\Delta m_\tau| & \text{if } sign(d_\tau) \neq sign(\Delta m_\tau) \\ 0 & \text{otherwise} \end{cases}, \tag{4.2}$$

$$|\Delta m_\tau^{+d}| = \begin{cases} |\Delta m_\tau| & \text{if } sign(d_\tau) = sign(\Delta m_\tau) \\ 0 & \text{otherwise} \end{cases}, \tag{4.3}$$

where Δm_τ denotes the mid-quote change in the 30-seconds prior to trade τ. In a regression of transaction spreads on these variables, Hypothesis 3 predicts that the coefficient of $|\Delta m_\tau^{-d}|$ is positive, reflecting client costs from asymmetric price adjustment, while the coefficient of

$|\Delta m_{\tau}^{+d}|$ is zero if dealers immediately update their quotes when it favors them. The sum of these coefficients reflects the net costs incurred by clients through this mechanism.

Trade Characteristics

Finally, we define variables to capture relevant trade characteristics. First, $Notional$ (in €million) is the notional amount of the forward contract. Research on bond markets documents that spreads decrease in 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 wider spreads for long maturity contracts in compensation for greater market (and possibly counterparty) 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 wider spreads for customized contracts, since these are more difficult to hedge in the inter-dealer market. Fourth, $Volatility$ is the realized volatility of the FX spot rate over the 30 minutes preceding a trade, based on one minute intervals. Spreads are expected to be higher in volatile market conditions to compensate dealers for added 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 insofar as there is a structural imbalance of buy or sell orders.

5 Descriptive Statistics

Table 1, Panel A provides summary statistics on the sophistication measures for the 10,087 clients in our sample. We observe heavily skewed distributions, implying that our sample consists of a few very sophisticated firms and many less sophisticated ones. More than half of clients trade with just one dealer, and even the client at the 75th percentile has just two counterparties. This is also reflected in HHI, whose average of 0.8 is close to perfect concentration.

On average, clients traded a total notional of €515 million in our sample. However, heterogeneity in trading volumes is very large: clients at the 10th and 90th percentiles traded notionals of €0.1 million and €114 million respectively. A similar picture emerges from $\#TradesFX$ and $\#TradesNonFX$. While the median client trades eight FX forwards, the mean trade count is 54, driven by a minority of active clients. More than three quarters of clients never trade any non-FX derivatives.

The five aforementioned variables are summarized in *Sophistication*, which is the demeaned first principal component of $Log\#Counterparties$, HHI, $LogTotalNotional$, $Log\#TradesFX$, and $Log\#TradesNonFX$. Nearly two-thirds of the 10,087 clients have a negative value of *Sophistication*, implying positive skewness.

Finally, we report three measures of counterparty risk for the clients in our sample. Available only for a subset of clients, these measures are based on data from Orbis and the four major rating agencies (S&P, Moody's, Fitch, and DBRS). The median $ZScore$ is 2.7, which is generally taken to imply a strong financial position. However, a quarter of clients have a $ZScore$ of 1.8 or lower, which suggests heightened bankruptcy risk.[21] This is confirmed by the tails of *Leverage* and *AvRating*, where the client at the 75th percentile has loans and long-term debt worth 40% of total assets and a credit rating of BB+, which is one notch below investment grade. [22]

Table 1, Panel B provides an overview of dealer characteristics. Since our empirical strategy involves dealer fixed effects, these are merely for background information. The average (median)

[21]Following Altman (1968), we define $ZScore = 1.2 \times (Working\ Capital/TA) + 1.4 \times (Retained\ Earnings/TA) + 3.3 \times (Ebitda/TA) + 1 \times (Sales/TA)$, where TA denotes $Total\ Assets$. We omit market equity from the original formula since there are few listed firms in our sample.

[22]We define $Leverage = (Loans + LT\ debt)/TA$. We assign numerical values to ratings using the following scale: "AAA"=1, "AA+"=2, ..., "D"=28. In the case of multiple ratings, we compute the average.

dealer has 81 (7) clients and trades a total notional of around €25 billion (€19 million). Overall, the cross-sectional distribution is similarly skewed to that of clients, meaning that much of the market is concentrated among a few core dealers. We also report bank size (total assets) and the ratio of net interest income to gross revenue (from Bankscope). Most dealers are mid-sized banks with relatively low shares of non-interest income, indicative of a traditional business model focused on lending. However, the tails of the distribution indicate the presence of large banks with significant fee income.

Table 1, Panel C provides summary statistics at the transaction level for the 548,298 EUR/USD forward contracts in our sample. The average spread over all trades is 6.9 pips. This is more than 20 times the average quoted half-spread of 0.3 basis points in the EUR/USD inter-dealer market, as reported by Karnaukh, Ranaldo & Söderlind (2015). The median is considerably below the mean at 2 pips, indicating substantial negative skew. Moreover, the dispersion is very large, with an inter-quartile range of 12.4 pips. We also note that some transactions incur negative transaction costs: the spread at the 25th percentile is -1.1 pips. While negative spreads can be explained by inventory rebalancing (Dunne, Hau & Moore, 2015), they may also arise in our data from occasional timestamp inaccuracies.[23] While individual observations can thus be subject to measurement error, the random-walk nature of exchange rates implies that errors will average out across a large number of observations.

Most contracts have an underlying notional value of less than €1 million; just under 10% of contracts have a notional exceeding €15 million. Half of all transactions pertain to contracts with an original maturity of fewer than 35 days; more generally, the frequency of executed FX forward trades is a decreasing function of the contract tenor. Clients enter long positions in

[23] Timestamps in the trade repository data are rounded to the nearest second, but quotes in the inter-dealer market can change at higher frequency. Moreover, practitioners report that timestamps can sometimes reflect the time when a trade was booked instead of the execution time, especially for voice trades.

around 40% of trades. Moreover, just under 40% of all trades are executed on a platform, in line with existing survey evidence (BIS, 2016). Among the 278,492 transactions for which we have information on credit relationships, 45% are executed with the relationship bank; in the subsample of clients that trade with only one dealer, the share of relationship trading increases to 68%. Finally, the distributions of $|\Delta m_\tau^{-d}|$ and $|\Delta m_\tau^{+d}|$ show that mid-quote changes over the preceding 30 seconds rarely exceed 1 pip. Additional summary statistics at client and transaction level are provided in the Online Appendix.[24]

6 Empirical Analysis

Figure 2 plots the cross-sectional distribution of average spreads at client level. The average client pays a spread of 18.1 pips, which is considerably higher than the transaction-level average of 6.9 pips. This indicates that less active clients tend to pay wider spreads.

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

$$Spread_{\tau,i,d,t} = X_i\beta + Z_\tau\theta + \delta_{d,t} + \gamma_m + \epsilon_{\tau,i,d,t}, \tag{6.1}$$

where $Spread_{\tau,i,d,t}$ denotes the spread for transaction τ between client i and dealer d on date t. The variable X_i represents a measure of client sophistication, while Z_τ is a row vector of control variables composed of the five trade characteristics defined in Subsection 4.2. Importantly, our specification includes dealer-date fixed effects ($\delta_{d,t}$). Thus, conditional on trade characteristics,

[24] Table A.2 cuts the data into terciles of low, medium and high client sophistication and according to whether clients ever use a platform. These sorts indicate a negative correlation between transaction costs and sophistication. Table A.3 provides a breakdown of clients according to their geographical location and industry sector. Consistent with FX market participation being motivated by hedging needs, most firms are involved in external trade or production, which can give rise to currency risk. For example, purchases of foreign goods are often 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.

we compare the spread that a dealer charges a client with the spread that the *same* dealer on the *same* date charges another client. This comparison within dealers allows us to interpret our results in terms of price discrimination, since we control for differences in spreads across trades that are driven by observable or unobservable dealer characteristics (e.g. dealer efficiency). Moreover, since we allow these dealer fixed effects to vary across trading days, we eliminate potential concerns related to time-variation in dealers' (unobservable) balance sheet capacity, which can affect market liquidity (e.g. Adrian, Boyarchenko & Shachar, 2017; Goulding, 2019). Finally, we also control for intraday patterns using minute-of-day (γ_m) fixed effects.

6.1 Client Sophistication

To provide early intuition, Figure 3 plots the average client spread by the number of dealers ($\#Counterparties$) with which a client trades in our sample. The size of each dot is proportional to the notional share for each group of clients. While clients with one dealer 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 tighter 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 clients, their aggregate notional accounts for 88% of the total.

To formally test Hypothesis 1, we estimate Equation 6.1 for each of the five proxies of client sophistication discussed in Subsection 4.2 as well as the composite measure ($Sophistication$). The resulting coefficient estimates, with standard errors clustered at the client level, are reported in Table 2. All five sophistication measures have the directional effect implied by Hypothesis 1, with coefficient estimates statistically significant at the 1% confidence level. Both Columns (1) and (2) indicate that clients with greater search efficiency—proxied by the number of dealers with which they trade and their concentration in those dealers—is associated with tighter spreads. In Columns (3) and (4), we find that clients with greater bargaining power derived from their market activity, either in terms of number of trades or notional traded, incur tighter spreads. Finally, Column (5) reveals that clients with more outstanding derivatives contracts in other asset classes benefit from tighter 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 of -1.522 is statistically significant at the 1% level. Accordingly, an increase in client sophistication by one standard deviation is associated with a decrease in spreads of 2.7 pips. Since the cross-sectional distribution of sophistication is very skewed, one may alternatively gauge the economic significance of price discrimination by benchmarking clients to a group of very sophisticated clients. We find that *Sophistication* averages 6.65 for the constituent firms of the EURO STOXX 50 blue-chip index (roughly corresponding to the 99th percentile).[25] Relative to this group, the median client (with $Sophistication = -0.5$) incurs a spread that is 10.9 pips wider.[26]

We briefly comment on the control variables. A larger notional amount commands tighter spreads, consistent with prior evidence from the corporate bond market (Schultz, 2001; Harris & Piwowar, 2006; Green et al., 2007). Longer maturities are associated with wider spreads, potentially reflecting higher counterparty risk (see Subsection 7.1). Moreover, trades with non-standard tenors command higher transaction costs: an increase in a trade's customization by one standard deviation is associated with a spread increase of approximately 1 pip. The coefficient of $Volatility$ has the expected positive sign but is statistically insignificant. Finally,

[25] We are able to identify 36 of the 40 non-financial index members in our data.

