

Bid-Ask Spreads in OTC Markets

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Abstract: According to well-accepted theory, the three primary components of bid-ask spreads reflect operating costs, inventory costs, and adverse selection. We challenge the idea that the traditional trinity applies in all markets, arguing that OTC spreads include a price discrimination component rather than an adverse-selection component. Because OTC trades are not anonymous, OTC dealers will price discriminate according to their clients' information, market sophistication, and trading volume. Adverse selection could influence the information dimension of price discrimination or it could be irrelevant. We support this view with an empirical analysis of transactions data from the world's largest OTC market that include venue and customer IDs. The estimated price discrimination component ranges from two-thirds to six times the combined operating and inventory cost components for different customer groups. Adverse selection is irrelevant for most customer groups, and its contribution to spreads paid by the other two customer groups, hedge funds and customer banks, is small in absolute terms but large relative to their average markup. We identify two structural determinants of the relevance of adverse selection: the presence of an active interdealer market and a customer's engagement in HFT.

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Bid-Ask Spreads in OTC Markets

Liquidity is arguably the most important product of financial markets, and the bid-ask spread is commonly the price of liquidity. The initial challenge undertaken by microstructure researchers was, therefore, to identify the fundamental determinants of bid-ask spreads (Demsetz, 1968; Cornell, 1978; Copeland and Galai, 1983). For roughly three decades the field has viewed this quest as essentially fulfilled. From classrooms to conferences to journal articles it is commonly stated that spreads reflect three specific dealing costs: operating costs, inventory costs, and adverse selection.

Evidence for this traditional trinity was initially based on auction markets for equities (Glosten and Harris, 1988; Madhavan and Smidt, 1993; Huang and Stoll, 1991; 1997), in part because these markets were an early source of high-frequency data. When high-frequency data became available for OTC markets, however, the traditional trinity performed poorly. Research into this puzzle reveals multiple reasons why OTC spreads could be determined differently from spreads in auction markets (e.g., Naik et al., 1999; Bernhardt et al., 2005; Green et al., 2007).

Synthesizing this research, we argue that in OTC markets the adverse-selection component of the spread should be replaced with a price-discrimination component. We support this perspective with empirical evidence from the largest OTC market in the world, the foreign exchange market. Our data, which comprise the complete trading record of a top-twenty dealing bank over three months in 2012, are outstanding insofar as they provide exact markups, trading venues, and customer identities.

We find that price discrimination is indeed important. In this OTC market the price-discrimination component of a customer's markup over the interdealer price ranges from two-thirds to six times the combined effects of operating costs and inventories. The influence of price discrimination thus meets or exceeds, in relative magnitude, estimates of the adverse-selection component for stocks (Madhavan and Smidt, 1993; Huang and Stoll, 1997). We find that adverse selection per se is irrelevant for unleveraged asset managers, brokers, MNCs, and SMEs. For hedge funds and customer banks the contribution of adverse selection is tiny in absolute magnitude but large relative to their normal markups.

The incentives and constraints facing market makers differ structurally between OTC and auction markets, so it is logical that spread determination might vary across these market settings. In auction markets the liquidity provider moves first by providing quotes which potential counterparties can view and compare directly; in traditional OTC markets the liquidity demander moves first by contacting the dealer, so a potential counterparty can see just one set of quotes at a time. If these quotes do not seem attractive the costs and risks involved in searching for a better price will sometimes dissuade traders from doing so. OTC dealers therefore hold a degree of market power at the moment they provide quotes (Bernhardt and Hughson, 2002). Auction and OTC markets also differ in terms of pre-trade anonymity. When providing quotes in an auction setting a market maker cannot know the identity of his ultimate counterparty; in an OTC setting the market maker necessarily knows the counterparty's identity. A rational OTC dealer will exploit this customer knowledge by price discriminating.

Existing theory shows that price discrimination in OTC markets will reflect three customer properties. First, the customer's market sophistication, meaning his familiarity with market conventions including customary markups as well as knowledge of current market conditions. More sophisticated customers have greater negotiating leverage vis-à-vis dealers and are therefore likely to pay narrower spreads (Green et al., 2007). Second, the customer's normal trading volume. Dealers will rationally seek to attract more active customers by providing volume discounts (Bernhardt and Hughson, 2002). Third, the customer's tendency to be informed about upcoming returns ("information") (Easley and O'Hara, 1987; Glosten, 1992; Naik et al., 1999).

These forms of price discrimination could help explain a consistent puzzling finding in the literature on OTC markets: a negative relation between spreads and trade size (Biais and Green, 2007). This pattern has been identified for every OTC market tested in the literature, including the London Stock Exchange (Reiss and Werner, 1996); the modern U.S. corporate bond market (Goldstein et al., 2007); the modern U.S. municipal bond market (Green et al., 2007), the pre-war corporate bond market (Biais and Green, 2007), and the foreign exchange market (Osler et al., 2011). This pattern "clearly defies conventional wisdom" (Bernhardt et al., 2005, p. 1344) because it appears to violate adverse selection. In

theory, large trades are most likely to be informed, so they should be quoted wider rather than narrower spreads under adverse selection (Easley and O'Hara, 1987).

The negative relation between spreads and a trade's likely information content, though inconsistent with standard expectations in the literature, is also observed in our dataset. The end-users considered most informed by forex dealers − specifically hedge funds, some customer banks, and some brokers − typically enjoy relatively low markups. By contrast, MNCs, SMEs, and funds with low leverage pay relatively high markups. The difference is economically substantial: SME markups are 22.7 pips, on average, and hedge-fund markups are just 0.03 pips, on average. (One pip = \$0.0001/€; at current exchange rates this is roughly equivalent to one basis point.)

An inverse relation between a trade's information content and spreads would not be surprising under price discrimination because better-informed customers tend to be more sophisticated and tend to trade in high volume. Better-informed customers will wisely expend the resources necessary to gain market sophistication and they will naturally exploit their information advantage by trading large amounts. An inverse relation between information and spreads could therefore emerge naturally if the dealers' tendency to price discriminate in favor of sophisticated and active customers outweighs any price discrimination on the basis of information per se. Our results confirm that forex customers are severely penalized for any lack of market sophistication and enjoy generous discounts if they trade in high volumes. A one-standard-deviation increase in a critical measure of market sophistication is estimated to decrease the cost of liquidity on a given trade by 2.4 pips, which is many multiples of the average markup of 0.4 pips and similar in magnitude to the average customer bid-ask spread. A one-standard-deviation increase in a customer's average daily trading volume is estimated to decrease the cost of liquidity by 1.2 pips. Together these two dimensions of price discrimination dominate the inverse relation between information and average spreads.

The negative relation between spreads and a trade's likely information content could also arise directly if dealers price discriminate in favor of better-informed customers. This could be rational in OTC

markets with active interbank trading, according to the strategic dealing hypothesis of Naik and Neuberger (1999). They show that rational dealers with access to an interbank market will seek to attract informed customers, anticipating a brief window of time for profitable trading before other dealers learn the customer's information. If strategic dealing applies anywhere it likely applies in forex, since it has the world's most active interdealer market. Our results indicate that this strategic dealing hypothesis does govern the way OTC dealers set markups for one customer group: brokers.

What determines how dealers price discriminate with respect to information? The dealers in our sample appear to ignore information for groups they consider generally uninformed, specifically funds with low leverage, MNCs, and SMEs. For other customers we hypothesize that the decision between strategic dealing and adverse selection is governed by the stage of the price discovery process at which customers typically trade with the dealer. OTC dealers will price discriminate in favor of informed customers whose trades – and thus information – arrive early enough to enable profitable exploitation in subsequent interdealer trades. By symmetry, the dealers will price discriminate against informed customers whose trades arrive too late for profitable exploitation.

