Price discovery in currency markets

Carol L. Osler[a], Alexander Mende[b,c], Lukas Menkhoff[c]

[a] Corresponding Author. Brandeis University, 415 South Street, Waltham, MA 02454, USA.
cosler@brandeis.edu. Tel: 781-736-4826. Fax: 781-736-2250.
[b] RPM Risk & Portfolio Management AB, Stockholm, Sweden
[c] Leibniz Universität Hannover, Germany,Königsworther Platz 1, D-30167 Hannover, Germany

Abstract: This paper examines the price discovery process in currency markets, basing its analysis on the pivotal distinction between the customer (end-user) market and the interdealer market. It first provides evidence that this price discovery process cannot be based on adverse selection between dealers and their customers, as postulated in standard models, because the spreads dealers quote to their customers are not positively related to a trade's likely information content. The paper then highlights three factors familiar in the literature – fixed operating costs, market power, and strategic dealing – that may explain the cross-sectional variation in customers' spreads. The paper finishes by proposing a price discovery process relevant to liquid two-tier markets and providing preliminary evidence that this process applies to currencies.

JEL Classification: F31, G14, G15.

Keywords: Exchange rates, Foreign exchange microstructure, Asymmetric information, Bid-ask spreads, Price discovery

August, 2011

Price discovery in currency markets

1. Introduction

Price discovery, or equivalently the process through which financial prices respond to information, is one of the central concerns of microstructure. Foreign exchange microstructure research typically assumes the price discovery mechanism outlined in Glosten and Milgrom (1985), which focuses on the adverse-selection problem faced by uninformed dealers. To protect themselves from losses to informed customers, dealers rationally quote prices that are "regret-free," meaning they reflect the customer's expected information. This implies that spreads are wider when customers are more likely to be informed, such as when they undertake large trades (Easley and O'Hara, 1987). Substantial evidence supports the relevance of this theory in U.S. equity markets (Bernhardt and Hughson, 2002; Peterson and Sirri, 2003).

The relevance of the Glosten-Milgrom (1985) framework for the foreign exchange market was initially suggested in Lyons (1995), who shows that trade size and interbank spreads were positively related for a particular dealer in 1992. Subsequent exchange rate research assuming the relevance of adverse selection includes Burnside et al.'s (2009) proposed explanation for the forward bias puzzle, Payne's (2003) Hasbrouck-inspired VAR decomposition of interdealer trades and quotes (Hasbrouck, 1991), and Marsh and O'Rourke's (2005) estimation of Easley et al.'s (1997) PIN using daily customer trade data.

This paper shows that the price discovery process based on Glosten and Milgrom (1985) cannot apply in foreign exchange. This conclusion stems from strong evidence that variation in bid-ask spreads across customers does not conform to the predictions of adverse selection. The paper then suggests three alternative explanations for the pattern of variation in currency spreads across customers. Finally, the paper outlines an alternative price discovery process – new to the literature – that predicts many of the stylized facts of currency market microstructure and is consistent with new evidence presented here.

We estimate three models of spread determination using detailed transaction data from a bank in Germany, specifically the models of Huang and Stoll (1997), Madhavan and Smidt (1991), and Glosten and Harris (1988). None of the models support the relevance of adverse selection. Among other findings contrary to adverse selection, customer spreads are not positively related to trade size.

Indeed, our econometric analysis consistently indicates the reverse pattern: spreads are wider for the trades *least* likely to carry information. According to dealers, informed trades tend to be large and/or to be placed by financial customers – hedge funds and other asset managers – rather than non-financial ("corporate") customers. Empirical evidence confirms the dealers' view (see Frömmel et al. (2008) and Bjønnes et al. (2011), inter alia). Since dealer-customer trades are not anonymous, adverse-selection theory predicts wider spreads for larger trades and for financial-customer trades, yet all three estimated models indicate the opposite pattern.

The paper's second contribution is to highlight three factors in the literature that could explain why foreign exchange spreads vary inversely with a trade's likely information content. The first, fixed operating costs, can explain the variation across trade size, because smaller trades require a larger proportionate spread to cover a given absolute cost. The cross-customer variation in spreads can be explained by the second and third factors. The second factor is the transitory "market power" dealers gain from their information about current market conditions (Green et al., 2004). It can be costly for customers to seek out the best quotes, so any individual dealer has market power during the moment of communicating with the customer, even in a market with hundreds of competitors. Since corporate customers are typically not well informed about market conditions, this could explain why dealers extract wider spreads from corporate customers than from financial customers. The third factor is the advantage to dealers of varying spreads across customers to optimize information flow. Building on theoretical results in Leach and Madhavan (1992) and Naik *et al.* (1999) as well as empirical evidence that customer order flow carries information (Evans and Lyons, 2007), we suggest that foreign exchange dealers strategically set narrower spreads to informed customers to gain information from which to profit in subsequent trading. This advantage can be especially strong in liquid two-tier markets like foreign exchange, where dealers exploit the information gathered from customers quickly and at low cost by trading in the interdealer market.

The paper's third contribution is to outline a process through which information brought to the market by customers ultimately becomes embedded in exchange rates. Like the process in Glosten and Milgrom (1985), this process begins with customers that are sometimes informed. In contrast to Glosten and Milgrom, however, the paper proposes that a customer's information is not immediately reflected in the prices quoted to him by a market maker. Instead, the dealer learns whether the informed customer is buying or selling and that information influences prices in the interbank market when the dealer subsequently trades with other dealers. Thereafter, prices quoted to customers finally incorporate the information because they are based on interdealer prices.