[26] In the Online Appendix (Table E.1), we allow the extent of price discrimination to vary across dealers. We find that larger and more sophisticated dealers engage in less price discrimination, although the extent to which they discriminate remains economically large.

the coefficient of the Buy dummy is statistically significant, consistent with persistent covered interest parity violations (Du, Tepper & Verdelhan, 2018).

6.2 Platforms

Platforms enable clients to query multiple dealers simultaneously, and thus reduce search costs and dealers' ability to exert market power. As detailed in Table 1, around 40% of trades in our sample are executed on platforms. However, these trades are due to only 1,218 clients (12%), which implies that most clients only trade bilaterally.

Hypothesis 2 predicts that trades on platforms incur tighter spreads. Before turning to the formal regression analysis, Figure 4 plots the average spread at the client level as a function of sophistication. Blue dots correspond to clients that trade only bilaterally, while red crosses represent firms that execute at least one of their trades on a platform. The associated non-parametric fit is indicated by the bold and dashed lines, respectively. Consistent with Hypothesis 2, platform users incur tighter spreads for a given level of sophistication. Moreover, the negative relationship between transaction costs and client sophistication holds only for non-users. In contrast, platform users obtain competitive spreads irrespective of their level of sophistication.

Table 3 reports results from a regression analysis with the transaction spread as the dependent variable. Controlling for trade characteristics as well as dealer-date and minute-of-day fixed effects, we find a negative and statistically significant coefficient of the $Platform$ dummy in Column (1): platform trading is associated with a spread compression of 7.4 pips. This effect diminishes to 3.9 pips when controlling for $Sophistication$ in Column (2), but remains both statistically and economically significant. In Column (3), we add an interaction term of $Sophistication$ and $Platform$, which yields a positive coefficient estimate of 1.97. This implies that the benefits of platform trading are larger for less sophisticated firms, in line with Hypothesis 2. In fact, this effect completely offsets the negative baseline effect of *Sophistication* (-1.94). Accordingly, platform trading fully eliminates discriminatory pricing based on client sophistication.

One potential concern is that unobserved client characteristics correlate with platform use. Sophisticated firms might self-select onto platforms and thereby introduce a selection bias. To address this issue, we augment our regression specification to include client fixed effects, so that we effectively compare spreads for the same client across on- and off-platform trades. The coefficient estimates in Columns (4) and (5) show some attenuation in the effect of platform use, consistent with a selection effect. Yet platform trading is still associated with substantial spread compression. In Column (4), platform trading implies a 1.4 pip reduction in spreads. The estimates reported in Column (5) show that the median client (with $\textit{Sophistication} = -0.5$) saves 4.5 pips when trading on a platform, while a highly sophisticated firm enjoys no savings.

Platform trading is thus a powerful tool that allows even unsophisticated clients to obtain competitive spreads. Importantly, the absence of central clearing in the FX derivatives market implies that the non-anonymity of counterparties is a necessary feature of this market. 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 on these platforms.

If platform trading is so beneficial, why don't more clients adopt it? Some insights can be gained from the literature on consumer search. In the model of Stahl (1989), some consumers observe all prices for free (platform users in our context) while others must engage in costly search. Naturally, the more informed consumers trade at more favorable prices. Suppose one were to modify the model to allow for consumer heterogeneity in terms of trading needs and enrich it with an ex-ante stage where consumers decide whether to acquire a search technology. In this setting, one would expect more active shoppers to be technology adopters.

Translated to our context, this suggests that clients with infrequent trading needs will rationally refrain from adopting platform trading if the expected benefits are not sufficient to cover the setup costs. While platforms typically do not charge fees to clients, costs can arise indirectly from the need to hire and train specialized staff or modify back-office procedures.

To assess whether such indirect costs can plausibly explain the limited adoption of platform trading, we compute the expected benefits of non-users moving all their trades to a platform. Following our regression analysis, we allow the benefits of platform adoption to vary with the level of client sophistication. Using the coefficient estimates from Column (3) of Table 3, they are computed as

$$PlatformBenefit_i = (1 - PlatformUser_i) \times \sum_{\tau} [(-13.2 + 1.97 \times Sophistication_i) \times Notional_\tau], \tag{6.2}$$

where $PlatformUser_i$ is a dummy that equals one if client i trades on a platform at least once in our sample, and zero otherwise. Summing over all clients, we estimate an aggregate gross benefit of €264 million per year in EUR/USD alone.

These aggregate benefits are distributed heterogeneously across clients. Consequently, when we assume a plausible annual cost of €0.1 million for platform trading, we find that over 95% of non-users rationally abstain, since their estimated benefits are smaller. However, the remaining 378 clients still account for a potential gross saving of €205 million, or €168 million net of the assumed setup cost.

Interestingly, our estimates are not overly sensitive to the assumed cost. We obtain aggregate net savings of €141 (€192) million when increasing (decreasing) the cost to €0.2 (€0.05) million. This is illustrated in Figure 5, which plots estimated aggregate net savings as a function of the number of clients that adopt platforms. Most savings would accrue to active clients; small changes in costs lead to the additional inclusion or exclusion of marginal clients, with relatively small aggregate effects.

Overall, the presence of plausible setup costs can partially explain the limited adoption of platforms. However, our estimates suggest that several hundred clients leave money on the table. One potential explanation for this apparent puzzle is that clients do not observe potential gains due to market opacity. Increased post-trade transparency, e.g. in the spirit of TRACE in the corporate bond market, would enable clients to compare the costs of different trading mechanisms and make more informed choices.

6.3 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. This approach mitigates potential endogeneity issues from identifying relationships from the structure of the trading network. In particular, our measure avoids the issue of reverse causality that can arise because clients tend to trade with dealers offering tighter spreads.

We start by regressing spreads on a relationship dummy as well as the standard set of trade characteristics, dealer-date and intraday fixed effects. Table 4, Column (1) shows that the coefficient of *Relationship* is positive and statistically significant, indicating an average premium of 2.9 pips per relationship trade. This differs from the existing literature, which typically finds that relationship trading is associated with a discount.

We proceed to explore how the effects of dealer-client relationships vary with the level of client sophistication. When we include *Sophistication* in Column (2), the premium for relationship trades is no longer statistically significant. In Column (3), we interact the *Relationship* dummy with *Sophistication*. The coefficient estimate of -1.12 is statistically significant at the 1% level. Moreover, we estimate a significant coefficient of the *Relationship* dummy (3.72). These estimates imply that the median client (with *Sophistication* $= -0.5$) pays a relationship premium of 8 pips relative to the most sophisticated firms (with *Sophistication* $= 6.65$). These results suggest that unsophisticated clients are captive to their relationship bank and thus incur wider spreads.By contrast, the most sophisticated clients (in the top fifth of the distribution) obtain small price concessions from their relationship banks in return for repeated business.

One potential concern is that a large share of relationship trading is driven by clients that interact only with only one dealer. To shed light on this issue, we split our sample into trades by single-dealer and multi-dealer clients. The fact that about one-third of single-dealer clients use a dealer that is not their relationship bank renders this a meaningful analysis. The results in Columns (4) and (5) of Table 4 indicate that the relationship premium is indeed related to client capture and not sophistication. Single-dealer clients trading with their relationship bank pay a significantly wider spread than single-dealer clients trading with a non-relationship bank. Importantly, this premium is statistically and economically significant even when controlling for *Sophistication*.[27] By contrast, Columns (6) and (7) reveal no relationship premium for multi-dealer clients after accounting for client sophistication. Taken together, these results corroborate the interpretation of the relationship premium as reflecting client capture.

Overall, these results paint a novel and 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 bank. This finding is driven by the predominance of low sophistication clients in our empirical setting. By contrast, a minority of highly sophisticated

[27] For this exercise, we re-define *Sophistication* to exclude *Log#Counterparties* and *HHI*.

clients obtain discounts from their relationship bank, in line with previous empirical work (Cocco et al., 2009; Hendershott et al., 2020).

6.4 Information Rents from Asymmetric Price Adjustment

Hypothesis 4 suggests that asymmetry between dealers and clients in their access to real-time price information can generate additional costs for clients. Using the definitions given in equations (4.2) and (4.3) for the alignment of recent mid-quote changes and clients' trade direction, we estimate the following linear regression:

$$Spread_{\tau,i,d,t} = \beta_1|\Delta m_\tau^{-d}| + \beta_2|\Delta m_\tau^{+d}| + Z_\tau\theta + \delta_{d,t} + \gamma_m + \epsilon_{\tau,i,d,t}. \tag{6.3}$$

Under Hypothesis 4, the cost $\beta_1 + \beta_2$ due to asymmetric price adjustment is predicted to be positive. It would be zero in a frictionless market.

Table 5, Column (1) shows a positive and statistically significant estimate for β_1, indicating that dealers charge wider spreads for trades preceded by a price change in the opposite direction of the client order. In contrast, β_2 is estimated to be negative and statistically significant, meaning clients enjoy somewhat tighter spreads in the alternate case. The latter finding suggests that stale quotes get "picked off" by clients, either deliberately or inadvertently. While the sum $\widehat{\beta_1}+\widehat{\beta_2} = 0.122$ is positive, it is not statistically significant (p-value 0.143), implying that dealers do not benefit from asymmetric price adjustment. We obtain qualitatively similar results when additionally controlling for client sophistication in Column (2).

Next, we explore whether less sophisticated clients incur costs from asymmetric price adjustment. To this end, we interact $|\Delta m_\tau^{d}|$ and $|\Delta m_\tau^{-d}|$ with *Sophistication* in Column (3). In this specification, the estimated coefficient sum $\widehat{\beta_1} + \widehat{\beta_2}$ increases to 0.44, and is significant at the 1% level. This shows that clients with average sophistication incur wider spreads due to asymmetric price adjustment. The sum of the coefficients of the interaction terms is equal to -0.08 and also statistically significant at the 1% level. Accordingly, client costs from asymmetric price adjustment decrease in client sophistication. Column (4) reveals that additionally controlling for platform trades does not change our estimates materially.

Overall, we find support for Hypothesis 4. Less sophisticated clients incur additional costs arising from dealers' asymmetric price adjustment, while more sophisticated clients do not. However, the economic magnitudes are small: while dealers earn a significant fraction of recent price movements (44% for clients with average sophistication), such movements rarely exceed 1 pip (see Table 1, Panel C).