We test this hypothesis by examining the influence of high-frequency trading. The high-frequency trades of hedge funds and customer banks are often intended to exploit triangular arbitrage opportunities and other evanescent mis-pricings. Our dealers' trades with HFT customers arrive late in the price discovery process, triggering adverse selection. Informed broker trades, by contrast, are often carried out on behalf of hedge funds that choose not to engage in HFT; the earlier arrival of such trades relative to the price discovery process could motivate dealers to attract such trades. Using the customer identities provided with our data we sort hedge funds into those that do and do not engage in HFT.

Consistent with our hypothesis, we find that adverse selection is primarily relevant for hedge funds that engage in HFT.

Our study is relevant to Biais and Green's (2007) investigation of the shift in corporate and municipal bond trading from an exchange-traded setting to an OTC market. They suggest that this shift explains why the spreads paid by retail traders, but not the spreads paid by institutional traders, rose after

the shift. Our analysis confirms that OTC price discrimination against less-sophisticated customers can have a substantial influence on bid-ask spreads.

We are not aware of any other comprehensive study of price discrimination in OTC markets. The workhorse spread-decomposition models consider only the traditional trinity of adverse selection, inventory costs, and operating costs (Glosten and Harris, 1988; Madhavan and Smidt, 1991; Huang and Stoll, 1997). These models do not incorporate the possibility of customer-level price discrimination. When applied to OTC markets they fail to confirm the predictions of adverse selection but the reasons for that failure are difficult to identify.

Each of the three dimensions of price discrimination relevant to OTC markets has been examined with bespoke empirical strategies. Market sophistication is examined in Green et al. (2007) and Reitz et al. (2012); volume discounts are examined in Bernhardt et al. (2005); strategic dealing is examined in Hansch and Neuberger (1996). These studies provide evidence of price discrimination but it is difficult to interpret them as uniquely supporting any single dimension of price discrimination given the correlation between information, market sophistication, and trading volume. With data on customer identities we can carefully distinguish all three dimensions of price discrimination.

The rest of this paper has four additional sections and a conclusion. Section I outlines our data. Section II describes our methodology. Section III provides our main results. Section IV presents extensions and robustness tests. Section V summarizes our analysis and suggests some implications for fix-price calculation methodologies.

I. DATA

Our data include all spot deals of a top-20 forex dealing bank over the 68 trading days from 2 January to 20 April, 2012. We focus on the most liquid currency pair, EURUSD, in which daily trading is estimated to be 24% of daily trading worldwide or roughly \$500 billion (B.I.S. 2013). The data provide standard information about each trade including the date and time to the second, transaction price quoted as dollars per euro, and quantity traded in euros. The data provide each trade's markup measured in pips

(\$0.0001/€) relative to the interbank bid or ask quote (as appropriate) at the time of the trade, which represents the customer's half-spread exclusive of interbank half-spreads. This information obviates the need, often encountered in earlier studies, to extract spreads indirectly from the sequence of traded prices (e.g., Madhavan and Smidt, 1993) or to estimate trade direction (e.g., Madhaven, Richardson, and Roomans, 1997). The data also include counterparty ID; counterparty category; an indicator for trades through a prime broker and, if so, the underlying trader as well as the prime broker. Finally, the data indicate the initiating party (our bank or counterparty), the sign of the trade (bank buys or sells), and the trading venue.

The data are superior for examining price discrimination than other high-frequency OTC datasets studied in the literature for a number of reasons. Many datasets exclude customer trades altogether (e.g.,; Green et al., 2007; Berger et al., 2008; Chinn and Moore, 2009; Killeen et al. 2006; Daníelsson and Love, 2006; Breedon and Vitale, 2010), or provide customer trades only on a daily basis (e.g., Evans and Lyons, 2005; Froot and Ramadorai, 2005; Gyntelberg et al., 2009; March and O'Rourke, 2005; Bjønnes et al. 2005a). The few OTC datasets with customer information group them into a few broad types, such as "financial" vs. "commercial" (e.g. Evans and Lyons, 2005; Osler et al., 2011; Reitz et al., 2012; Ramadorai, 2005); our data, by contrast, provide individual customer identifiers and six separate customer categories. The data are also more relevant to the forex market in its current somewhat-fragmented state since they identify over 20 trading venues. Most other dataset are limited to interdealer platforms (e.g., Evans and Lyons, 2002), predate the market's fragmentation (Osler et al., 2011; Reitz et al., 2014); or simply do not provide transaction-level information on venues for customer trades.

Every markup in our dataset is tailored to the individual customer. The vast majority (over 95%) are set by an automated quotation system rather than by the active intervention of a salesperson or an interdealer trader. Even so, the markup algorithm is designed and parameterized by the salesforce together with a dedicated e-commerce team. Our focus is the way OTC dealers set the price of liquidity for endusers so we exclude the bank's "internal" trades and trades with other top 50 *Euromoney* dealing banks,

the latter of which are generally pure interdealer trades. We also exclude a few customer trades where our bank is a price taker. After exclusions the sample includes 257,421 transactions.

Table 1 provides basic descriptive statistics for key variables. For the entire sample (Column A), the overall mean mark-up is 0.4 pips. For comparison purposes we note that interbank half-spreads are typically about 0.5 pips during European trading hours. The average customer trades about €4 million per day through our bank. Individual trades are worth on average about €0.5 million; the largest single trade is worth €184 million. Markups, trading volume, and average trade sizes vary widely across and, more importantly, within customer types. This is helpful since our empirical strategy relies on customer-specific information.

Our empirical analysis fully exploits the customer identities provided in our data. The regression model, for example, includes customer-specific variables for each transaction. Nonetheless, it proves helpful to characterize markups and other variables according to the six counterparty types designated by the bank. These can be crudely divided into two broad categories: low-markup customers include hedge funds, customer banks, and brokers; high-markup customers include real-money funds, multinational corporations and large non-financial firms ("MNCs"), and small and medium enterprises ("SMEs"). ²

The average markup for low-markup group is well below 1 pip, ranging from 0.01 pip for brokers to 0.3 pip for customer banks. In effect, these customers pay little more than the interbank spread. Among high-markup customers the average markup ranges from 2 − 3 pips for real-money funds and MNCs to a striking 23 pips for SMEs. Later analysis shows that high-markup customers tend to be better informed than the high-markup customers, and positive correlation between information and trading activity discussed in the introduction is certainly apparent. Average daily trading volume for low-markup customers ranges from €9 million for hedge funds and customer banks to €34 million for brokers. The

¹In the traditional OTC market our bank by definition is the price-setter when dealing with customers, but for at least a decade customers have had the option of trading with their banks in limit-order market settings such as Reuters and EBS. We exclude trades when our bank serves as prime broker for a customer who trades against other banks on limit-order trading platforms. For these trades, our bank earns a fixed fee per million of base currency but is not, in any meaningful economic sense, either the liquidity maker or the liquidity taker, so the markup would not reflect this bank's pricing strategies.

² SMEs and MNCs are generally non-financial firms but the SME designation is also assigned to private clients and firms with annual sales below €100 million. An MNC will have a specialized treasury unit or at least €100 million in annual sales.

high figure for broker is largely driven by the retail aggregators who make hundreds or even thousands of trades per day. Sverage daily trading volume for high-markup customers ranges only from 0.05 for SMEs to 2 million for MNCs.

