MANAGEMENT SCIENCE
Articles in Advance, pp. 1–18
http://pubsonline.informs.org/journal/mnsc
ISSN 0025-1909 (print), ISSN 1526-5501 (online)

Discriminatory Pricing of Over-the-Counter Derivatives

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Received: November 21, 2019
Revised: May 4, 2020
Accepted: July 11, 2020
Published Online in Articles in Advance: March 22, 2021

https://doi.org/10.1287/mnsc.2020.3787

Abstract. For the first time, new regulatory data allow precise measurement of price discrimination against nonfinancial clients in the foreign exchange 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 because of 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 multidealer 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.

History: Accepted by Haoxiang Zhu, finance.
Funding: The paper benefited from a research grant of the Schweizerischer Nationalfonds zur Förderung der Wissenschaftlichen Forschung.
Supplemental Material: The online appendix is available at https://doi.org/10.1287/mnsc.2020.3787.

Keywords: transaction costs • OTC markets • multi-dealer platforms • relationship trading

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, leaders of the "Group of Twenty" (G20) 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 foreign exchange (FX) markets, banks have brandished efforts to enhance posttrade 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 et al. 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 euro/U.S. dollar (EUR/USD) forward contracts with 10,087 nonfinancial 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]

We find that transaction costs—measured by the effective spread (henceforth "spread") of contractual forward rates relative to midquotes in the interdealer (D2D) 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 because of 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 multidealer 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 assess the role of dealer-client relationships for execution quality. Our novel methodology identifies relationships from firm-bank linkages in the credit market instead of transaction data, which mitigate concerns about reverse causality. We find a nuanced role of relationships that varies with the level of client sophistication. Although 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 midquote 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 nonfinancial clients. Third, our results are robust to a sample split into platform users and nonusers.

Our findings can inform policy. In our sample, nearly 90% of clients never trade on a platform. Some of this nonadoption can be explained by small trading needs and costs associated with platform trading. 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.

2. 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. Although early empirical studies provide evidence of price dispersion in fixed-income OTC markets (Schultz 2001, Harris and Piwowar 2006, Green et al. 2007), this does not necessarily imply discrimination in the absence of client identifiers.

Our work is closely related to O'Hara et al. (2018) and Hendershott et al. (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 nonfinancial 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 nonfinancial clients. This suggests that studies restricted to sophisticated clients underestimate economic magnitudes.

Our analysis is also related to the work of Osler et al. (2016), who document price discrimination by a single FX dealer. We generalize their finding to a wider set of dealers and clients. Moreover, the wider coverage of our data set yields several 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 seem 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 amounts 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 et al. (1993) and Guay and 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.

3. 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 markups because they expose dealers to sequential competition. Moreover, large or active clients have more bargaining power in bilateral negotiations with dealers compared with small and inactive ones. Because 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.*

Although trading in OTC markets has long been dominated by bilateral voice trading, hybrid mechanisms such as multidealer 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 and Madhavan 2015), in line with predictions from laboratory experiments (Flood et al. 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.*

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), coinsurance 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 interdealer and dealer-to-client markets, clients are generally less well informed about market conditions in the absence of benchmark prices (Duffie et al. 2017). Dealers can exploit this information advantage by adjusting prices asymmetrically in response to market conditions.[10] Such behavior has been observed in the U.S. municipal bond market (Green et al. 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.*

4. 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 Bank for International Settlements Triennial Central Bank Survey, daily transaction volumes in FX markets grew from U.S. $1.5 trillion in 1998 to U.S. $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 U.S. dollar is one leg of a transaction in 88% of the volume, followed by the euro (32%) and the yen (17%).[13] Although the market is dominated by financial institutions, trading by nonfinancial firms accounts for nearly 7% of the activity in FX derivatives globally. Many nonfinancial firms face currency mismatches, typically because their revenues are denominated in domestic currency, whereas 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 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 (Schrimpf and Sushko 2019). In the D2C segment, trades have traditionally been negotiated by phone.

However, trading has become increasingly electronic, with several multidealer 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 with 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 other dealers provide (streamed) quotes to the client on the platform but not how many dealers do so. After 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 toward 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 credit default swaps (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 noncentrally cleared derivatives. A variation margin must be posted by financial clients and the most active nonfinancial clients, but these rules were fully phased in only by 2018, after our sample ends.[16] Consequently, most trades in our sample do not involve any exchange of variation margin, potentially giving rise to counterparty risk (see Section 8.1).