7 Robustness

This section presents robustness tests. First, we show that our results on price discrimination are robust to controlling for counterparty risk. Second, we repeat our analysis for financial clients. Third, we perform separate analyses for platform users and non-users.

7.1 Counterparty Risk

Concerns related to counterparty risk in the OTC derivatives market played a major role during the 2007-08 financial crisis. Financial regulators subsequently introduced requirements for central clearing and margining of certain derivatives contracts. However, FX forwards are exempt from initial margin requirements, and non-financial clients were also exempt from variation margin requirements during our sample period. Accordingly, none of the trades in our sample is subject to mandatory clearing or margining, which means there is a potential role for counterparty risk. We do not observe actual margining because reporting was not mandatory for non-financial firms during our sample period.

This begs the question of whether this risk is priced, and whether accounting for this price component affects our findings on price discrimination. To address this issue, we construct client-level measures of risk based on credit ratings and balance sheet data.[28] First, we compute the average of the long-term credit ratings assigned by the four major agencies (S&P, Moody's, Fitch, and DBRS). Only about 5% of clients in our sample have a credit rating, and these firms are disproportionately sophisticated. Second, we construct two risk measures, namely $ZScore$ and $Leverage$, based on accounting information from Orbis.

Table 6 shows the results. To set benchmarks, Columns (1), (6) and (9) report the effect of $Sophistication$ in the subsamples of clients for which the respective credit risk measure is available. In Column (1), we obtain a coefficient estimate of −0.352, which is considerably smaller than the baseline result of −1.522 in Table 2, consistent with less price discrimination among the subsample of rated (and generally more sophisticated) clients. Column (2) adds the linearized credit rating, where higher values correspond to greater client credit risk. The coefficient of this variable is positive (as expected), but statistically insignificant. Importantly, our main finding regarding sophistication does not change. In Column (3), we interact credit ratings with $LogTenor$, since counterparty risk may become important at longer maturities. The coefficient of the interaction is indeed positive and statistically significant, but the coefficient of the rating becomes negative and statistically significant. This suggests a small discount for risky counterparties at short maturities (roughly up to two weeks), but a larger premium at long maturities. For one-year contracts, for example, a B-rated client pays an average of 1.8 pips more than a A-rated client.

[28] Since the vast majority of the firms in our sample are relatively small, we cannot rely on market-based risk measures such as CDS or bond spreads.

In Columns (4) and (5), we repeat the exercise by replacing the linearized rating variable with a dummy equal to one for firms with an investment grade rating (BBB− or better) and zero otherwise. The coefficient of *Sophistication* remains unaffected, and the coefficients of the ratings dummy and its interaction with $LogTenor$ are not statistically significant.

Columns (6)-(11) display the estimation results for the risk measures based on accounting data. The benchmarks in Columns (6) and (9) are close to Table 2 because of near-complete coverage. Adding the risk measures does not lead to material changes in these estimates. The coefficient of $ZScore$ in Column (7) is positive as expected (since a higher $ZScore$ signals higher risk), but statistically insignificant. When adding the interaction with $LogTenor$ in Column (8), we observe a similar pattern as with ratings. The coefficient of the interaction term is positive, meaning riskier firms incur wider spreads for longer tenors, but that of $ZScore$ turns negative. Finally, Columns (10) and (11) suggest that higher *Leverage* commands wider spreads, although we find no evidence that this varies with $LogTenor$.

To summarize, the inclusion of client-level risk measures does not materially affect our findings regarding price discrimination based on sophistication. While we find some evidence that counterparty risk is priced, the picture is mixed. This is consistent with existing evidence from the CDS market (Arora, Gandhi & Longstaff, 2012; Du, Gadgil, Gordy & Vega, 2016).

7.2 Financial Clients

Our analysis has focused on non-financial clients, based on the argument that this is a particularly heterogeneous group and therefore a richer empirical setting. Nevertheless, to provide a broader perspective, we replicate our analysis for trades by financial clients. For brevity, we just summarize our findings, and report the detailed results in the Online Appendix.

Our first set of financial clients concerns non-banks (Appendix B). We observe 977,595 transactions between 13,314 non-bank financial clients (identified through Orbis) and 95 dealers. In this sample, we again find evidence for price discrimination by sophistication. Yet, the economic magnitude is small: coefficient estimates are approximately 1/10th of those for non-financial clients. Similarly, platform trading is associated with less price discrimination than bilateral trading. However, since there is less price discrimination among financial clients, the marginal benefit of platform use is correspondingly smaller.

Our second set of financial clients concerns banks (Appendix C). For this exercise, we classify the G16 group of banks most actively involved in derivatives markets as dealers, while any bank outside this group is defined as a client.[29]. In this sample, we observe 370,713 transactions between 725 customer banks and the 16 dealers. The findings for sophistication broadly echo those for non-bank financial clients. For banks, the use of platforms is not associated with any spread compression.

7.3 Platform Users vs. Non-Users

Our findings provide strong evidence that platform trades exhibit tighter spreads. One potential concern with this finding is that firms trading on platforms are different from those that do not. A logit regression of a dummy variable set to one for clients that use a platform at least once in our sample (and zero otherwise) on *Sophistication* yields a pseudo R^2 of 0.37. To account for potential differences in clienteles, we test our four hypotheses separately for platform users and non-users. The results are shown in the Online Appendix (Appendix D). Summarizing, we find price discrimination by sophistication in both sub-samples, but with economically larger effects

[29]The group of G16 dealers includes Bank of America, Barclays, BNP Paribas, Citigroup, CrÃĺdit Agricole, Credit Suisse, Deutsche Bank, Goldman Sachs, HSBC, JPMorgan Chase, Morgan Stanley, Nomura, Royal Bank of Scotland, SociÃĺtÃĺ GÃĺnÃĺrale, UBS, and Wells Fargo

for non-users. Moreover, platform trading reduces price discrimination even in the subsample of platform users. Finally, we find evidence for a relationship premium and asymmetric price adjustment among non-users. These results are in line with our main analysis.

8 Conclusion

For the first time, new regulatory data with counterparty identities allow a comprehensive analysis of transaction costs in the FX derivatives market. Against the background of a global policy agenda on derivatives markets, careful measurement of OTC market quality and the scope of price discrimination is scarce. Our paper fills this gap.

We find extensive price discrimination in the FX derivative market. Due to its lower level of sophistication, the median non-financial client pays 10.9 pips more than the largest blue-chip companies when trading with the same dealer. However, discrimination based on observable measures of client sophistication is fully eliminated when trading occurs on multi-dealer platforms rather than bilaterally. We also show that sophisticated clients obtain a discount when trading with their relationship bank compared to trades with other dealers, while unsophisticated clients pay a premium.

For policymakers, our results suggest that there is considerable scope to improve OTC market quality. Enhanced post-trade transparency would enable clients to better monitor the quality of their trades and counteract widespread price discrimination. Moreover, while platforms are effective at reducing dealers' market power, several hundred clients refrain from platform trading. Greater transparency would also enable clients to compare the costs of different trading mechanisms, and facilitate an evolution towards a more efficient market structure.

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Table 1: Summary Statistics

Panel A: Clients	Observations	Mean	St.Dev	p10	p25	p50	p75	p90
$\#Counterparties$	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
$ZScore$	6,188	2.9	1.8	1.0	1.8	2.7	3.8	5.1
$Leverage$	8,157	0.2	0.2	0	0.03	0.2	0.4	0.6
$AvRating$	462	9.4	3.1	6	7.4	9	11.1	14
Panel B: Dealers	**Observations**	**Mean**	**St.Dev**	**p10**	**p25**	**p50**	**p75**	**p90**
$\#Clients$	204	81	235	1	3	7	30	187
$TotalNotional$ (in €mn)	204	25,484	87,225	1	4	19	181	56,215
$TotalAssets$ (in €bn)	204	215.4	488.9	2.0	3.7	7.8	87.8	816.6
$NII/Revenue$ (%)	204	35.7	19.4	22.1	24.1	27.7	42.9	61.3
Panel C: Transactions	**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
$Platform$	548,298	0.4	0.5	0	0	0	1	1
$Relationship$	278,492	0.45	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 EUR/USD forwards between April 2016 and March 2017; Panel B shows dealer-level data for the 204 dealer counterparties; and Panel C shows transaction-level data for the 548,298 trades between clients and dealers. In Panel A, $\#Counterparties$ is the number of dealers with which a client trades; HHI is the Herfindahl-Hirschman index of counterparty concentration; $TotalNotional$ (in €million) is the total notional traded during the sample period; $\#TradesFX$ is the number of forward contracts traded; $\#TradesNonFX$ is the total number of outstanding interest rate, credit and commodity derivatives positions at the beginning of the sample period; and $Sophistication$ is the first principal component of the five aforementioned variables. $ZScore$ is the linear combination of working capital, retained earnings, profits, and sales; $Leverage$ is the sum of loans and long-term debt divided by total assets; and $AvRating$ is the linearized credit rating averaged at client-level (where AAA = 1, $AA+$ = 2, ..., D = 28, averaged across rating agencies). In Panel B, $\#Clients$ is the number of clients with which a dealer trades; $TotalNotional$ (in €million) is the total notional traded during the sample period; $TotalAssets$ (in €billion) is balance sheet size; and $NII/Revenue$ is the ratio of non-interest income to gross revenue. In Panel C, $Spread$ is the effective spread (in pips) paid by the client; $Notional$ (in €million) is the notional amount of the contract; $Tenor$ is the original maturity (in days); $Customization$ is the difference in days between the contractual tenor and its nearest standard tenor (i.e. 0, 1, 7, 30, 60, 90, 180, 270, or 360 days); $Volatility$ is the realized volatility of the FX spot rate over the preceding 30 minutes, based on one-minute intervals; Buy is a dummy equal to one for client forward-buys of euro against dollar, and 0 otherwise; and $Platform$ is a dummy equal to one when a trade occurs on a platform, and zero otherwise.