II. METHODOLOGY

We regress each trade's markup on explanatory variables that capture the three critical dimensions of price discrimination – information, market sophistication, and trading volume – plus variables that capture operating costs and inventory risk. Our model is straightforward, a luxury made possible by the accuracy of our markup data and the detailed information available for each trade. Many previous studies of the price of liquidity rely on the sequence of price changes (Glosten and Harris, 1988; Madhavan and Smidt, 1991; Huang and Stoll, 1997), which introduces modeling complications and does not necessarily produce reliable estimates of adverse selection (Van Ness et al., 2001). No previous model of OTC spreads has had sufficiently disaggregated data to identify more than one dimension of price discrimination.

A. The model

We initially regress the markup for each trade on variables to capture the customer properties associated with price discrimination as well as variables to capture operating costs and inventory risk:

$$Markup_t = \alpha + \pi Info_c + \mu' Venue_c + \gamma AvgTradeVol_c + \beta' OpCost_t + \psi Volatility_t + \varepsilon_t.$$
 (1)

We identify the variables and then provide detailed information on measurement. $Markup_t$ is the markup on transaction t initiated by customer c. $Info_c$ is a measure of the extent to which customer c's trades tend to carry information about upcoming returns. The vector $Venue_c$ captures the extent to which customer c relies on different trading venues, where venues vary in sophistication. $AvgTradVol_c$ is customer c's average trading volume. The vector $OpCost_t$ captures dimensions of transaction t relevant to operating costs including trade size. $Volatility_t$ is the market's volatility.

B. Variables to capture price discrimination

This sub-section describes how our model identifies the three dimensions of price discrimination.

Price discrimination on the basis of information. Following the literature we measure the extent to which customer c is informed by his average post-trade returns, $Info_c$. The coefficient on $Info_c$ should be positive under adverse selection and negative under strategic dealing. We measure returns over one minute in the baseline analysis and over thirty minutes in a robustness test; the results are consistent. Returns are calculated using mid-quotes from Reuters Dealing 3000, a highly liquid interbank limit-order market. By using mid-quotes we ensure that variation in markups across customers does not generate endogenous variation in $Info_c$, as would occur if we used actual transaction prices.

Though our empirical analysis is carried out at the level of the individual customer it is instructive to consider how it varies on average across customer types. As shown in Table 1, Row 10, hedge funds have the highest average post-trade returns. At the one-minute horizon their mean post-trade return is 0.27 pips. Average post-trade returns for all other customer groups are below 0.05 pip. The implication that hedge funds are better informed than real-money funds or corporate customers is consistent with their incentives. Hedge-fund managers tend to trade at short horizons and they participate handsomely in the profits. The compensation of real-money asset managers is generally less sensitive to performance. Further, real-money funds generally focus little on the currency component of returns (Taylor and Farstrup, 2006). The incentives of corporate traders to gather information are weaker still, since their employers primarily use currencies as a medium of exchange rather than a store of value.

Average post-trade returns are tiny for brokers and customer banks; nonetheless, that these low averages mask important variation. Among the brokers in our sample, the retail brokers are unlikely to be informed because retail traders are generally uninformed (Heimer and Simon, 2014; Heimer 2015). The broker-dealers that trade for hedge funds, by contrast, could well be informed. Among customer banks, those that develop proprietary algorithms are likely to be best informed.

<u>Price discrimination on the basis of market sophistication</u>. We capture a customer's market sophistication by the share of its trading carried out through specific venues. The twenty-plus platforms and exchanges through which our dealers traded are grouped into five categories.

Venue 1: Direct trading. This category includes the least sophisticated trading channels, such as telephone sales, sales via fax and e-mail, and direct sales through bank branches.

Venue 2. Single-bank platforms. Single-bank platforms, which have been around for roughly two decades, come in many forms. At one extreme are platforms on which customers simply list amounts to be traded at daily fixing prices. At the other extreme are platforms that give customers access to click-and-deal trading on a graphical user interface with executable streaming prices. All single-dealer platforms permit straight-through processing.

Venues 3 & 4: Application Programming Interface (API) connections used by brokers (Venue 3) and other traders (Venue 4). Customers can execute algorithmic and high-frequency trades through an API connection embedded in the bank's single bank platform. These connections are most popular among customers who trade frequently – retail brokers, customer banks, and hedge funds that engage in HFT – because it allows them to spread high set-up costs across many trades. We consider the two API connections separately because they may capture different dimensions of market sophistication. The technological sophistication of the retail brokers' API connections is not necessarily matched by the familiarity of their customers with market conventions and market conditions.

Venue 5: Multibank platforms. Multibank platforms allow multiple dealing banks to compete simultaneously, thereby eliminating most of the special features of OTC trading that permit price discrimination. Request-for-quote systems, which allow customers to make a single request for quotes from multiple dealer banks, are most popular with hedge funds, real-money funds, and MNCs (Table 1, line 8). Other multibank systems are essentially electronic limit-order markets. Hedge funds with prime

brokerage arrangements can trade algorithmically on the multibank platforms. The list of multibank platforms also includes voice brokers, which now serve select end-users as well as banks.³

Wide variance in customer sophistication is suggested by wide variation in execution costs across venues, shown in Table 2. Average markups are 19 basis points for direct trades, 0.4 basis points for normal trades on the single-bank platform, and 0.1 basis point or less for API trades or trades on multibank platforms. Given the high cost of direct trading, many customers avoid it. Hedge funds and brokers rely on direct trading for less than 5% of their trades; real-money funds for just 14% of trades, and MNCs for 25% of trades (Table 1, Row 6), and when they do rely on direct trading it is usually because they need to make a large transaction. SMEs, by contrast, rely on direct trading over two-thirds of the time even though the vast majority of their trades are small. This suggests that SMEs are relatively unfamiliar with other trading platforms or at least relatively unfamiliar with the magnitude of the cost advantage to those platforms – that is, it suggests that SMEs are relatively unsophisticated about the market. The same pattern of relative sophistication emerges if we consider the other extreme, the API. SMEs never use the API but brokers and hedge funds use it for over half of their trades.

<u>Volume discounts: $AvgTradeVol_c$.</u> To capture the possibility that dealers price discriminate in favor of high-volume customers we include the customer's (log) average daily trading volume, $AvgTradeVol_c$. Under the volume-discount hypothesis the coefficient of $AvgTradeVol_c$ will be negative.

C. Additional variable definitions and measures

OTC spreads will also be influenced by operating costs and inventory costs.

Operating costs. Operating costs – which include salaries, furniture, buildings, news services, etc. – are mostly fixed and can therefore be covered with a smaller proportionate spread on a larger trade. We thus include (log) trade size, ln(*Size*), with trade amount measured in euros, expecting a negative coefficient.

³ The list of multibank platforms also includes a very small number of trades through voice and electronic brokers, which have in recent years begun serving selected end-users as well as banks.

In theory, the trade size variable could also capture price discrimination if trade size and information are correlated. Informed could rationally place larger orders when their information is more reliable (Easley and O'Hara, 1987). However, empirical evidence indicates that informed traders try to avoid detection by order splitting (Chakravarty, 2001; Anand and Chakravarty, 2007), a process that has long been standard in forex. In this case the coefficient on trade size will only reflect operating costs.