5. Data and Measurement

The European Market Infrastructure Regulation 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 and the European Securities and Markets Authority—have access to the full EU-wide transaction-level data set.[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 (Bank for International Settlements 2019).

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 data set, 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 nonfinancial firm (the "client") and the other as a bank (the "dealer").

We implement various filters and checks on data quality. The raw data set comprises dual-sided reporting whenever both counterparties to a trade are EU domiciled. We check the consistency of dual reports and discard observations that feature discrepancies, such as different execution time stamps. Reports without dual reporting are retained only if they come from dealers, which are subject to more stringent oversight. Consequently, in our data set all dealers are resident in the EU, but clients can reside anywhere.

5.1. Transaction Costs

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

$$Spread_\tau = d_\tau \times (f_\tau - m_\tau) \times 10^4, \tag{1}$$

where f_τ is the contractual forward rate, m_τ is the contemporaneous midquote, and d_τ is a trade direction indicator (defined as $d_\tau = 1$ for client long positions in EUR/USD and $d_\tau = -1$ for short positions).[18]

To construct the midquote 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., nonexecutable) and collected in real time from the interdealer 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.

We compute the midquote 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 midquote for a given tenor is the sum of the midquotes of the spot exchange rate and the respective forward points. For nonstandard maturities, we linearly interpolate the forward points across adjacent standard maturities.[20] To mitigate the effects of outliers, we discard transactions where the effective spread exceeds 100 pips in absolute value.

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

5.2. 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.

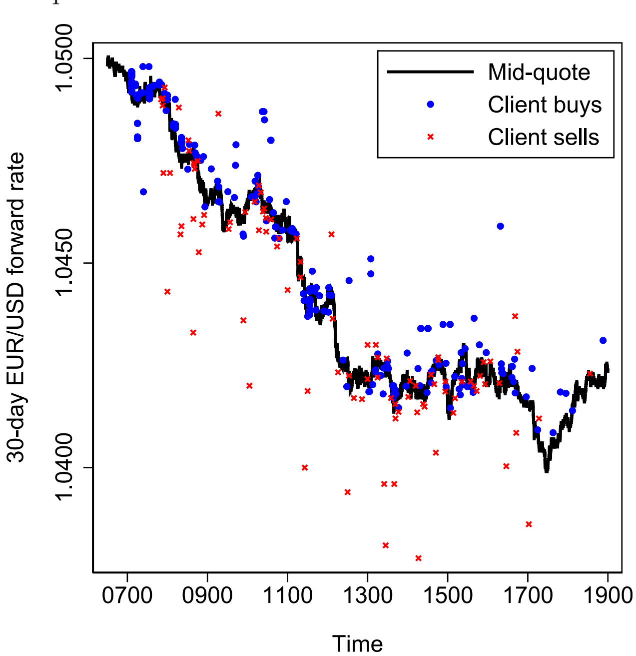
5.2.1. Client Sophistication. We propose five measures of client sophistication. *#Counterparties* denotes the number of dealers with which a client trades during our one-year sample period. We also compute the Herfindahl–Hirschman index (*HHI*) of the share of a client's trades with each dealer. *HHI*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

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 A, 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).

Figure 1. (Color online) Contracted Forward Rates Vs. the Midquote



Notes. This figure plots contractual forward rates vs. the midprice on a single trading day. The midquote is shown by the solid line, which tracks intraday midprices for 30-day EUR/USD forward contracts (constructed from Thomson Reuters interdealer quote data). To approximately match this 30-day midprice, we depict contracts with an original maturity between 25 and 35 days. Client long and short positions are indicated by dots and crosses, respectively. Dots (crosses) above (below) the solid line imply that the client pays a positive spread. Time is Greenwich Mean Time.

5.2.2. Platforms. The second hypothesis concerns the role of platforms. Our transaction-level data identify 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.

5.2.3. 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 gives rise to endogeneity concerns. In particular, the econometrician cannot rule out that firms concentrate their trading in certain banks because they offer tighter spreads. We avoid this problem by retrieving information on firms' credit relationships outside the FX market. More specifically, we obtain the identities of firms' main relationship lenders from Orbis. These data are only available for a subset of all 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.