Table 2: Spreads and Client Sophistication (Hypothesis 1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sophistication measures:							
Log#Counterparties		−3.887***					
		(0.225)					
HHI			8.868***				
			(0.674)				
LogTotalNotional				−1.568***			
				(0.072)			
Log#TradesFX					−1.782***		
					(0.102)		
Log#TradesNonFX						−1.003***	
						(0.104)	
Sophistication							−1.522***
							(0.079)
Trade characteristics:							
LogNotional	−0.918***	−0.633***	−0.514***	−0.307***	−1.105***	−0.808***	−0.619***
	(0.121)	(0.082)	(0.099)	(0.090)	(0.102)	(0.102)	(0.084)
LogTenor	1.284***	1.127***	1.168***	0.930***	1.130***	1.211***	1.076***
	(0.090)	(0.092)	(0.094)	(0.088)	(0.090)	(0.092)	(0.089)
LogCustomization	1.075***	0.974***	1.131***	0.889***	0.878***	1.017***	0.949***
	(0.125)	(0.105)	(0.116)	(0.102)	(0.105)	(0.113)	(0.106)
Volatility	7.553	1.660	1.911	−3.753	−3.401	4.798	−1.431
	(15.785)	(15.424)	(15.497)	(15.447)	(15.098)	(15.408)	(15.260)
Buy	−6.594***	−6.242***	−6.510***	−5.935***	−6.139***	−6.387***	−6.141***
	(0.320)	(0.296)	(0.304)	(0.285)	(0.293)	(0.326)	(0.290)
R-squared	0.304	0.334	0.328	0.346	0.332	0.318	0.339
Observations	544,433	544,433	544,433	544,433	544,433	544,433	544,433
Dealer-date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intraday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports OLS regressions of the spread on measures of client sophistication. Each specification controls for dealer-date and intraday fixed effects. 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 Platform Use (Hypothesis 2)

	(1)	(2)	(3)	(4)	(5)
$Platform$	−7.355***	−3.934***	−13.20***	−1.441***	−4.241***
	(0.460)	(0.427)	(0.627)	(0.277)	(0.933)
$Sophistication$		−1.193***	−1.938***		
		(0.088)	(0.080)		
$Platform \times Sophistication$			1.967***		0.463***
			(0.139)		(0.131)
R-squared	0.328	0.345	0.356	0.549	0.549
Observations	544,433	544,433	544,433	542,912	542,912
Client FE	No	No	No	Yes	Yes
Dealer-date FE	Yes	Yes	Yes	Yes	Yes
Intraday FE	Yes	Yes	Yes	Yes	Yes
Trade characteristics	Yes	Yes	Yes	Yes	Yes

Note: This table reports OLS regression estimations of spreads on the $Platform$ dummy, $Sophistication$, and an interaction of these two variables. Each specification controls for dealer-date fixed effects, intraday fixed effects, and trade characteristics (i.e. $LogNotional$, $LogTenor$, $LogCustomization$, $Volatility$, and Buy). In addition, Columns (4) and (5) control for client fixed effects. 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)	(6)	(7)
	All clients			Single-dealer clients		Multi-dealer clients	
Relationship	2.995***	0.710	3.724***	1.825*	2.461***	1.900***	0.371
	(0.648)	(0.597)	(0.801)	(1.072)	(0.903)	(0.656)	(0.658)
Sophistication		−1.754***	−1.340***		−3.281***		−1.423***
		(0.172)	(0.137)		(0.277)		(0.208)
Relationship × *Sophistication*			−1.122***				
			(0.215)				
R-squared	0.364	0.388	0.391	0.479	0.498	0.328	0.344
Observations	274,790	274,790	274,790	73,536	73,536	198,995	198,995
Dealer-date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intraday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trade characteristics	Yes	Yes	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 (2), (3) (5) and (7), we add *Sophistication*, which is the first principal component of $Log\#Counterparties$, HHI, $LogTotalNotional$, $Log\#TradesFX$, and $Log\#TradesNonFX$. Additionally, each specification controls for dealer-date fixed effects, intraday fixed effects, and trade characteristics (i.e. $LogNotional$, $LogTenor$, $LogCustomization$, $Volatility$, and Buy). Columns (4)-(5) and (6)-(7) replicate Columns (1)-(2) for the subsamples of clients with $\#Counterparties = 1$ and $\#Counterparties > 1$ respectively. 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)
$\lvert\Delta m_\tau^{-d}\rvert$	0.406***	0.401***	0.643***	0.643***
	(0.050)	(0.053)	(0.072)	(0.072)
$\lvert\Delta m_\tau^{d}\rvert$	−0.284***	−0.273***	−0.208***	−0.205***
	(0.049)	(0.048)	(0.078)	(0.078)
Sophistication		−1.521***	−1.484***	−1.153***
		(0.079)	(0.084)	(0.093)
$\lvert\Delta m_\tau^{-d}\rvert \times$ *Sophistication*			−0.0599***	−0.0616***
			(0.015)	(0.015)
$\lvert\Delta m_\tau^{d}\rvert \times$ *Sophistication*			−0.0159	−0.0169
			(0.015)	(0.015)
$Platform$				−3.929***
				(0.428)
p-value $\beta_1 + \beta_2$	0.143	0.131	0.000	0.000
R-squared	0.305	0.340	0.340	0.345
Observations	544,433	544,433	544,433	544,433
Dealer-date FE	Yes	Yes	Yes	Yes
Intraday FE	Yes	Yes	Yes	Yes
Trade characteristics	Yes	Yes	Yes	Yes

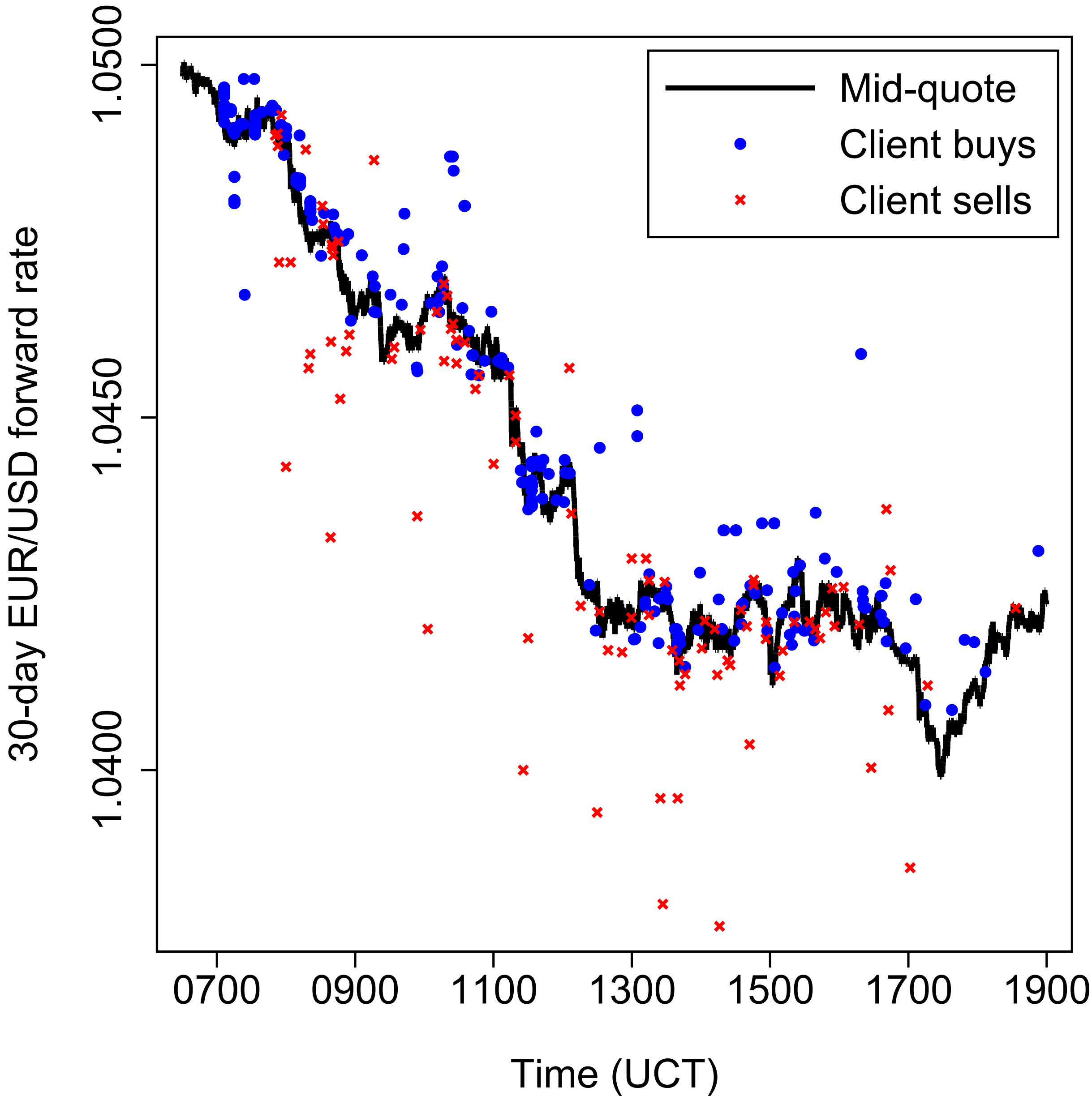
Note: This table reports OLS regression estimations of spreads on measures of price staleness. $|\Delta m_\tau^{-d}|$ ($|\Delta m_\tau^{+d}|$) is the absolute value of the change in the mid-quote over the preceding 30 seconds (in pips) if the price change was in the opposite (same) direction of the client order, and zero otherwise. Columns (2) and (3) control for *Sophistication*, which is the first principal component of *Log#Counterparties*, HHI, $LogTotalNotional$, *Log#TradesFX*, and *Log#TradesNonFX*; and Column (4) controls for $Platform$, which is a dummy equal to one for trades on a platform, and zero otherwise. The column "p-value $\beta_1 + \beta_2$" reports the p-value from a Wald-test of the hypothesis $\beta_1 + \beta_2 = 0$. Additionally, each specification controls for dealer-date fixed effects, intraday fixed effects, and trade 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: Spreads and Counterparty Risk