Operating costs are likely to be higher for trades priced by a salesperson or an interbank dealer, so we include the (log) of absolute size interacted with a dummy for human trades, $\ln(Size_t)xHuman_t$. Whether a trade is priced by a human is indicated in the original bank data. We allow for the possibility that trade size and markups have a non-monotonic relation by including a zero-one dummy for trades above \in 5 million, Large. The operating cost component of the spread is thus:

Operating Cost Component = $\beta'OpCost_t = \beta_0 + \beta_1 \ln(Size_t) + \beta_2 \ln(Size_t) \times Human_t + \beta_3 Large_t$.

Inventory Costs. We capture the inventory component of spreads with a common measure of intraday price volatility, the high-low range of the previous trading hour measured in pips. *Volatility* has mean and standard deviation of 31.7 pips and 17.5 pips, respectively. We do not include inventory carrying costs because the vast majority of forex dealer positions are closed out within a few minutes (Bjønnes et al., 2005).

<u>Additional control variable: *Interdealer spread*</u>. To capture the influence of market conditions other than volatility we include the interdealer bid-ask spread from the Reuters Dealing 300 platform.

III. RESULTS

We estimate Equation (1) using OLS with Newey-West robust standard errors, following Chaboud (2014) and Bernhardt et al. (2005) (Table 2, columns 1 and 2). The adjusted R^2 of 0.45 exceeds those in Bernhardt et al.'s (2005) analysis of price discrimination on the London Stock Exchange, which are generally below 0.10. It also exceeds adjusted R^2 's in Osler et al.'s (2011) application of standard adverse-selection models to forex customer trades, which are generally between 0.30 and 0.40. It is

reassuring to note that the coefficient on the interbank spread is insignificant, suggesting that our model has captured the dominant determinants of markups. The coefficients on our explanatory variables all have the theoretically-predicted sign and are statistically significant with one critical exception: $Info_c$. We discuss these findings briefly and then undertake an in-depth analysis of price discrimination according to information.

Adverse selection and strategic dealing. The high explanatory power of Equation (1) does not appear to reflect the relevance of either adverse selection or strategic dealing: the coefficient on customer information, $Info_c$, is insignificant. This appears to conflict with testimony from the dealers, who consistently stress the importance of customer information. However, it could instead simply mean that dealer behavior is more nuanced than assumed in Equation (1). Our estimates of Equation (2), presented below, confirm the relevance of this interpretation.

Market sophistication. Consistent with the market-sophistication hypothesis (Green et al., 2007), customers who rely more heavily on direct trading pay distinctly wider markups. Indeed, market sophistication alone can account for over half of the overall cost advantage associated with informed trades. Let hedge funds represent informed customers and SMEs represent uninformed customers. A rise in the direct-trading share from 2.0%, the average for hedge funds, to 69%, the average for SMEs, is predicted to reduce the markup by 12.4 pips. This represents 55% of the 22.7-pip gap in markups between uninformed and informed traders.

Coefficients on the other venue shares are two orders of magnitude smaller, though still statistically significant and statistically different from each other. The coefficient on multibank platforms is lowest, indicating that dealers have the least negotiating leverage on these platforms. This is logical given the structure of these platforms. Some are auction markets, in which pre-trade anonymity precludes customer-based price discrimination. Others are RFQ (request-for-quote) platforms, in liquidity there is no pre-trade anonymity but liquidity providers compete directly so the potential for price discrimination is minimized. The dealers' ability to price discriminate is not much greater on the other non-direct

platforms. A customer that shifts 10% of trading from the single-bank platform to a multi-bank platform would pay merely €2 less in markups per €1 million traded.

Volume discounts. Our OTC dealers clearly price discriminate in favor of customers who trade actively, consistent with the volume discount hypothesis of Bernhardt et al. (2005). Volume discounts account for roughly one tenth of the gap in average spreads between SMEs and hedge funds. A rise in daily volume from the SME average of $\{0.05\}$ million to the hedge-fund average of $\{0.88\}$ million would reduce the markup 1.9 pips, or 8% of the 22.7-pip gap. A further rise in daily volume to the brokers' average of 33.8 per day would reduce the cost of liquidity by another 0.5 pips. These changes are small compared to the gap in markups between informed and uninformed customers but they are large relative to the average markups of both hedge funds and brokers.

Trade size: The negative coefficient on trades priced by interdealer traders is inconsistent with adverse selection and consistent with strategic dealing. Forex dealers have long stressed the importance of knowing when large trades are moving through the market, so setting attractive prices for such business could be entirely rational. We note, however, that the negative coefficient could also reflect strategic customer behavior, who might either schedule large trades for days or times when spreads are lower or search more aggressively for better prices when making large trades (Bjønnes et al., 2005).

The remaining coefficient estimates from Equation (1) confirm the relevance of operating costs and inventory risk for OTC spreads.

Operating costs: The estimated coefficients on all trade-size variables are negative and significant, consistent with the influence of fixed operating costs.

Inventory Risk: The coefficient on volatility is positive and significant, consistent with inventory-theoretic models (e.g., Ho and Stoll, 1981) and consistent with existing evidence (e.g., Bollerslev and Melvin, 1994; Pirim et al., 2009).

A. Adverse selection and strategic dealing: A closer look

The results so far provide no evidence for price discrimination on the basis of a customer's information, though they do support the existence of price discrimination according to market sophistication and average trading volume. Indeed, the results so far suggest that adverse selection is entirely irrelevant in the world's largest OTC market. A closer look, however, indicates that adverse selection matters after all.

We examine whether dealers apply different price discrimination strategies to different customer types. Dealers might discriminate in favor of better informed customers of one type, as predicted by the strategic dealing hypothesis, and against better-informed customers of another type, as predicted by adverse selection. And of course dealers might ignore information altogether if they view a given customer type as generally uninformed. We examine this possibility by using OLS with Newey-West standard errors to estimate Equation (2), in which $Info_c$ is interacted with a dummy variable for customer category j: $D_c^j = 1$ if customer c is of type j and zero otherwise for $j = \{hedge fund, broker, bank, real money, MNC, SME\}.$

$$Markup_{t} = \alpha + \pi Info_{c}D_{c}^{j} + \mu Venue_{c} + \gamma AvgTradeVol_{c} + \beta'OpCost_{t} + \psi Volatility_{t} + \varepsilon_{t}. \quad (2)$$

The results continue to support our earlier conclusions (see Table 3, Colums 3 and 4). They also show that dealers do vary their information-based price discrimination strategy across customer groups. The coefficient on $Info_c$ is now positive for hedge funds and customer banks, negative for brokers, and insignificant for the remaining customer groups. The insignificance of $Info_c$ in our earlier regression thus reflects the subtlety of the dealers' reactions to information rather than the absence of any reaction.

The insignificant coefficients for real-money funds, MNCs, and SMEs suggest that dealers consider most of these customers to be uninformed (a view supported by dealer comments). The negative coefficient on $Info_c$ for brokers is consistent with strategic dealing; the positive coefficients on $Info_c$ for hedge funds and customer banks is consistent with adverse selection. The hedge-fund coefficient is significantly larger than the customer-bank coefficient, which suggests that dealers consider informed

hedge-fund trades to be more potentially damaging, on average. This is plausible given that many customer banks do not develop proprietary trading algorithms.

The non-zero information effects are large relative to the markups paid by informed customers. A one-standard-deviation rise in $Info_c$ for either hedge funds or customer banks is estimated to increase their markup by 0.1 pip. This is definitely big enough to matter, since it is roughly four times the hedge funds' average markup and roughly half the customer banks' average markup. The effect of information on the markups quoted to brokers is similar in magnitude though in the opposite direction. A one-standard-deviation rise in $Info_c$ for the brokers is estimated to decrease their markup by roughly 0.1 pip, which is over ten times the brokers' average markup of 0.01 pip.