5.2.4. Information Rents from Asymmetric Price Adjustment. To identify whether dealers adjust prices asymmetrically following changes in the midquote, we denote by $|\Delta m_\tau^{-d}|$ ($|\Delta m_\tau^{d}|$) the absolute value (in pips) of the change in the midmarket 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

$$\left|\Delta m_\tau^{-d}\right| = \begin{cases} |\Delta m_\tau| & \text{if } sign(d_\tau) \neq sign(\Delta m_\tau) \\ 0 & \text{otherwise.,} \end{cases} \tag{2}$$

$$\left|\Delta m_\tau^{+d}\right| = \begin{cases} |\Delta m_\tau| & \text{if } sign(d_\tau) = sign(\Delta m_\tau) \\ 0 & \text{otherwise.,} \end{cases} \tag{3}$$

where Δm_τ denotes the midquote change in the 30 seconds prior to trade τ. In a regression of spreads on these variables, Hypothesis 3 predicts that the coefficient of $|\Delta m_\tau^{-d}|$ is positive, reflecting client costs from asymmetric price adjustment, whereas the coefficient of $|\Delta m_\tau^{+d}|$ is zero if dealers immediately update their quotes when it favors them. The sum of these two coefficients reflects the net costs incurred by clients through this mechanism.

5.2.5. Trade Characteristics. Finally, we define several variables which 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 because these are more difficult to hedge in the interdealer market. Fourth, *Volatility* is the realized volatility of the FX spot rate over the 30 minutes preceding a trade, based on 1-minute intervals. Spreads are expected to be higher in volatile market conditions to compensate dealers for added execution risk. Fifth, *Buy* is a dummy that 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.

6. Descriptive Statistics

The final data set 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. Table 1, Panel A provides summary statistics for the cross-section of 10,087 clients. 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*. Although 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*, log*Total-Notional*, 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. Because our empirical strategy involves dealer fixed effects, these are merely for background information. The average (median) 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 midsized banks with relatively low shares of noninterest 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

Table 1. Summary Statistics

	Observations	Mean	Standard deviation	p10	p25	p50	p75	p90
			Panel A: Clients					
#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 € million)	10,087	515	7,396	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					
#Clients	204	81	235	1	3	7	30	187
TotalNotional (in € million)	204	25,484	87,225	1	4	19	181	56,215
TotalAssets (in € billion)	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					
Spread	548,298	6.9	19.4	−4.9	−1.1	2.0	11.3	31.0
Notional (in € million)	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

Notes. Panel A shows client-level data for the 10,087 nonfinancial clients that trade EUR/USD forwards between April 2016 and March 2017. Panel B shows dealer-level data for the 204 dealers 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 $AAA = 1, AA+ = 2, \ldots, D = 28$, 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 noninterest 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 1-minute intervals; *Buy* is a dummy equal to one for client forward buys of euro against dollar and zero otherwise; and *Platform* is a dummy equal to one when a trade occurs on a platform and zero otherwise.

EUR/USD interdealer market, as reported by Karnaukh et al. (2015). The median is considerably below the mean at two pips, indicating substantial positive skew. Moreover, the dispersion is very large, with an interquartile 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. Although negative spreads can be explained by inventory rebalancing (Dunne et al. 2015), they may also arise in our data from occasional time stamp inaccuracies.[23] Whereas 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 around 40% of trades. Moreover, just under 40% of all trades are executed on a platform, in line with existing survey evidence (Bank for International Settlements 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 midquote changes over the preceding 30 seconds rarely exceed one pip. Additional summary statistics at client and transaction levels are provided in the online appendix.[24]

7. Empirical Analysis

Figure 2 plots the cross-sectional distribution of average spreads at the 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