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Credit Ratings					Accounting Measures					
		Linear Scale		IG dummy			Z-Score			Leverage	
Sophistication	−0.352***	−0.345***	−0.340***	−0.348***	−0.349**	−1.471***	−1.464***	−1.481***	−1.549***	−1.583***	−1.583***
	(0.123)	(0.125)	(0.124)	(0.132)	(0.136)	(0.110)	(0.110)	(0.107)	(0.094)	(0.091)	(0.091)
LogTenor	0.181***	0.182***	−0.324	0.183***	0.165	0.894***	0.893***	−0.107	0.905***	0.909***	0.899***
	(0.062)	(0.062)	(0.201)	(0.062)	(0.152)	(0.090)	(0.091)	(0.161)	(0.083)	(0.084)	(0.147)
Risk		0.0219	−0.150*	−0.0777	−0.141		0.0375	−1.468***		3.597***	3.447**
		(0.033)	(0.076)	(0.314)	(0.392)		(0.132)	(0.278)		(1.099)	(1.651)
$Risk \times LogTenor$			0.0598**		0.0226			0.437***			0.0437
			(0.025)		(0.191)			(0.077)			(0.506)
R-squared	0.244	0.244	0.245	0.244	0.244	0.313	0.313	0.317	0.351	0.352	0.352
Observations	152,884	152,884	152,884	152,884	152,884	328,589	328,589	328,589	424,347	424,347	424,347
Dealer-date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intraday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trade characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

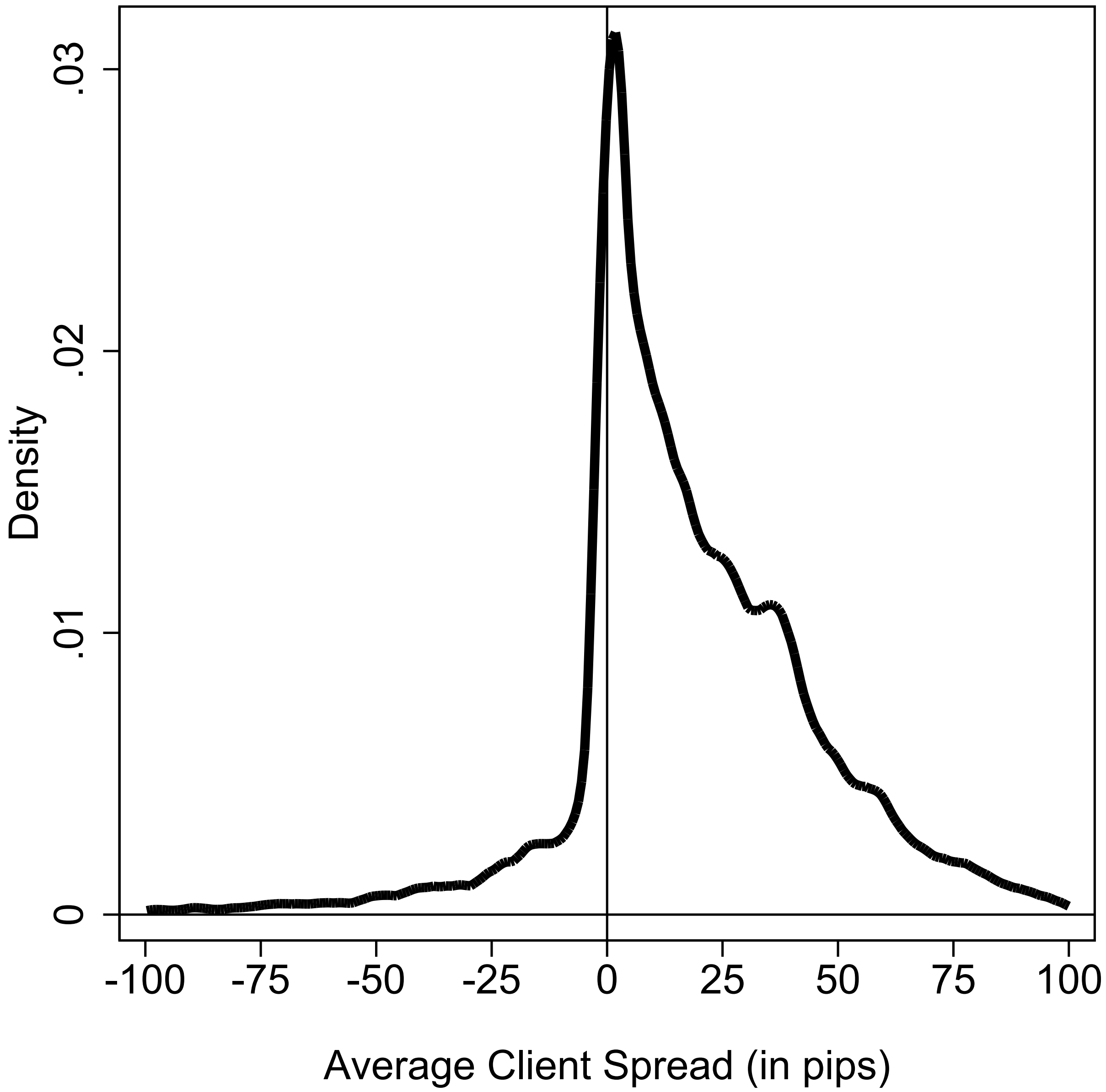
Note: This table reports OLS regression estimations of spreads on measures of counterparty credit risk. Two types of measures are used: those based on credit ratings and those based on balance sheet items. Credit ratings are obtained from Standard & Poor's, Moody's, Fitch and DBRS. In Columns (2) and (3), these ratings are coded as 1 for AAA, 2 for AA+, and so on through to D which is coded as 28. In Columns (4) and (5), ratings are instead coded as a dummy which equals one when the credit rating is at least $BBB-$ (i.e. investment grade), and zero otherwise. In terms of accounting measures, *ZScore* (used in Columns (7) and (8)) is the modified Altman Z-score, calculated as the linear combination of working capital, retained earnings, profits, and sales; and *Leverage* (used in Columns (10) and (11)) is the sum of loans and long-term debt divided by total assets. Each specification controls for *LogTenor*, which is the natural logarithm of a contract's original maturity (in days), and in Columns (3), (5), (8) and (11) *LogTenor* is also interacted with the counterparty risk measures. Additionally, each specification controls for dealer-date fixed effects, intraday fixed effects, and other trade characteristics (i.e. *LogNotional*, *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: Contracted Forward Rates versus the Mid-Quote



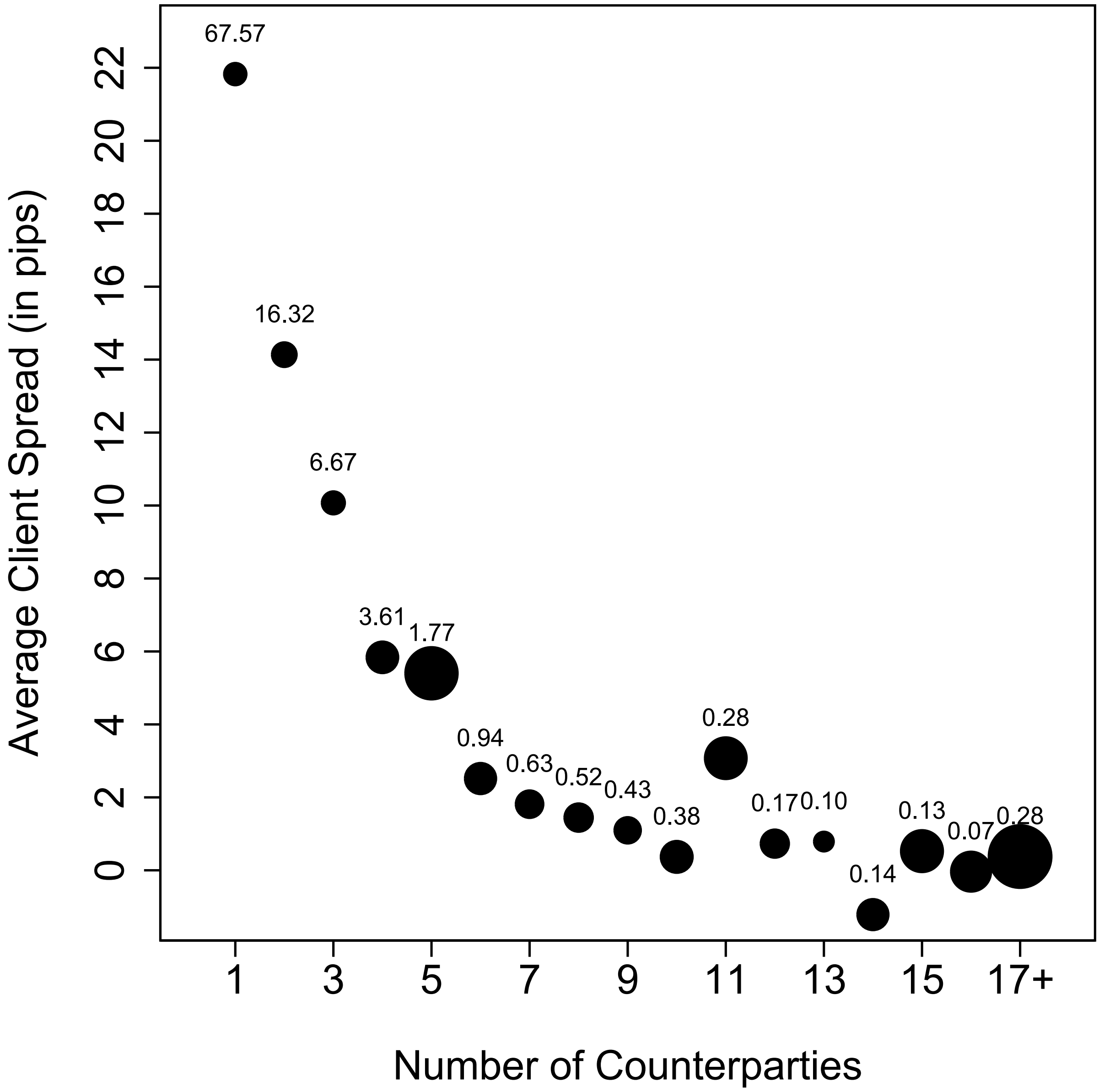
Note: This figure plots contractual forward rates versus the mid-price on a single trading day. The mid-quote is shown by the solid black line, which tracks intraday mid-prices for 30-day EUR/USD forward contracts (constructed from Thomson Reuters inter-dealer quote data). To approximately match this 30-day mid-price, we depict contracts with an original maturity 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