Though these effects are large relative to the markups charged informed customers, they are small relative to the effects of market sophistication, volume discounts, and trade size. If a hedge fund's information ($Info_c$) were to rise from the SME level of 0.03 to the hedge-fund level of 0.27, the markup would rise by just 0.13 basis points, or less than 1 percent of the gap between average hedge-fund and SME markups. We infer that adverse selection may have been difficult to detect in OTC markets in part because its influence on liquidity costs is small.

It is natural to wonder how dealers decide to apply either adverse selection or strategic dealing to a given customer group. Section IV provides evidence that this choice is governed by structural factors.

B. Quantifying spread components

The estimates of Equation (2) enable us to calculate the components of the markup. Our analysis enables us to calculate these components for individual trades of individual customers. To spare our readers that level of detail we calculate representative components for each customer group using the average values of the key regression variables.

The price discrimination component is the sum of contributions from information, market sophistication, and volume discounts. For a given dimension the contribution for a given customer group is calculated as the difference between zero price discrimination and the relevant markup adjustment for

that customer group. The benchmark for zero discrimination with respect to $Info_c$ is naturally a client with zero information. The contribution of information to a customer's markup is thus $\pi_k Info_c$, where π_k is the information coefficient for customer type j, j={ $Hedge\ fund$, $Customer\ bank$, Broker, Real-money fund, MNC, SME}. The benchmark for zero discrimination with respect to market sophistication is logically the multibank platforms, where price discrimination is essentially impossible due to the structure of trading. The contribution of market sophistication to the markup is thus $\sum_K (\mu_k - \mu_{MBP})(Venue_c^k - Venue_c^{MBP})$, $k = \{Direct\ trade, SBP, API-1, API-2\}$ and $\mu_k - \mu_{MBP}$ is the difference between the coefficient on the $Venue^k$ shares and the MBP shares.

The benchmark for zero price discrimination with respect to average daily trading volume will evidently be some low level of trading volume. Though the exact level is unclear, we take it to be the average for SMEs, who trade the least. The average across SMEs of individual average log trading volume is 9.285, so the contribution of volume discounts to the markup is thus $\gamma(AvgTradeVol_c - 9.285)$.

The overall price discrimination component need not be positive. The information sub-component can be positive (under adverse selection), negative (under strategic dealing), or zero; the market sophistication sub-component is non-negative; and the volume discount sub-component is non-positive. As shown in Table 4, the overall price discrimination component is positive for high-markup customers – SMEs, MNCs, and real-money funds – and negative for low-markup customers. The negative price discrimination components of low-markup customers are similar in magnitude to the combined operating and inventory cost component. The positive price discrimination component for real-money funds is likewise similar in magnitude to the combined operating and inventory cost component. For corporate customers the price discrimination component dominates the markup; indeed, for SMEs the price discrimination component is roughly six times the rest of the markup.

The average asymmetric information sub-component is small for all customer types, varying only from -0.04 to 0.147 basis points. Nonetheless, this sub-component can be substantial for individual

clients. The adverse selection component for the best-informed customer bank, for example, is 2.8 pips wider than the average markup for an uninformed customer bank.

The price-discrimination components for low-markup customers are dominated by their volume discounts: They trade between \$9 and \$33 million per day, on average, whereas the remaining customer types only trade between \$0.05 and \$2 million per day. These customers consistently make less than 2% of trades directly and thus leave little on the table due to a lack of market sophistication.

High-markup customers get relatively little in the way of volume discounts given their low trading volumes. Market sophistication – or the lack thereof – is more likely to be relevant because they rely on direct trades for at least 14% of their transactions. Real-money funds and MNCs typically turn to direct trading for large transactions, which suggests there may not actually be a lack of sophistication. SMEs, by contrast, make over two-thirds of trades directly and pay an extra 13 pips *per trade* as a result.

These results permit us to unpack the inverse relation between spreads and customer information in OTC markets. Because this pattern is generally inconsistent with what the literature predicts under adverse selection, it has raised questions about the relevance of adverse selection in OTC markets. These results show that the inverse relation is due primarily to differences across customers in their market sophistication and trading volume, rather than differences in information. The results also indicate adverse selection matters, after all, but only for hedge funds and customer banks.

IV. EXTENSIONS AND ROBUSTNESS TESTS

This section extends our results in important directions and provides robustness tests. We continue to rely on OLS estimates of Equation (2) with Newey-West standard errors.

A. Information-based price discrimination and market structure

Why do dealers seek to attract some informed customers while worrying about adverse selection with other informed customers? In keeping with our theme that the determinants of liquidity costs vary according to market structure, we identify a structural explanation. We focus on interdealer markets, which are often found in OTC markets but not limit-order markets. The interdealer market was critical to

the original strategic dealing hypothesis of Naik et al. (1997), which highlighted the potential for a dealer to profit from learning a customer's information through subsequent trades with other dealers.

That the mere existence of an active interdealer market may not be sufficient to motivate strategic dealing, however. If the price discovery process is largely complete by the time the dealer learns whether an informed customer is buying or selling, the dealer will have no opportunity to profit from that information in the interdealer market – or at least will have insufficient opportunities to fully offset the likely losses to customers associated with adverse selection. Dealers could price discriminate in favor of certain informed customers and against other informed customers, basing the distinction on the stage of the price discovery process at which he typically learns the customer's information or equivalently the extent to which he can exploit the customer's information via interdealer trading.

This distinction can potentially explain the difference in treatment between customer banks and hedge funds, on the one hand, and brokers, on the other, identified in Section III. Customer banks often trade on information gained from their own end users.⁴ When our dealer learns such information it is effectively second-hand, and the price discovery process is presumably far advanced. This could justify our banks' price discrimination against better informed customer banks.

Many hedge funds and some other customer banks engage in HFT, often to exploit mis-pricings that disappear very quickly such as violations of covered interest parity and triangular arbitrage. These mis-pricing are probably gone by the time our dealer can process the information from an HFT trade – that is, price discovery is essentially over before the dealer can react. It could thus be logical for them to quote wider spreads to such customers, consistent with adverse selection.

Quoting wider spreads to better-informed customer banks could also be logical. These are typically medium-sized banks from developed economies or medium-to-large financial institutions from emerging economies. Many engage in EURUSD trading primarily to provide liquidity to customers in niche markets and to support non-dealing operations. Though theory portrays market makers as

⁴ Informed counterparties do not exclusively trade with the biggest banks because they know they can get lower liquidity prices by having dealers to compete for their business.

uninformed, they would be informed in a meaningful sense when executing any large customer trade, given price pressures (Huang and Stoll, 1997; Hendershott and Menkveld, 2014). Some of these customer banks also trade on information they generate via sophisticated proprietary trading algorithms.⁵

Dealers appear to apply strategic dealing to brokers. This may seem surprising, since this category includes retail foreign exchange brokers. Retail brokers provide access to the foreign exchange market for small private investors and institutional clients, and retail forex traders are generally uninformed (Heimer and Simon, 2014). One might expect the dealers to ignore information from such customers. The broker category also includes broker-dealers, however, which often trade on an agency basis for hedge funds that do not engage in high-frequency trading. Information from broker-dealers may arrive relatively early in the price discovery process because their hedge-fund clients do not engage in HFT. Dealers therefore have time to react and profit from the information carried by such trades.