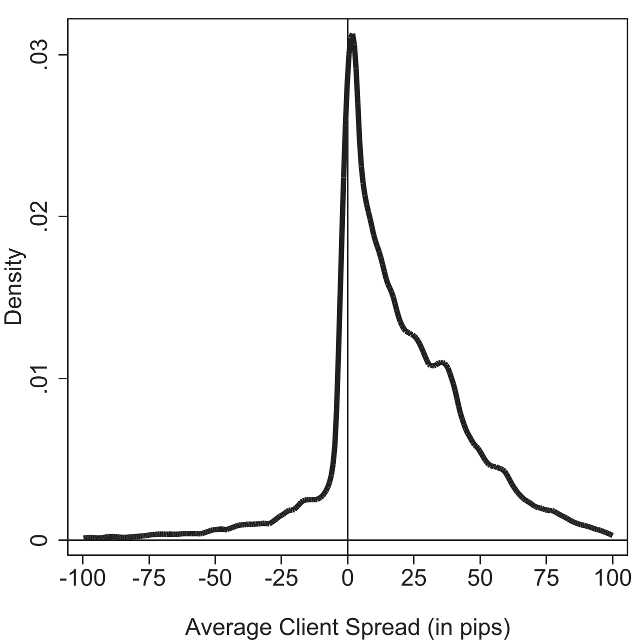
$$Spread_{\tau,i,d,t} = X_i\beta + \boldsymbol{Z}'_\tau\boldsymbol{\theta} + \delta_{d,t} + \gamma_m + \epsilon_{\tau,i,d,t}, \quad (4)$$

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, whereas $\boldsymbol{Z}_\tau$ is a column vector of control variables composed of the five trade characteristics defined in Section 5.2. Importantly, our specification includes dealer-date fixed effects ($\delta_{d,t}$). Thus, conditional on trade characteristics, we compare spreads across clients that trade with the *same* dealer on the *same* date. This comparison within dealers allows us to interpret our results in terms of price discrimination because we control for observable and unobservable dealer characteristics (e.g., dealer efficiency). Moreover, because 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 has been shown to affect market liquidity (e.g., Adrian et al. 2017, Goulding 2019). Finally, we also control for intraday patterns using minute-of-day (γ_m) fixed effects.

7.1. Client Sophistication

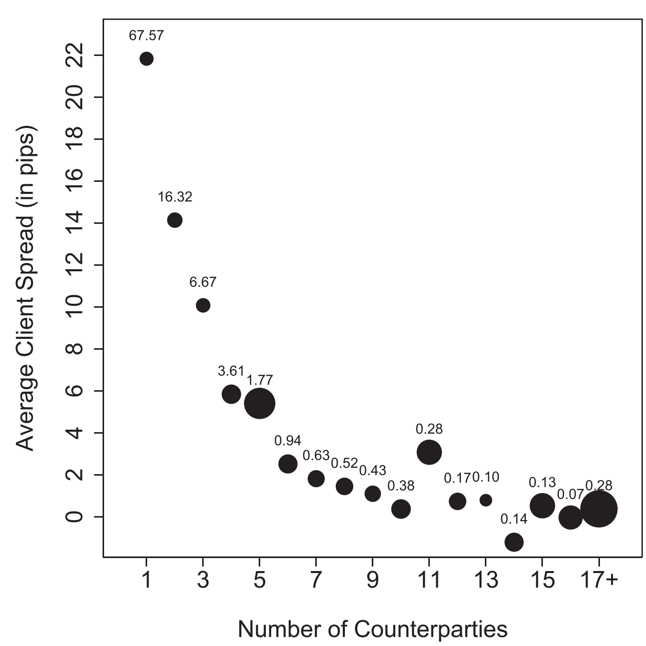
To provide early intuition, Figure 3 plots the average client spread by the number of dealers (#*Counterparties*) with which a client trades in our sample. The size of each dot is proportional to the notional share for each group of clients. Although clients with one dealer account for only 2% of the 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. Although this group represents only 6% of clients, their aggregate notional accounts for 88% of the total.

Figure 2. Distribution of Average Client Spread



Notes. 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 Counterparties



Notes. This figure plots the average spread paid by clients with a given number of 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 counterparties. For readability, the 17+ counterparty group aggregates all clients with 17 or more counterparties.

To formally test Hypothesis 1, we estimate Equation (4) for each of the five proxies of client sophistication discussed in Section 5.2 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 (2) and (3) indicate that clients with greater search efficiency—proxied by the number of dealers with which they trade and their concentration in those dealers—are associated with tighter spreads. In columns (4) and (5), 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 (6) reveals that clients with more outstanding derivatives contracts in other asset classes benefit from tighter spreads on average.