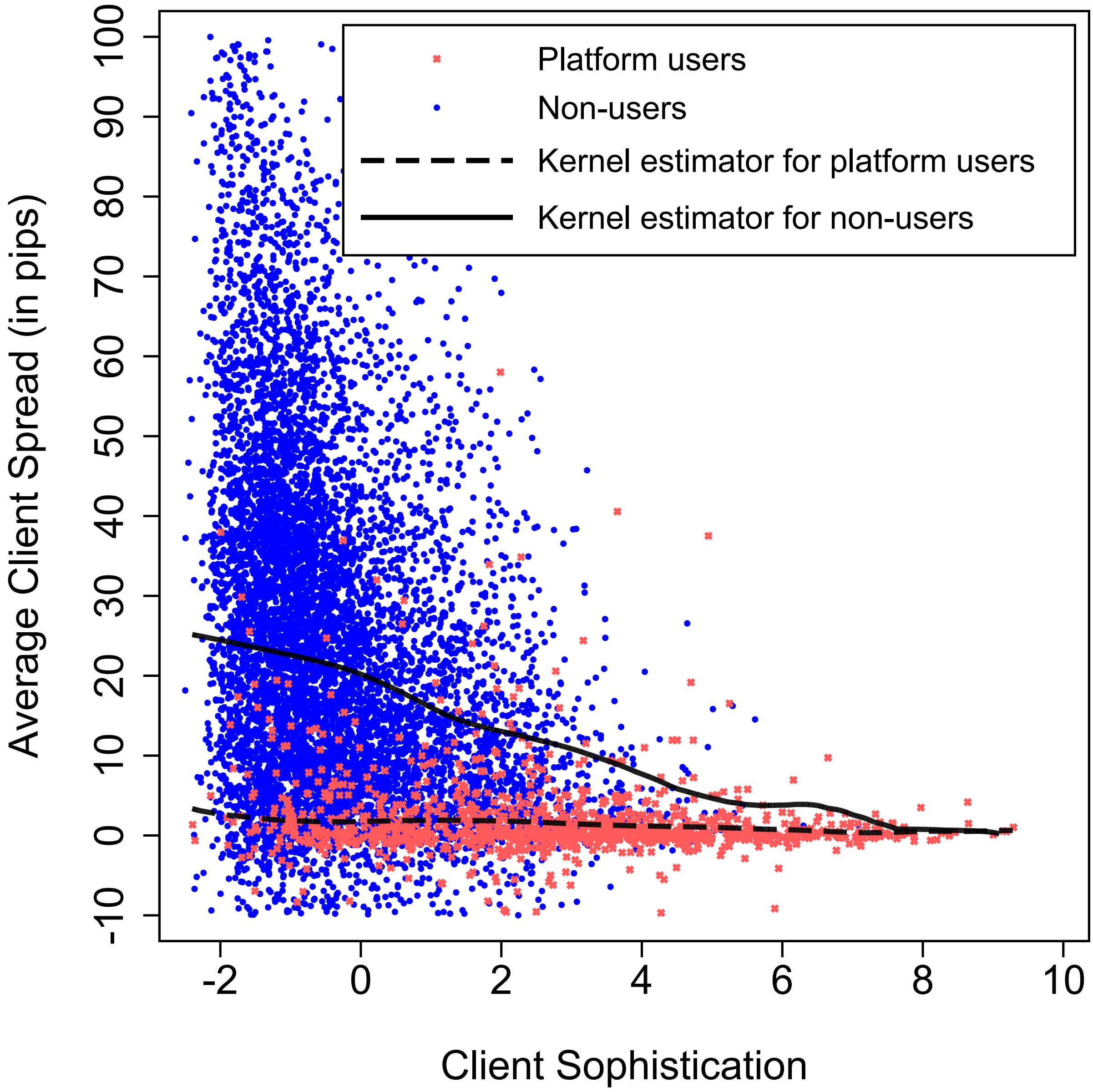
Note: This figure plots the cross-sectional distribution of average client spreads, based on 548,298 EUR/USD forward transactions between 10,087 clients and 204 dealers. The sample period is April 1, 2016 to March 31, 2017. Positive spreads are costly to the client and advantageous to the dealer.

Figure 3: Average Client Spread by Number of Dealer Counterparties



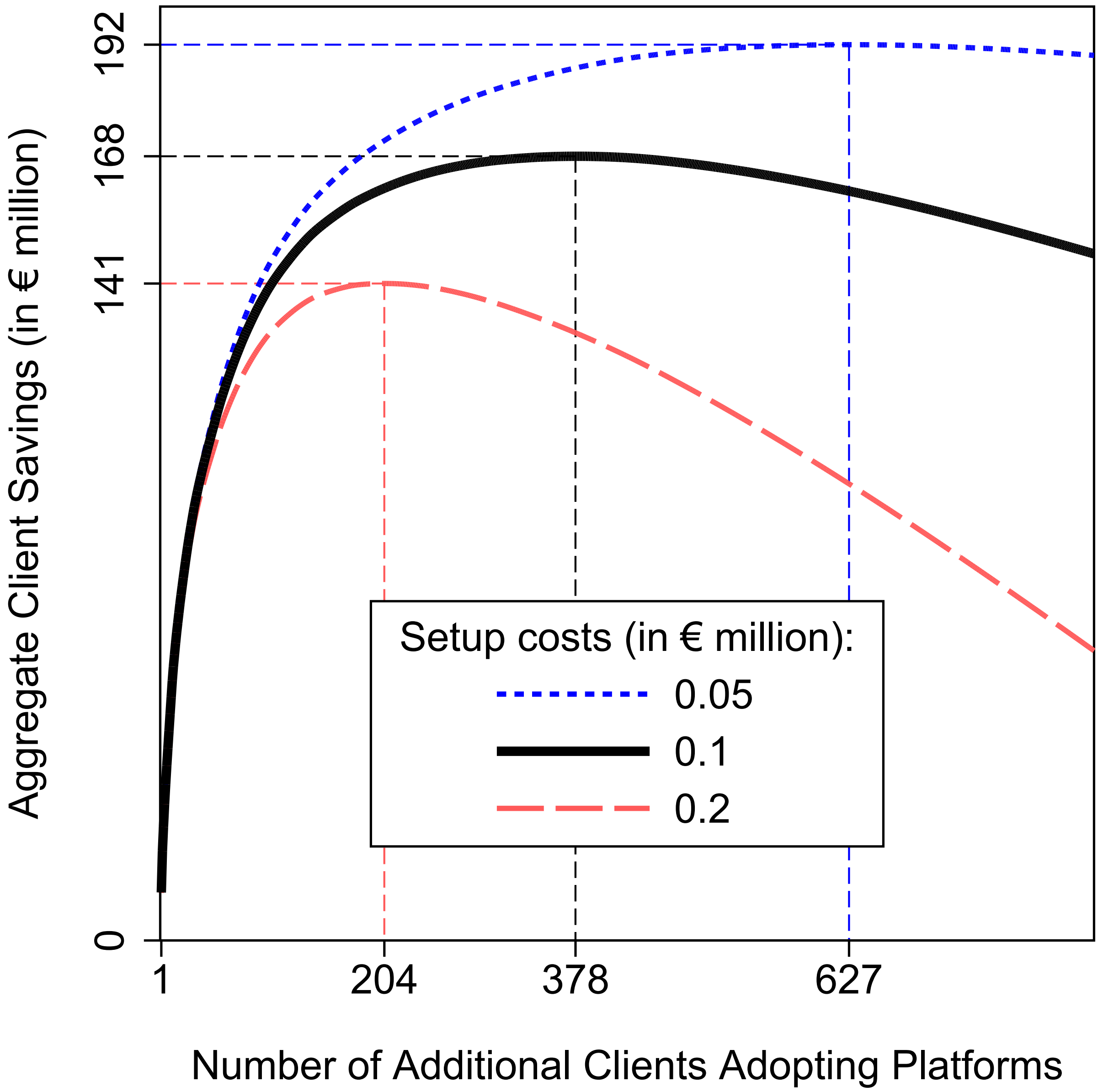
Note: This figure plots the average spread paid by clients with a given number of dealer counterparties in the EUR/USD forwards market. Marker size is proportional to aggregate notional traded. Marker labels indicate the percentage of clients with a given number of dealer counterparties. For readability,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

Figure 4: 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 a platform at least once in our sample period are marked by red crosses; clients that never use a platform are marked by blue dots. 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 on a platform. The dashed black line plots the same regression for the subset of clients that trade on a platform at least once during our sample period. For readability, the vertical axis is truncated at -10 pips.

Figure 5: Aggregate Client Savings from Adopting Platforms



Note: We sort non-platform users in decreasing order of their estimated annual savings from lower transaction costs if they were to switch from bilateral trading to platform trading. We then plot aggregate savings as a function of the number of clients that adopt platform trading, assuming costs of (i) €0.05 million (blue dotted line), (ii) €0.1 million (solid black line), and (iii) €0.2 million (red dashed line). Under these cost assumptions, platform adoption is optimal for 627 clients, 378 clients, and 204 clients, respectively. The corresponding aggregate saving is €192 million, €168 million, and €141 million, respectively.

Online Appendix

A Additional Summary Statistics

Table A.1: Correlation Matrix of Client Sophistication Measures

	Log#Counterparties	*HHI*	*LogTotalNotional*	*Log#TradesFX*	*Log#TradesNonFX*	*Sophistication*
Log#Counterparties	1					
HHI	−0.770***	1				
LogTotalNotional	0.839***	−0.621***	1			
Log#TradesFX	0.716***	−0.405***	0.797***	1		
Log#TradesNonFX	0.697***	−0.474***	0.665***	0.607***	1	
Sophistication	0.947***	−0.750***	0.905***	0.815***	0.836***	1

Note: This table reports the pairwise correlations of the measures of sophistication. *Log#Counterparties* is the natural logarithm of 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. *LogTotalNotional* is the natural logarithm of the total notional traded by a client during the sample period. *Log#TradesFX* is the natural logarithm of the number of EUR/USD forwards traded by a client. *#TradesNonFX* is the natural logarithm of one plus the total number of a client's outstanding interest rate, credit and commodity derivatives positions at the beginning of our sample period on April 1, 2016. *Sophistication* is the first principal component of the five aforementioned variables. Three asterisks represent statistical significance at the 1% confidence level.

Table A.2: Client and Transaction Characteristics by Sophistication and Platform Use

	Low Sophistication			Medium Sophistication			High Sophistication		
Platform User	Yes	No	Diff	Yes	No	Diff	Yes	No	Diff
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Client Data									
Spread	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: This 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 concerns whether a client uses a platform at least once in our sample period. The first two columns of each group report mean values for all variables, while Columns (3), (6), and (9) report mean differences and mark their statistical significance according to a non-parametric Wilcoxon test. In Panel A, which reports client-level data, *Spread* 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 €million) 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 the five aforementioned variables. In Panel B, which reports transaction-level data, *Spread* is the difference (in pips) between the contractual forward rate and the mid-quote. *Notional* (in €million) 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.3: 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: This 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.