We test our stage-of-price-discovery hypothesis by examining more closely the relation between adverse selection and HFT. We disaggregate hedge funds into two categories, those that trade at high frequencies and those that do not, and re-estimate Equation (2). If HFT undermines the dealer's ability to profit from customer information, adverse selection should be particularly relevant for HFT hedge funds.

We identify HFT hedge funds two different ways, first as those that trade under a prime brokerage contract and second as those that list HFT explicitly on their website. The first definition might be too broad because a prime brokerage account is necessary but not sufficient for HFT, but has the advantage of sharing a similar spirit with to the trade-classification algorithm of Chaboud et al. (2014).

The results of this regression support the importance of HFT – and thus the relevance of the interdealer market – in determining the dealers' reaction to customer information (Table 5, columns A and B). Regardless of how we define HFT hedge funds, the coefficient on $Info_c$ is positive and roughly twice the size of the coefficient on all hedge funds reported in Table 3. By implication, dealers are more concerned about adverse selection with HFT hedge funds than with other hedge funds.

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⁵ Evidence that forex dealing banks bring original information to the market is presented in Bjønnes et al. (2015); evidence that government bond dealers bring information to their markets is presented in Valseth (2013).

The coefficient on $Info_c$ for non-HFT hedge funds varies in sign. When HFT funds are identified as those with a prime brokerage account the sign is negative, consistent with strategic dealing, though the coefficient is small and only marginally significant. When HFT funds are identified more narrowly as those listing HFT on their websites the sign is positive. This raises the possibility that any hedge fund that trades through a prime broker is considered a threat.

B. Human Trades

So far this paper has stressed that the forces driving liquidity costs in OTC markets differ from those in limit-order markets due to differences in market structure. The relevance of structure could logically extend to different pricing mechanisms within a given OTC market. We therefore examine how spread determination varies between trades priced by algorithms and trades priced by human dealers.

The bank's software includes flags for trades that might require special handling by the dealers. These are mostly large trades: the 3,066 "human" trades in the sample represent 1% of all trades but 15% of total trade value. Forty-three percent of these are direct trades, twenty-two percent come in through the single-bank platform, and the rest come in through the multi-bank platforms (presumably RFQ systems).

We run Equation (2) on the subsample of human trades. The results (Table 5, Column C) indicate that markups on trades priced in real time by a human are more sensitive to customer information and the dealers seem to be consistently worried about informed traders. The coefficients on $Info_c$ rise dramatically for hedge funds and customer banks and switch from negative to positive for brokers. The hedge fund coefficient on $Info_c$ rises from 0.55 to 19.32, which suggests that the dealers may intend to discourage all large trades from these customers. A one-standard-deviation increase in hedge fund information raises the markup on human trades by 4 pips, far more than the 0.1-pip increase estimated for the whole sample. The coefficient on $Info_c$ for customer banks likewise rises by many multiples, going from 0.44 to 3.11. A one-standard-deviation rise in customer-bank information raises the markup by 0.7 pip for human trades, substantially more than the 0.1-pip increase estimated for the whole sample. The coefficient on broker

 $Info_c$ shifts from roughly -1.0 to almost 4.0. A one-standard-deviation rise in broker information raises the markup on human trades by 0.5 pip.

Markups on trades priced by a human are less sensitive to a customer's market sophistication. Aone-standard deviation decrease in the customer's share of direct trading, which is reduces the markup by
2.4 pips in the baseline regression, reduces the markup by only 0.6 pip for trades priced by humans. This
may not be surprising given that over half of the human trades originate with customer banks, who
certainly know how the market works.

Markups on trades priced by a human are more sensitive to a customer's trading volume. A one-standard-deviation rise in customer trading volume, reduces the markup by 2.3 pips for human trades, roughly double the effect estimated for the whole sample. Like the muted effect of market sophistication, this could also reflect the dominance of customer-bank trades in this sample. In the sample as a whole, over half of the trades are initiated with brokers, and within that mostly by the retail aggregators. They pre-negotiate narrow spreads, so the spreads quoted on their individual trades presumably have little influence over their total trading volume. Over half of the human trades are initiated by customer banks who negotiate spreads on a trade-by-trade basis.

Trade size and markups are negatively related when humans price the trades, as before, but the influence of trade size per se is greatly magnified. The dummy variable for large trades, by contrast, is no longer significant, presumably because most of these trades are large.

C. Robustness Tests

We finish our empirical analysis by examining the robustness of our results with respect to changes in our measures of information and volatility and to clustering the residuals.

Measuring Information

Theory does not dictate a specific time horizon for measuring a customer's information. Indeed, the relevant time horizon presumably varies across customer types, with short horizons of greatest relevance for traders engaged in HFT and longer horizons relevant for other members of the active trading

community. We check the robustness of our results to calculating post-trade returns over a longer time horizon, specifically thirty minutes.

Measuring a customer's information by 30-minute post-trade returns leaves most of our results unchanged (Table 5, Column D): OTC dealers price discriminate according to a customer's information, market sophistication, and trading volume. Further, dealers still price discriminate against informed hedge funds and in favor of informed brokers. The coefficients on information are smaller in magnitude but this merely reflects the higher standard deviations of $Info_c$ that naturally accompany the longer time horizon. The coefficient on $Info_c$ is no longer significant for customer banks, suggesting that customer-bank information is only relevant at relatively short time horizons.

Markups remain insensitive to post-trade returns for real-money funds, SMEs, and counterparty banks. Technically they are still insensitive to post-trade returns for MNCs, as well, but the coefficient on MNC information is now borderline significant at the 10% level. This is notable because it conforms to dealer comments that a few MNCs – those that maintain active trading floors – are often informed. Since such firms trade quite differently from hedge funds, however, their trades are not considered toxic and dealers set narrower spreads for the best-informed of them. Nonetheless, there are few of these MNCs so one would not expect them to dominate our statistical results.

Measuring Market Volatility

We next examine whether our conclusions are sensitive to our measure of market volatility. We estimate Equation (2) with volatility measured as the standard deviation of returns over a 60-minute interval instead of the high-low range (over the same 60-minute interval) used in the baseline regressions. Returns measured as the mid-quote change between customer transactions. We return to the one-minute horizon for measuring $Info_c$. Our qualitative conclusions are unchanged though the coefficient on volatility itself declines and is no longer statistically significant.

Clustered Residuals

In a final robustness we test allow residuals to cluster according to trading day. The regression coefficients are of course unchanged (so we do not list the results in Table 5) and some standard errors

increase, as one would expect. All previously-significant variables remain significant and the significance levels do not decline, so our qualitative conclusions are once again unchanged.

V. CONCLUSION

This paper examines the determinants of the cost of liquidity in OTC markets. We argue that the traditional trinity – operating costs, inventory costs, and adverse selection – must be modified in this context by replacing the adverse-selection component with a price discrimination component. The modification is appropriate due to structural differences between OTC and other markets. Unlike call and limit-order markets, OTC dealers know their counterparties when placing quotes. In addition, OTC dealers have a brief moment of market power after providing quotes. These features make it rational for OTC dealers to price discriminate across customers. They could price discriminate against better-informed customers, consistent with adverse selection; dealers might find it necessary to quote narrower spreads to more sophisticated customers, meaning those who are familiar with market conditions and customs, just to keep their business (Green et al., 2007); and they might provide volume discounts to customers with high trading volume (Bernhardt and Hughson, 2005; Bernhardt et al., 2005), in an effort to attract more of their business.