Column (7) 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. Because 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

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)				
log*TotalNotional*				−1.568***			
				(0.072)			
log #*TradesFX*					−1.782***		
					(0.102)		
log #*TradesNonFX*						−1.003***	
						(0.104)	
Sophistication							−1.522***
							(0.079)
Trade characteristics							
log*Notional*	−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)
log*Tenor*	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)
log*Customization*	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^2	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

Notes. This table reports coefficient estimates from ordinary least squares regressions of spreads on measures of client sophistication. Each specification controls for dealer-date and intraday fixed effects (FE). Standard errors clustered at client level are reported in parentheses.

***Statistical significance at 1%.

bond market (Schultz 2001, Harris and Piwowar 2006, Green et al. 2007). Longer maturities are associated with wider spreads, potentially reflecting higher counterparty risk (see Section 8.1). 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 one pip. The coefficient of *Volatility* has the expected positive sign but is statistically insignificant. Finally, the coefficient of the *Buy* dummy is statistically significant, consistent with persistent covered interest parity violations (Du et al. 2018).

7.2. 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.

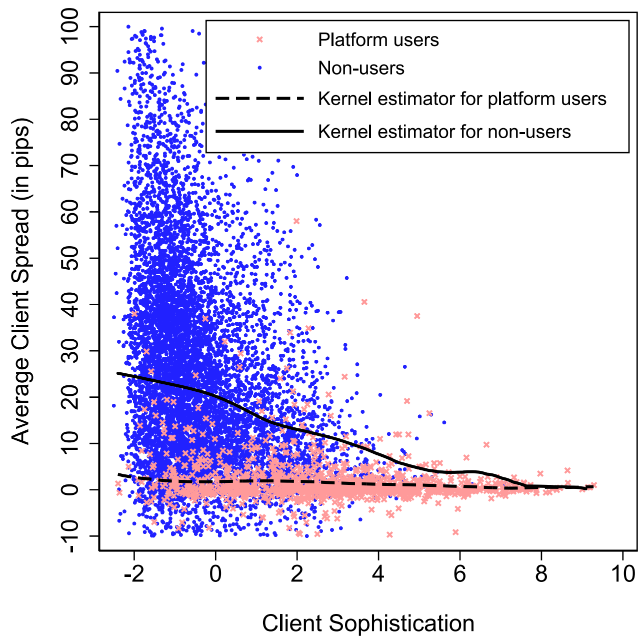
Hypothesis 2 predicts that trades on platforms incur tighter spreads. Before turning to the formal regression analysis, Figure 4 plots the average spread at the client level as a function of sophistication. Dots correspond to clients that trade only bilaterally, whereas crosses represent firms that execute at least one of their trades on a platform. The associated nonparametric fits are 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 nonusers. In contrast, platform users obtain competitive spreads irrespective of their level of sophistication.

Table 3 reports results from a regression analysis with the 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 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 *Sophistication* = −0.5) saves 4.5 pips when trading on a platform, whereas 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. 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.

Figure 4. (Color online) Average Client Spread by Sophistication and Platform Use



Notes. 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*, log*TotalNotional*, log *#TradesFX*, and log *#TradesNonFX*. Clients using a platform at least once in our sample period are marked by crosses; clients that never use a platform are marked by dots. The solid 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 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.

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 × *Sophistication*			1.967***		0.463***
			(0.139)		(0.131)
R^2	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

Notes. This table reports coefficient estimates from ordinary least squares regressions of spreads on the *Platform* dummy, *Sophistication*, and an interaction of these two variables. Each specification controls for dealer-date fixed effects (FE), intraday fixed effects, and trade characteristics (i.e., log*Notional*, log*Tenor*, log*Customization*, *Volatility*, and *Buy*). In addition, columns (4) and (5) control for client fixed effects. Standard errors clustered at client level are reported in parentheses.

***Statistical significance at 1%.

If platform trading is so beneficial, why do not 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), whereas 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 shopping 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 platforms if the expected benefits are not sufficient to cover costs associated with platform trading. Although 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 nonusers 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

$$\begin{aligned} &PlatformBenefit_i \\ &\quad = (1 - PlatformUser_i) \times \sum_{\tau} [(-13.2 + 1.97 \\ &\qquad \times Sophistication_i) \times Notional_\tau], \end{aligned} \tag{5}$$