B Non-Bank Financial Clients

Table B.1: Summary Statistics—Non-Bank Financial Clients

Panel A: Clients	Observations	Mean	St.Dev	p10	p25	p50	p75	p90
$\#Counterparties$	13,314	2.8	2.5	1	1	2	4	6
HHI	13,314	0.6	0.4	0.03	0.1	0.8	1	1
$TotalNotional$ (in €million)	13,314	1,455	33,108	1	4	36	275	1,395
$\#TradesFX$	13,314	74	442	1	4	14	45	134
$\#TradesNonFX$	13,314	31	362	1	1	1	2	30
$Sophistication$	13,314	0	1.7	−2.1	−1.4	−0.1	1.3	2.3

Panel B: Transactions	Observations	Mean	St.Dev	p10	p25	p50	p75	p90
$Spread$	977,595	0.3	12.1	−8.4	−2.7	0.2	3.2	9.3
$Notional$ (in €mn)	977,595	19.7	149.0	0.01	0.10	0.6	4.5	27.0
$Customization$	977,595	5.1	8.3	1	1	3	5	12.0
$Tenor$	977,595	36	46	2	5	22.0	47.0	92
$Volatility$	977,595	0.007	0.004	0.004	0.005	0.006	0.008	0.01
Buy	977,595	0.5	0.5	0	0	1	1	1
$Platform$	977,595	0.3	0.5	0	0	0	1	1

Note: Panel A shows client-level data for the 13,314 non-bank financial clients that trade EUR/USD forwards between April 2016 and March 2017, and Panel B shows transaction-level data for the 977,595 individual trades of EUR/USD forwards between non-bank financial clients and dealers. In Panel A, *#Counterparties* is the number of counterparties with which a client or dealer interacts; HHI is the Herfindahl-Hirschman index of counterparty relationships; $TotalNotional$ (in €million) is the total notional traded during the sample period; $\#TradesFX$ is the number of forward contracts traded; $\#TradesNonFX$ is the total number of outstanding interest rate, credit and commodity derivatives positions at the beginning of the sample period; and *Sophistication* is the first principal component of the five aforementioned variables. In Panel B, *Spread* is the effective spread (in pips) paid by the client; $Notional$ (in €million) is the notional amount of the contract; *Tenor* is the original maturity (in days); $Customization$ is the difference in days between the contractual tenor and its nearest standard tenor (i.e. 0, 1, 7, 30, 60, 90, 180, 270, or 360 days); $Volatility$ is the realized volatility of the FX spot rate over the preceding 30 minutes, based on one minute interval; *Buy* is a dummy which equals one for client forward-buys of euro against dollar, and 0 otherwise; and $Platform$ is a dummy equal to one when a trade occurs on a platform, and zero otherwise.

Table B.2: Spreads and Client Sophistication—Non-Bank Financial Clients

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sophistication measures:							
$Log\#Counterparties$		−0.258***					
		(0.036)					
HHI			0.328***				
			(0.078)				
$LogTotalNotional$				−0.0971***			
				(0.012)			
$Log\#TradesFX$					−0.0988***		
					(0.011)		
$Log\#TradesNonFX$						−0.0503***	
						(0.010)	
$Sophistication$							−0.170***
							(0.020)
Trade characteristics:							
$LogNotional$	−0.0254**	−0.0156	−0.0182	0.000430	−0.0365***	−0.0184	−0.0112
	(0.012)	(0.012)	(0.012)	(0.011)	(0.010)	(0.012)	(0.011)
$LogTenor$	0.000373	−0.00327	−0.00256	0.00253	0.0110	0.00302	0.00439
	(0.062)	(0.062)	(0.061)	(0.063)	(0.063)	(0.062)	(0.063)
$LogCustomization$	0.0744	0.0791	0.0750	0.0848	0.0910	0.0733	0.0868
	(0.086)	(0.086)	(0.087)	(0.084)	(0.082)	(0.086)	(0.085)
$Volatility$	38.75***	39.23***	39.02***	38.37***	38.34***	38.94***	38.96***
	(10.130)	(10.092)	(10.125)	(10.071)	(10.093)	(10.091)	(10.051)
Buy	−3.504***	−3.502***	−3.503***	−3.510***	−3.510***	−3.508***	−3.510***
	(0.154)	(0.154)	(0.154)	(0.154)	(0.153)	(0.154)	(0.154)
R-squared	0.0762	0.0764	0.0763	0.0765	0.0764	0.0763	0.0766
Observations	976,065	976,065	976,065	976,065	976065	976,065	976,065
Dealer-date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Minute of day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports OLS regressions of the spread on measures of client sophistication for a sample of non-bank financial clients. Each specification controls for dealer-date fixed effects and intraday fixed effects. 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 B.3: Spreads and Platform Use—Non-Bank Financial Clients

	(1)	(2)	(3)	(4)	(5)
$Platform$	-0.297^{***}	-0.202^{***}	-0.538^{***}	0.00272	0.0541
	(0.084)	(0.076)	(0.106)	(0.051)	(0.083)
$Sophistication$		-0.164^{***}	-0.214^{***}		
		(0.020)	(0.027)		
$Platform \times Sophistication$			0.140^{***}		-0.0176
			(0.030)		(0.024)
R-squared	0.0762	0.0766	0.0767	0.101	0.101
Observations	976,065	976,065	976,065	974,627	974,627
Client FE	No	No	No	Yes	Yes
Dealer-date FE	Yes	Yes	Yes	Yes	Yes
Intraday FE	Yes	Yes	Yes	Yes	Yes
Trade characteristics	Yes	Yes	Yes	Yes	Yes

Note: This table reports OLS regression estimations of spreads on the $Platform$ dummy, *Sophistication*, and an interaction of these two variables for a sample of non-bank financial clients. Each specification controls for dealer-date fixed effects, intraday fixed effects, and trade characteristics (i.e. *LogNotional*, *LogTenor*, *LogCustomization*, *Volatility*, and *Buy*). In addition, Columns (4) and (5) control for client fixed effects. One, two and three asterisks represent statistical significance at 10%, 5% and 1% respectively. Standard errors clustered at client level are reported in parentheses.

C Bank Clients

Table C.1: Summary Statistics—Bank Clients

Panel A: Clients	Observations	Mean	St.Dev	p10	p25	p50	p75	p90
$\#Counterparties$	725	4.4	4.1	1	1	2	6	11
HHI	725	0.6	0.3	0.2	0.3	0.6	1	1
$TotalNotional$ (in €mn)	725	68,019	330,027	5	37	642	9,033	77,452
$\#TradesFX$	725	729	2,329	5	15	98	453	1,614
$\#TradesNonFX$	725	2,670	14,847	0	0	23	428	2,594
$Sophistication$	725	0	2.0	-2.5	-1.8	-0.2	1.6	2.8
Panel B: Transactions	**Observations**	**Mean**	**St.Dev**	**p10**	**p25**	**p50**	**p75**	**p90**
$Spread$	370,713	0.3	12.6	-4.2	-1.6	0.2	2.0	4.8
$Notional$ (in €mn)	370,713	94	220	0.05	0.6	10	100	250
$Customization$	370,713	4.6	9.5	1	1	2	3	8
$Tenor$	370,713	28.4	54	1	2	4	30	93
$Volatility$	370,713	0.007	0.004	0.004	0.005	0.006	0.008	0.01
Buy	370,713	0.5	0.5	0	0	0	1	1
$Platform$	370,713	0.3	0.5	0	0	0	1	1

Note: Panel A shows client-level data for the 725 bank clients that trade EUR/USD forwards between April 2016 and March 2017, and Panel B shows transaction-level data for the 370,713 individual trades of EUR/USD forwards between bank clients and dealers. In Panel A, $\#Counterparties$ is the number of counterparties with which a client or dealer interacts; HHI is the Herfindahl-Hirschman index of counterparty relationships; $TotalNotional$ (in €million) is the total notional traded during the sample period; $\#TradesFX$ is the number of forward contracts traded; $\#TradesNonFX$ is the total number of outstanding interest rate, credit and commodity derivatives positions at the beginning of the sample period; and $Sophistication$ is the first principal component of the five aforementioned variables. In Panel B, $Spread$ is the effective spread (in pips) paid by the client; $Notional$ (in €million) is the notional amount of the contract; $Tenor$ is the original maturity (in days); $Customization$ is the difference in days between the contractual tenor and its nearest standard tenor (i.e. 0, 1, 7, 30, 60, 90, 180, 270, or 360 days); $Volatility$ is the realized volatility of the FX spot rate over the preceding 30 minutes, based on one minute interval; Buy is a dummy which equals one for client forward-buys of euro against dollar, and 0 otherwise; and $Platform$ is a dummy equal to one when a trade occurs on a platform, and zero otherwise.