Adverse selection could even be irrelevant in OTC markets. Many OTC markets have active interdealer markets, which provide dealers with strategic possibilities not available in auction and call markets. As shown in Naik et al. (1999), dealers could profitably price discriminate in favor of their better-informed customers if the information they infer from customer trades can be exploited in the interdealer market. Dealers could also ignore information altogether for certain customers, assuming that they are uninformed.

Previous efforts to identify the determinants of OTC spreads have encountered numerous challenges. The standard spread-decomposition models assume pre-trade anonymity, which is counterfactual in OTC markets, and they assume that adverse selection is relevant (Glosten and Harris, 1988; Madhavan and Smidt 1991; Huang and Stoll 1997). When these models reject the implications of

adverse selection, as they typically do, the findings are difficult to interpret. The few existing studies of price discrimination in OTC markets focus on just one of its three dimensions. However, it is difficult to interpret these tests as confirming a specific form of price discrimination because information, market sophistication, and trading volume are positively correlated across customers.

We examine price discrimination in OTC markets using highly detailed data from the world's largest OTC market, the foreign exchange market. Our data comprise the complete record of customer trades in the euro-dollar currency pair at a top-20 foreign exchange dealing bank during the first 68 trading days of 2012. The data include exact markups, customer identities, and detailed information about each trading venue. With this level of detail it is possible to disentangle all three dimensions of price discrimination.

We find that OTC dealers price discriminate along all three dimensions and price discrimination has a substantial influence on the price of liquidity. In absolute magnitude the contribution of price discrimination ranges from two-thirds of average markups to six times the average markup, figures that exceed, in relative magnitude, the contribution of adverse selection estimated for other markets (Glosten and Harris, 1988; Madhavan and Smidt, 1991; Huang and Stoll, 1997). The price discrimination component is negative for hedge funds, customer banks, and brokers, largely because these groups get big volume discounts. It is positive for unlevered asset managers, MNCs, and SME, largely because these groups tend to be less sophisticated.

Adverse selection is relevant in this OTC market, but only for hedge funds and customer banks. With brokers, by contrast, the pattern of information-based price discrimination is consistent with strategic dealing. Dealers seem to ignore information altogether for commercial customers and unleveraged asset managers. The effects of both adverse selection and strategic dealing are small in absolute terms, representing less than one percent of gap in spreads between uninformed and informed customers. These effects could be economically influential, nonetheless, because they are large relative to the average markups paid by the customers in question.

We investigate the factors that drive the dealers' choice between adverse selection, strategic dealing, and ignoring information altogether. The customers for whom they seem to ignore information face the lowest incentives to gather information and are generally considered least informed. For other customers we hypothesize that the decision between adverse-selection and strategic dealing is driven by whether the dealer gets access to the customer's information early or late in the price discovery process. For customers whose information arrives late, the dealer may be unable to exploit it profitably and will thus price discriminate against those who are better informed, consistent with adverse selection.

Otherwise the dealer will price discriminate in favor of his better-informed customers. In support of this hypothesis we identify HFT with information that arrives late in the price discovery process. Results indicate that dealers apply adverse selection only to hedge funds that engage in HFT.

We examine whether our results are robust to alternative approaches to measuring volatility and information and to restricting the sample to include only trades priced in real time by a person as opposed to a software algorithm. These tests confirm our qualitative findings.

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Table 1: Descriptive statistics.

API-Not-Brokers

Share

(%)

(%)

Trade Size*

(€ Mil)

Multi-Bank

Platform Share

10

Table shows summary statistics by counterparty group. Data include all market-making EURUSD trades by a top-20 forex dealing bank with non-dealing-bank counterparties during the 68 trading days from 2 January through 20 April, 2012.

Customer Real Hedge **Brokers** Total **MNC SME** Funds Banks Money N. observations 257,241 6,624 73,730 170,668 1,185 1,261 3,773 Average Markup 0.44 0.26 2.59 3.09 22.74 Mean 0.03 0.01 325 2 (pips: \$/€) Max 325 15.7 53 96 130 104 (Std Dev.) (0.48)(2.51)(10.80)(18.56)(3.96)(48.75)(11.59)Post-trade 1min Mean 0.03 0.27 -0.01 0.04 0.05 -0.03 0.03 return Max 8.35 2.16 6.42 2.47 3.82 4.9 8.35 (Std Dev.) (0.24)(0.21)(0.24)(0.13)(0.70)(1.21)(pips) (0.13)Post-trade 30 min -0.22 Mean -0.00 0.44 -0.01 -0.02 -0.18 0.05 48.2 48.9 Max 48.9 7.3 39.6 14.8 28.6 return (pips) (Std Dev.) (0.99)(4.32)(6.28)(1.11)(1.10)(0.36)(4.41)Average Daily Mean 4.09 8.88 8.59 33.8 0.82 2.03 0.05 Volume Max 135 17.4 52.4 135 4.11 12.2 0.98 (€ Mil) (Std Dev.) (29.7)(5.06)(13.2)(32.1)(9.24)(2.18)(0.11)Direct Trading Mean 1.87 1.97 2.04 0.065 13.80 24.57 68.56 Share Max 100 100 100 100 100 100 100 (%) (Std Dev.) (12.32)(46.25)(12.46)(11.24)(1.78)(32.04)(36.35)Single-Bank Mean 29.61 1.17 68.57 13.95 32.83 17.68 29.61 Platform Share Max 100 100 100 100 100 100 100 (%) (Std Dev.) (44.43)(10.07)(43.97)(33.68)(44.68)(34.03)(45.52)Mean 39.13 0.00 0.00 58.98 0.00 0.00 0.00 **API-Brokers Share** Max 100 0.0 0.0 100 0.0 0.0 0.0 (%) (Std Dev.) (47.98)(0.0)(48.05)(0.0)(0.0)(0.0)(0.0)

Mean

Max

(Std Dev.)

Mean

Max

(Std Dev.)

Mean

Max

(Std Dev.)

2.24

100

(14.52)

27.15

100

(42.71)

0.49

184.0

(1.91)

49.86

100

(48.15)

47.00

100

(47.68)

1.20

56.0

(1.81)

3.29

100

(9.59)

26.11

100

(41.22)

0.88

184.0

(3.15)

0.00

0.0

(0.0)

27.00

100

(43.02)

0.28

44.2

(0.62)

0.19

4.84

(0.93)

53.18

100

(47.95)

2.08

100.0

(6.60)

0.00

0.0

(0.0)

57.75

100

(47.00)

2.53

50.0

(5.48)

0.93

100

(9.59)

0.91

100

(9.23)

0.22

25.0

(0.82)

^{*} Trade size, shown here in EUR millions, is measured in EUR in regressions.

Table 2: Markups by venue

Table shows summary statistics for markups, measured in pips, by venue. Data include all market-making EURUSD trades by a top-20 forex dealing bank with non-dealing-bank counterparties during the 68 trading days from 2 January through 20 April, 2012.

	Mean	Standard deviation	N
Direct trades	19.226	339.5	4,316
Single-bank platform	0.378	107.0	75,329
Multi-bank platform	0.003	11.4	108,045
API – others	0.110	70.9	8,755
API – brokers	0.009	8.0	60,796

Table 3. Determinants of Forex Customer Markups.