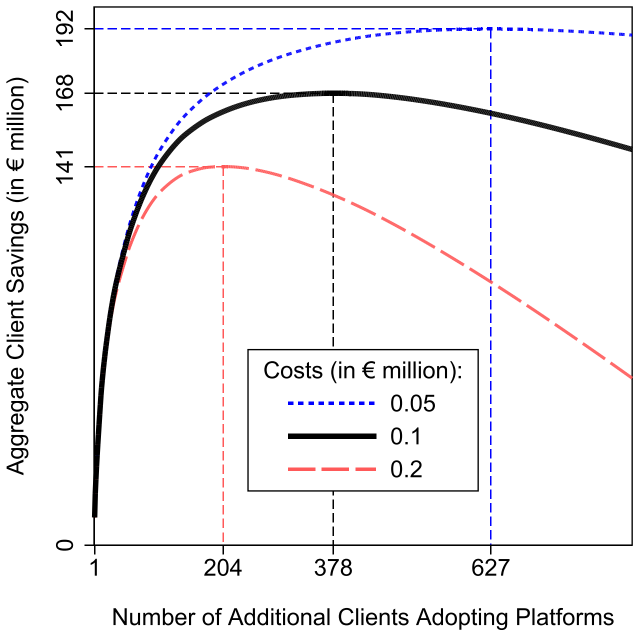
where $PlatformUser_i$ is a dummy that equals 1 if client i trades on a platform at least once in our sample and 0 otherwise. Summing over all clients, we estimate an aggregate gross benefit of € 264 million per year in EUR/USD alone.

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 nonusers rationally abstain because their estimated benefits are smaller. However, the remaining 378 clients still account for a potential gross annual saving of € 205 million or € 168 million net of the assumed cost.

Interestingly, our estimates are not overly sensitive to the assumed cost. We obtain aggregate net savings of € 141 (€ 192) million per year 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 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 because of market opacity. Increased posttrade transparency (e.g., in the spirit of the Trade Reporting and Compliance Engine (TRACE) in the U.S. corporate bond market) would enable clients to compare the costs of different trading mechanisms and make more informed choices.

Figure 5. (Color online) Aggregate Annual Client Savings from Adopting Platforms



Notes. We sort nonplatform 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 euros (dotted line), (ii) 0.1 million euros (solid line), and (iii) 0.2 million euros (dashed line). Under these cost assumptions, platform adoption is optimal for 627 clients, 378 clients, and 204 clients, respectively. The corresponding aggregate annual saving is 192 million euros, 168 million euros, and 141 million euros, respectively.

7.3. 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 3 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 eight 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 multidealer 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 nonrelationship 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 multidealer 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 clients obtain discounts from their relationship bank, in line with previous empirical work (Cocco et al. 2009, Hendershott et al. 2020).

7.4. 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 (2) and (3) for the alignment of recent midquote changes and clients' trade direction, we estimate the following linear regression:

$$Spread_{\tau,i,d,t} = \beta_1 |\Delta m_\tau^{-d}| + \beta_2 |\Delta m_\tau^{+d}| + \boldsymbol{Z}'_\tau \boldsymbol{\theta} + \delta_{d,t} + \gamma_m + \epsilon_{\tau,i,d,t}. \tag{6}$$

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All clients			Single-dealer clients		Multidealer 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^2	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

Notes. This table reports coefficient estimates from ordinary least squares regressions 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*, log*TotalNotional*, log *#TradesFX*, and log *#TradesNonFX*. Additionally, each specification controls for dealer-date fixed effects (FE), intraday fixed effects, and trade characteristics (i.e., log*Notional*, log*Tenor*, log*Customization*, *Volatility*, and *Buy*). Columns (4) and (5) and columns (6) and (7) replicate columns (1) and (2) for the subsamples of clients with *#Counterparties* = 1 and *#Counterparties* > 1, respectively. Standard errors clustered at client level are reported in parentheses.

*Statistical significance at 10%; ***statistical significance at 1%.

Under Hypothesis 4, the cost $\beta_1 + \beta_2$ because of 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 that 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. Although the sum $\widehat{\beta_1} + \widehat{\beta_2} = 0.122$ is positive, it is not statistically significant ($p = 0.143$), 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 because of 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, whereas more sophisticated clients do not. However, the economic magnitudes are small: whereas dealers earn a significant fraction of recent price movements (44% for clients with average sophistication), such movements rarely exceed one pip (see Table 1, Panel C).

8. 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 nonusers.