Table C.2: Spreads and Client Sophistication—Bank Clients

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sophistication measures:							
Log#Counterparties		-0.281**					
		(0.109)					
HHI			0.617**				
			(0.247)				
LogTotalNotional				-0.0630**			
				(0.029)			
Log#TradesFX					-0.0894**		
					(0.042)		
Log#TradesNonFX						-0.0320**	
						(0.015)	
Sophistication							-0.114**
							(0.045)
Contract characteristics:							
LogNotional	-0.0863***	-0.0656***	-0.0732***	-0.0610**	-0.0812***	-0.0736***	-0.0661***
	(0.021)	(0.024)	(0.023)	(0.025)	(0.021)	(0.023)	(0.024)
LogTenor	-0.0199	-0.0132	-0.0163	-0.0143	-0.0197	-0.0185	-0.0157
	(0.033)	(0.034)	(0.033)	(0.034)	(0.033)	(0.033)	(0.033)
LogCustomization	0.138**	0.144**	0.144**	0.143**	0.144**	0.145**	0.147**
	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)
Volatility	4.731	5.014	5.017	4.767	4.751	4.836	4.920
	(6.595)	(6.575)	(6.587)	(6.570)	(6.582)	(6.581)	(6.574)
Buy	-5.653**	-5.650**	-5.652**	-5.653**	-5.652**	-5.653**	-5.652**
	(2.428)	(2.429)	(2.428)	(2.428)	(2.428)	(2.428)	(2.429)
R-squared	0.0659	0.0661	0.0660	0.0660	0.0660	0.0660	0.0660
Observations	370,655	370,655	370,655	370,655	370,655	370,655	370,655
Dealer-day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intraday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports OLS regressions of the spread on measures of client sophistication for a sample of bank clients. Each specification controls for dealer-date fixed effects and intraday fixed effects. 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 C.3: Spreads and Platform Use—Bank Clients

	(1)	(2)	(3)	(4)	(5)
$RFQPlatform$	-0.109	-0.102	-0.438	0.0231	0.114
	(0.075)	(0.074)	(0.271)	(0.076)	(0.187)
$Sophistication$		-0.114**	-0.144**		0.00195
		(0.045)	(0.057)		(0.004)
$RFQPlatform \times Sophistication$			0.110		-0.0264
			(0.074)		(0.050)
R-squared	0.0659	0.0661	0.0661	0.0768	0.0768
Observations	370,655	370,655	370,655	370,629	370,629
Client FE	No	No	No	Yes	Yes
Dealer-day FE	Yes	Yes	Yes	Yes	Yes
Intraday FE	Yes	Yes	Yes	Yes	Yes
Contract characteristics	Yes	Yes	Yes	Yes	Yes

Note: This table reports OLS regression estimations of spreads on the $Platform$ dummy, $Sophistication$, and an interaction of these two variables for a sample of bank clients. Each specification controls for dealer-date fixed effects, intraday fixed effects, and trade characteristics (i.e. $LogNotional$, $LogTenor$, $LogCustomization$, $Volatility$, and Buy). In addition, Columns (4) and (5) control for client fixed effects. One, two and three asterisks represent statistical significance at 10%, 5% and 1% respectively. Standard errors clustered at client level are reported in parentheses.

D Sample Split by Platform Use

Table D.1: Spreads and Client Sophistication—Sample Split
Panel A: Platform Users

	(1)	(2)	(3)	(4)	(5)	(6)
Log#Counterparties	−0.606***					
	(0.202)					
HHI		2.351***				
		(0.798)				
LogTotalNotional			−0.262***			
			(0.075)			
Log#TradesFX				−0.265***		
				(0.056)		
Log#TradesNonFX					−0.172***	
					(0.048)	
Sophistication						−0.287***
						(0.067)
R-squared	0.190	0.192	0.191	0.190	0.190	0.191
Observations	310,182	310,182	310,182	310,182	310,182	310,182
Dealer-date FE	Yes	Yes	Yes	Yes	Yes	Yes
Intraday FE	Yes	Yes	Yes	Yes	Yes	Yes
Trade characteristics	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Platform Non-Users

	(1)	(2)	(3)	(4)	(5)	(6)
Log#Counterparties	−3.274***					
	(0.492)					
HHI		4.778***				
		(0.710)				
LogTotalNotional			−1.715***			
			(0.198)			
Log#TradesFX				−1.588***		
				(0.312)		
Log#TradesNonFX					−0.938***	
					(0.193)	
Sophistication						−1.866***
						(0.202)
R-squared	0.366	0.365	0.376	0.369	0.363	0.372
Observations	233,209	233,209	233,209	233,209	233,209	233,209
Dealer-date FE	Yes	Yes	Yes	Yes	Yes	Yes
Minute of day FE	Yes	Yes	Yes	Yes	Yes	Yes
Trade characteristics	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports OLS regression estimations of spreads on the *Platform* dummy, *Sophistication*, and an interaction of these two variables. Each specification controls for dealer-date fixed effects, intraday fixed effects, and trade characteristics (i.e. *LogNotional*, *LogTenor*, *LogCustomization*, *Volatility*, and *Buy*). In addition, Columns (4) and (5) control for client fixed effects. 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 D.2: Spreads and Platform Use—Platform Users Only

	(1)	(2)	(3)	(4)	(5)
$Platform$	-2.431^{***}	-2.378^{***}	-6.972^{***}	-1.560^{***}	-4.039^{***}
	(0.504)	(0.486)	(1.532)	(0.244)	(0.813)
$Sophistication$		-0.271^{***}	-0.902^{***}		
		(0.062)	(0.199)		
$Platform \times Sophistication$			0.807^{***}		0.409^{***}
			(0.207)		(0.114)
R-squared	0.196	0.198	0.202	0.276	0.277
Observations	310,182	310,182	310,182	310,130	310,130
Client FE	No	No	No	Yes	Yes
Dealer-date FE	Yes	Yes	Yes	Yes	Yes
Intraday FE	Yes	Yes	Yes	Yes	Yes
Trade characteristics	Yes	Yes	Yes	Yes	Yes

Note: This table reports OLS regression estimations of spreads on the $Platform$ dummy, $Sophistication$, and an interaction of these two variables. Each specification controls for dealer-date fixed effects, intraday fixed effects, and trade characteristics (i.e. $LogNotional$, $LogTenor$, $LogCustomization$, $Volatility$, and Buy). In addition, Columns (4) and (5) control for client fixed effects. 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 D.3: Spreads and Dealer-Client Relationships—Sample Split

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All clients			Single-Dealer Clients		Multi-Dealer Clients	
Panel A: Platform Users							
Relationship	0.964	0.706	0.698	−3.257*	−2.688	0.824	0.517
	(0.673)	(0.723)	(2.033)	(1.913)	(1.878)	(0.695)	(0.750)
Sophistication		−0.250	−0.251		−1.279		−0.322*
		(0.160)	(0.159)		(1.166)		(0.180)
Relationship × *Sophistication*			0.00176				
			(0.370)				
R-squared	0.252	0.253	0.253	0.866	0.867	0.245	0.247
Observations	124,454	124,454	124,454	2,375	2,375	121,445	121,445
Dealer-date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intraday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trade characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Platform Non-Users							
Relationship	0.708	−0.0564	1.627**	1.874*	2.401***	−0.820	−1.332*
	(0.696)	(0.651)	(0.777)	(1.091)	(0.916)	(0.843)	(0.773)
Sophistication		−2.297***	−1.651***		−3.196***		−2.085***
		(0.164)	(0.219)		(0.282)		(0.271)
Relationship × *Sophistication*			−1.194***				
			(0.316)				
R-squared	0.403	0.416	0.417	0.478	0.496	0.414	0.421
Observations	149,319	149,319	149,319	70,584	70,584	76,725	76,725
Dealer-date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intraday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trade characteristics	Yes	Yes	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 (2), (3) (5) and (7), we add *Sophistication*, which is the first principal component of $Log\#Counterparties$, HHI, $LogTotalNotional$, $Log\#TradesFX$, and $Log\#TradesNonFX$. Additionally, each specification controls for dealer-date fixed effects, intraday fixed effects, and trade characteristics (i.e. $LogNotional$, $LogTenor$, $LogCustomization$, $Volatility$, and Buy). Columns (4)-(5) and (6)-(7) replicate Columns (1)-(2) for the subsamples of clients with $\#Counterparties = 1$ and $\#Counterparties > 1$ respectively. 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 D.4: Information Rents from Asymmetric Price Adjustment—Sample Split

	(1)	(2)	(3)	(4)	(5)	(6)
	Platform Users			Platform Non-Users		
$\lvert\Delta m_\tau^{-d}\rvert$	0.238***	0.240***	0.380***	0.571***	0.564***	0.661***
	(0.072)	(0.072)	(0.138)	(0.065)	(0.064)	(0.088)
$\lvert\Delta m_\tau^{d}\rvert$	−0.290***	−0.287***	−0.150	−0.304***	−0.300***	−0.227**
	(0.062)	(0.061)	(0.128)	(0.080)	(0.079)	(0.098)
Sophistication		−0.287***	−0.265***		−1.864***	−1.802***
		(0.067)	(0.067)		(0.202)	(0.204)
$\lvert\Delta m_\tau^{-d}\rvert \times$ *Sophistication*			−0.0236			−0.0716*
			(0.025)			(0.037)
$\lvert\Delta m_\tau^{d}\rvert \times$ *Sophistication*			−0.0230			−0.0539
			(0.025)			(0.038)
R-squared	0.190	0.193	0.193	0.362	0.372	0.372
Observations	310,182	310,182	310,182	233,209	233,209	233,209
Dealer-date FE	Yes	Yes	Yes	Yes	Yes	Yes
Intraday FE	Yes	Yes	Yes	Yes	Yes	Yes
Trade characteristics	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports OLS regression estimations of spreads on measures of price staleness. $|\Delta m_\tau^{-d}|$ ($|\Delta m_\tau^{+d}|$) is the absolute value of the change in the mid-quote over the preceding 30 seconds (in pips) if the price change was in the opposite (same) direction of the client order, and zero otherwise. Columns (2)-(3) and (5)-(6) control for *Sophistication*, which is the first principal component of $Log\#Counterparties$, HHI, $LogTotalNotional$, $Log\#TradesFX$, and $Log\#TradesNonFX$. Additionally, each specification controls for dealer-date fixed effects, intraday fixed effects, and trade 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.

E Price Discrimination Across Dealers

Table E.1: Price Discrimination Across Dealers

	(1)	(2)	(3)	(4)
Sophistication	-2.239***	-1.994***	-3.951***	-1.696***
	(0.391)	(0.120)	(0.382)	(0.091)
Sophistication × *Dealer Sophistication*	0.168*			
	(0.092)			
Sophistication × $G16$		0.832***		
		(0.116)		
Sophistication × *LogAssets*			0.576***	
			(0.088)	
Sophistication × $NII/Revenue$				2.572***
				(0.385)
R-squared	0.340	0.343	0.342	0.342
Observations	554,420	554,420	554,420	554,420
Dealer-date FE	Yes	Yes	Yes	Yes
Intraday FE	Yes	Yes	Yes	Yes
Trade characteristics	Yes	Yes	Yes	Yes

Note: This table reports the coefficient estimates from OLS regressions of spreads on *Sophistication* and its interaction with four different dealer characteristics. *Dealer Sophistication* is the first principal component of $\#Counterparties$, HHI, $TotalNotional$, $\#TradesFX$, and $\#TradesNonFX$, which are constructed analogously to their counterparts for non-financial clients. $G16$ is a dummy variable equal to one for G16 dealers, and zero otherwise. *LogAssets* denotes the natural logarithm of total assets, and $NII/Revenue$ denotes the ratio of non-interest income to gross revenues. Each specification controls for dealer-date fixed effects, intraday fixed effects, and trade 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.