Table reports results from Equations (1) and (2), repeated below:

$$Markup_{t} = \alpha + \sum_{i} \beta_{i} Size Var_{c}^{i} + \psi HLRange_{t} + \pi Info_{c} + \sum_{k} \mu^{k} Venue_{c}^{k} + \gamma Avg Vol_{c} + \varepsilon_{t}.$$
 (1)

$$Markup_{t} = \alpha + \sum_{i} \beta_{i} Size Var_{c}^{i} + \psi HLRange_{t} + \pi Info_{c} + \sum_{k} \mu^{k} Venue_{c}^{k} + \gamma Avg Vol_{c} + \varepsilon_{t}.$$

$$Markup_{t} = \alpha + \sum_{i} \beta_{i} Size Var_{c}^{i} + \psi HLRange_{t} + \sum_{k} \mu^{k} Venue_{c}^{k} + \gamma Avg Vol_{c} + \sum_{j} \pi^{j} Info_{c} D_{c}^{j} + \varepsilon_{t}.$$

$$(2)$$

 $Markup_t$ is the dealing bank's price on trade t relative to the prevailing interbank price at that second. $Info_c$ is customer c's average signed 1-minute post-trade return. Ven_c^k is the share of customer c's trades that took place over venues of type k. AvgTradVolc, is customer c's average daily trading volume per day. Ln(Sizet) is log of trade t's absolute amount in euros; the regressions also include this variable interacted with a dummy for large trades, meaning those at or above €5 million and this variable interacted with a dummy for trades involving human interaction. All regressions include volatility, measured as the high-low range over the previous hour; the contemporaneous interbank spread; and a constant. Data include all customer trades through a top-20 foreign exchange dealing bank during the first 68 trading days of 2012. Robust standard errors. *, ** and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Equa	ation (1)	Equation (2)		
	Coefficient	Standard Error	Coefficient	Standard Error	
Info _c	0.042	0.115			
x Hedge $Fund_c$			0.546***	0.124	
x Cust. Bk _c			0.442***	0.120	
x Brokers _c			-0.988***	0.061	
x Real Money $_c$			0.306	0.206	
$x MNC_c$			-0.426	0.811	
$x SME_c$			0.171	0.278	
Venues					
$Direct_c$	0.192***	3.94e-3	0.192***	4.07e-3	
Single-bank _c	1.54e-3***	0.37e-3	2.45e-3***	0.33e-3	
API Brokers _c	1.59e-3***	0.38e-3	3.17e-3***	0.38e-3	
Multi-bank _c	-2.07e-3***	0.34e-3	-0.68e-3***	0.32e-3	
Average Daily Trac	ding Volume				
$Ln(AvgVol_c)$	-0.359***	0.010	-0.376***	0.011	
Trade Size					
$Ln(Size_t)$	-0.077***	0.008	-0.074***	0.008	
x Human	-0.267***	0.024	-0.265***	0.025	
$Large_t$	-1.222***	0.150	-1.268***	0.151	
Other Controls					
Volatility	1.92e-3***	0.44e-3	2.13e-3***	0.45e-3	
Interbk sprd	1.06e-3	4.94e-3	0.45e-3	0.50e-3	
Constant	6.687***	0.197	6.811***	0.199	
Adj. R^2	0.448		0.449		
N. Obs.	257,241		257,241		

Table 4. Markup components

Table reports markup shares for various spread components based on estimates of Equation (2):

$$Markup_{t} = \alpha + \sum_{i} \beta_{i} SizeVar_{c}^{i} + \psi HLRange_{t} + \sum_{k} \mu^{k} Venue_{c}^{k} + \gamma AvgVol_{c} + \sum_{j} \pi^{j} Info_{c} D_{c}^{j} + \varepsilon_{t}.$$

Component	Total	Hedge Funds	Customer Banks	Brokers	Real Money	MNC	SME
Markups (bps)							
Actual average	0.44	0.03	0.26	0.01	2.59	3.09	22.74
Predicted average	0.29	0.46	0.74	-0.35	2.77	5.05	15.57
Markup components in basis points Operating + Inventory 2.41 2.23 2.25 2.50 1.17 1.83 2.33							
Price Discrimination	-2.12	-1.77	-1.51	-2.84	1.60	3.21	13.24
Information	0.00	0.15	-0.00	-0.04	0.02	0.01	0.01
Market Sophistication	0.42	0.51	0.55	0.03	2.70	4.72	13.24
Volume Discount	-2.55	-2.42	-2.06	-2.83	-1.12	-1.52	0.00

Table 5. Extensions and Robustness Tests

Table reports robustness tests for Equation (2):

$$Markup_{t} = \alpha + \sum_{i} \beta_{i} SizeVar_{c}^{j} + \psi HLRange_{t} + \sum_{k} \mu^{k} Venue_{c}^{k} + \gamma AvgVol_{c} + \sum_{j} \pi^{j} Info_{c} D_{c}^{j} + \varepsilon_{t}.$$

 Markup_t is the dealing bank's price on trade t relative to the prevailing interbank price at that second. Info_c is customer c's average signed 1-minute or 30-minute post-trade return; D^i_c is a zero-one dummy for customer type j. Ven^k_c is the share of customer c's trades that took place over venues of type k. AvgVol_c , is customer c's average daily trading volume per day. $\mathit{Ln}(\mathit{Size}_t)$ is log of trade t's absolute amount in euros; the regressions also include this variable interacted with a dummy for large trades, meaning those at or above e5 million and this variable interacted with a dummy for trades involving human interaction. All regressions include volatility, measured as the high-low range over the previous hour or the standard deviation of returns over the previous hour; the contemporaneous interbank spread; and a constant. Data include all customer trades through a top-20 foreign exchange dealing bank during the first 68 trading days of 2012. Newey-West robust standard errors. Significance at the 10%, 5%, and 1% levels, respectively, are indicated by *, ** and ***.

	A	В	C	D	E
	Prime	High	Human	30-min	Alternative
	Brokerage	Frequency	Trades	$Info_c$	Volatility
Info _c					-
x Hedge Fund _c			19.32***	0.277***	0.534***
x HFT-Hedge $_c$	0.924***	1.053***			
x Other-Hedge $_c$	-0.136**	0.254***			
$x Cust Bk_c$	0.444***	0.444***	-0.53	0.002	0.443***
$x Brokers_c$	-0.993***	-0.991***	3.76***	-0.148***	-0.978***
x Real Money _c	0.306	0.306	0.00	-0.032	0.308
$x MNCs_c$	-0.426	-0.426	0.92	-0.174	-0.438
$x SMEs_c$	0.171	0.171	3.11***	-0.033	0.169
Venues					
Direct $Trading_c$	0.193***	0.193***	0.045***	0.193***	0.192***
Single-bank _c	0.003***	2.99e-3***	-0.037***	2.14e-3***	2.42e-3***
API Brokers _c	0.004***	3.72e-3***	0.049	2.47e-3***	3.13e-3***
Multi-bank _c	-4.75e-5	-0.12e-3	-0.099***	-1.48e-3***	-0.71e-3***
Average Daily Tradia	ng Volume				
$Ln(AvgVol_c)$	-0.376***	-0.376***	-0.687*	-0.363***	-0.375***
Trade Size					
$Ln(Size_t)$	-0.073***	-0.071***	-2.051**	-0.071***	-0.074***
x Human	-0.265***	-0.267***		-0.267***	-0.265***
$Large_t$	-1.269***	-1.232***	0.395	-1.232***	-1.269***
Other Controls					
Volatility	2.15e-3***	1.87e-3***	0.0182	1.87e-3***	4.13e-3**
Interbank spread	0.440e-3	0.97e-3	77.9e-3	0.97e-3	-1.61e-3
Constant	6.748***	6.613***	43.73***	6.613***	6.869***
Adj. R^2	0.449	0.448	0.214	0.448	0.449
N. Observations	257,241	257,241	3,066	257,241	257,212