8.1. Counterparty Risk

Concerns related to counterparty risk in the OTC derivatives market played a major role during the 2007–2008 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 nonfinancial clients were also exempt from variation margin requirements during our sample period. Accordingly, none of the trades in our sample are 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 nonfinancial firms during our sample period.

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)
$\lvert\Delta m_\tau^{-d}\rvert$ × *Sophistication*			−0.0599***	−0.0616***
			(0.015)	(0.015)
$\lvert\Delta m_\tau^{d}\rvert$ × *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^2	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

Notes. This table reports coefficient estimates from ordinary least squares regressions of spreads on measures of price staleness. $\lvert\Delta m_\tau^{-d}\rvert$ ($\lvert\Delta m_\tau^{+d}\rvert$) is the absolute value of the change in the midquote 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*, log*TotalNotional*, 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 row 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 (FE), intraday fixed effects, and trade characteristics (i.e., log*Notional*, log*Tenor*, log*Customization*, *Volatility*, and *Buy*). Standard errors clustered at client level are reported in parentheses.

***Statistical significance at 1%.

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 log*Tenor* because 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.

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 log*Tenor* 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 (because a higher *ZScore* signals higher risk) but statistically insignificant. When adding the interaction with log*Tenor* in column (8),

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)
log*Tenor*	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 × log*Tenor*			0.0598**		0.0226			0.437***			0.0437
			(0.025)		(0.191)			(0.077)			(0.506)
R^2	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

Notes. This table reports coefficient estimates from ordinary least squares regressions 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 that equals one when the credit rating is at least *BBB*− (i.e., investment grade, denoted by IG) 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 log*Tenor*, which is the natural logarithm of a contract's original maturity (in days), and in columns (3), (5), (8), and (11), log*Tenor* is also interacted with the counterparty risk measures. Additionally, each specification controls for dealer-date fixed effects (FE), intraday fixed effects, and other trade characteristics (i.e., log*Notional*, log*Customization*, *Volatility*, and *Buy*). Standard errors clustered at client level are reported in parentheses.

*Statistical significance at 10%; **statistical significance at 5%; ***statistical significance at 1%.

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 log*Tenor*.

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

8.2. Financial Clients

Our analysis has focused on nonfinancial 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 nonbanks (Online Appendix B). We observe 977,595 transactions between 13,314 nonbank 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 nonfinancial clients. Similarly, platform trading is associated with less price discrimination than bilateral trading. However, because 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 (Online Appendix C). For this exercise, we classify a group of banks most actively involved in derivatives markets as dealers and any bank outside this group as clients.[29] In this sample, we observe 370,713 transactions between 725 customer banks and 16 dealers. The findings for sophistication broadly echo those for nonbank financial clients, although the use of platforms is not associated with any spread compression for banks.

8.3. Platform Users Vs. Nonusers

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 nonusers. The results are shown in Online Appendix D. Summarizing, we find price discrimination by sophistication in both subsamples but with economically larger effects for nonusers. 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 nonusers. These results are in line with our main analysis.

9. 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 absent. Our paper fills this gap.

We find extensive price discrimination in the FX derivative market. Because of its lower level of sophistication, the median nonfinancial 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 multidealer platforms rather than bilaterally. We also show that sophisticated clients obtain a discount when trading with their relationship bank compared with trades with other dealers, whereas unsophisticated clients pay a premium.

For policy makers, our results suggest that there is considerable scope to improve OTC market quality. Enhanced posttrade transparency would enable clients to better monitor the quality of their trades and counteract widespread price discrimination. Moreover, although platforms are effective at reducing dealers' market power, several hundred clients do not trade on a platform despite it being optimal for them to do so. Greater transparency would also enable clients to compare the costs of different trading mechanisms—thus facilitating convergence to a more efficient market structure. Consequently, measuring price discrimination based on regulatory disclosure of OTC trades represents an indispensable input into the high-stakes policy debate to which this paper seeks to contribute.

Acknowledgments

The authors thank the editor (Haoxiang Zhu) and two anonymous referees for useful comments and suggestions. Special thanks go to Philippos Kassimatis for imparting extensive knowledge of FX markets, Martin Neychev for excellent research assistance, and their conference discussants for their valuable feedback: Puriya Abbassi, Pasquale Della Corte, Monika Gehde-Trapp, Simon Jones, Timo Klein, Roman Kozhan, Tomy Lee, Richard Payne, Loriana Pelizzon, Silvia Pezzini, Thomas Ruchti, Stephen Schaefer, and Zhaogang Song. The authors also benefited from conversations with Markus Brunnermeier, Jeroen Dalderop, Darrell Duffie, Maryam Farboodi, Thierry Foucault, Burton Hollifield, Bo Honoré, Jakub Kastl, Ricardo Lagos, Albert Menkveld, Marco Pagano, Randy Priem, Dagfinn Rime, Norman Schürhoff, Stefan Sperlich, James Swinnerton, Michalis Vasios, and Adrien Verdelhan. In addition, they thank participants at the European Finance Association 2018 (Warsaw), Society for Financial Studies Cavalcade 2018 (Yale), Western Finance Association 2018 (San Diego), the Annual Conference in International Finance 2018 (Oslo), the Annual Meeting of the Central Bank Research Association 2018 (Frankfurt), the 2nd Sustainable Architecture for Finance in Europe Market Microstructure Conference (Frankfurt), the Centre for Economic Policy Research Spring Symposium 2018 (London), the Spring 2018 Meeting of Young Economists (Spain), the First Annual Conference of the European Systemic Risk Board (Frankfurt), the 2017 conference "OTC Markets and their Reform" (Switzerland), the conference "Securities Markets: Trends, Risks, and Policies" (Milan), 13th Annual Central Bank Conference on the Microstructure of Financial Markets (London), and seminars at the Australian National University, Deutsches Institut für Wirtschaftsforschung Berlin, the UK Financial Conduct Authority, Katholieke Universiteit Leuven, International Monetary Fund, Princeton University, Stockholm Business School, University of New South Wales, the University of Sydney, the University of Technology Sydney, the European Central Bank, the Bank of Lithuania, and the Central Bank of Ireland. The views expressed herein are those of the authors and do not necessarily represent the views of the institutions to which they are affiliated. The authors declare that they have no relevant or material financial interests that relate to the research described in this paper.

Endnotes

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

[2] Because our analysis predates Brexit, we capture the large fraction of trades by United Kingdom-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" in *Financial Times* (September 26, 2013; available at https://www.ft.com/content/338d3d5a-269c-11e3-bbeb-00144feab7de).

[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 one pip refers to a 0.0001-point difference. In our sample,

the EUR/USD exchange rate was close to one, so pips are close to basis points.

[6] See, for example, Hendershott and Madhavan (2015), Benos et al. (2020), Collin-Dufresne et al. (2020), and Riggs et al. (2020).

[7] See Bernhardt et al. (2004), Cocco et al. (2009), Afonso et al. (2013), Di Maggio et al. (2017), and Hendershott et al. (2020).

[8] Bessembinder et al. (2006), Goldstein et al. (2006), and Edwards et al. (2007) document that the introduction of TRACE in the U.S. 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 posttrade transparency (Loon and Zhong 2014, 2016).

[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.

[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).

[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 prespecified 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 trade.

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

[14] For example, Monarch, a United Kingdom-based airline, filed for bankruptcy in part owing to the depreciation of sterling (in which much of its revenues were denominated) against the U.S. dollar (the invoice currency for expenses such as fuel and aircraft). See "Monarch Airlines goes bust" in *Reuters* (October 2, 2017; available at https://goo.gl/YR7Q7P).

[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).

[17] The data set is described by Abad et al. (2016).

[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.

[20] For example, the midquote for a 10-day forward is calculated as the weighted average of the one-week and two-week midquotes, where the weights are 4/7 and 3/7, respectively.

[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 because 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.

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

[24] Online Appendix A, 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. Online Appendix A, 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 and Rigobon 2008). Likewise, firms are primarily domiciled in export-oriented economies, such as Germany.

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

[26] In Online Appendix E, Table E.1, we examine how price discrimination varies according to dealer characteristics. We find that larger and more sophisticated dealers engage in less price discrimination, although the extent to which they discriminate remains economically large.

[27] For this exercise, we redefine *Sophistication* to exclude log *#Counterparties* and *HHI*.

[28] Because 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.

[29] The group of dealers comprises Bank of America, Barclays, BNP Paribas, Citigroup, Crédit Agricole, Credit Suisse, Deutsche Bank, Goldman Sachs, HSBC, JPMorgan Chase, Morgan Stanley, Nomura, Royal Bank of Scotland, Société Générale, UBS, and Wells Fargo.

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