This proposed price discovery process, which synthesizes institutional information about the foreign exchange market and abstract concepts already in the literature (Harris, 1998; Foucault, 1999; Reiss and Werner, 2004), predicts a number of the key stylized facts in foreign exchange microstructure. First, it predicts the positive relation between exchange rate returns and interdealer order flow documented in Evans and Lyons (2002) and related studies. (Order flow is defined as the net of buy-initiated and sell-initiated trades.) It also predicts that the relation should be substantially permanent if dealers are responding to fundamental information, consistent with evidence presented in Payne (2003) and Bjønnes et al. (2005), inter alia. In addition, our proposed price discovery process predicts a positive relation between exchange rate returns and financial order flow, on the one hand, and a non-positive relation between returns and corporate order flow, on the other. Such relations have already been documented in Bjønnes et al. (2005); Marsh and O'Rourke (2005); and Evans and Lyons (2007), and we document them again using our data. Finally, our proposed price discovery process predicts that the response of exchange rates to financial order flow is substantially permanent, consistent with evidence in Bjønnes and Rime (2005). We test two further implications: the likelihood of aggressive interbank trades is higher (i) after larger customer trades than after smaller customer trades and (ii) after financial-customer trades than after corporate-customer trades. The evidence supports these hypotheses.

The paper's microstructure message is directly relevant to the literature on exchange-rate dynamics, which is in some ways analogous to the asset pricing literature within finance. A critical development in exchange rate economics was the recognition that order flow strongly influences returns (Evans and Lyons, 2002). Though research shows that order flow matters in part because it carries information (Evans and Lyons, 2002, 2007), it has not articulated the mechanism through which the customers' information is incorporated into exchange rates. Our proposed price discovery process helps fill this gap.

Our analysis suggests that a market's price discovery process varies according to the market's transaction structure. The familiar adverse-selection based process outlined in Glosten and Milgrom (1985) assumes a one-tier market, so it may not be relevant in markets with active interdealer trading like foreign exchange. Our proposed price discovery process may also be relevant in other liquid two-tier markets, such as the U.S. Treasury market and the London Stock Exchange. The potential relevance of an alternative process for two-tier markets is suggested by evidence showing a negative relation between trade size and spreads on the two-tier London Stock Exchange (Bernhardt et al., 2005). The mechanism we outline differs, however, from the one outlined in Dunne et al.'s (2008) discussion of the two-tier euro-sovereign bond market. In their model, all customers are equally informed and all trades are the same size, while our analysis features asymmetric information among customers.

Our data comprise the entire USD/EUR transaction record of a single dealer at a bank in Germany during four months in 2001. These data have two advantages relative to other tick-by-tick transaction datasets in foreign exchange: they distinguish between financial and corporate transactions and they include all customer and interdealer trades in the correct order.

Since our sample period the currency market has evolved and new trading systems with enhanced transparency have brought a compression of customer bid-ask spreads (King et al., 2011). Changes in the market's transaction structure have not, however, changed the underlying reasons most agents trade currencies, so the market's *information* structure is unlikely to have changed substantially. Financial customers continue to rely on currencies as a store of value so they still have a strong incentive to gather information; non-financial customers continue to use currencies primarily as a medium of exchange so their incentives to gather information are still relatively limited; dealers continue to provide liquidity and bear associated inventory risk so they still have strong incentives to gather information from customers. The wide cross-sectional variation of bid-ask spreads during our sample period thus serves as a magnifying glass for the market's underlying information structure, a structure that might be less easily discerned with more recent data.

The rest of the paper has four sections and a conclusion. Section 2 describes the foreign exchange market and our data. Section 3 shows that customer spreads in foreign exchange are narrowest for the trades most likely to carry information and thus violate the predictions of adverse-selection theory. Section 4 discusses how cross-sectional variation in customer spreads may be explained by fixed operating costs, transitory market power, and strategic dealing. Section 5 articulates our proposed price discovery process and presents supporting evidence. Section 6 concludes.

2. Foreign exchange market structure and data

The foreign exchange market – or the "FX" market as it is called by market participants – is the world's largest, with daily trading last estimated at $4.0 trillion (Bank for International Settlements, 2010). Though over 100 currencies are traded, the euro, which we study here, is involved in almost one-fifth of all trades. Roughly 1,300 dealers compete for business in spot, forward, swap, and derivative contracts (Bank for International Settlements, 2010). Dealers can be found in almost every country, with roughly half of each day's trading accounted for by Tokyo, London, and New York. Banks compete intensely in terms of spreads and also in terms of transaction speed, pricing consistency, trading strategies, electronic products, and the quality of customer relationships (Euromoney, 2007).

Though the market's transaction technologies are always changing, at its core there are two main segments, or tiers. In the customer segment, dealers provide currency end-users with liquidity in an over-the-counter context. In the interbank segment dealers trade with each other on order-driven exchanges and in the OTC market. The share of the interdealer market has dropped noticeably in recent decades, and it now accounts for less than 40 percent of total trading (Bank for International Settlements, 2010).[1] The contemporary best bid and offer in the interdealer market serve as the anchor for customer prices.

In contrast to equity markets, where individuals can account for half of all trading, the overwhelming majority of banks customers are institutions. Dealers have historically divided their customers into two main categories: financial firms, a group that includes hedge funds, pension funds, and broker-dealers; and "corporates," meaning firms engaged in international trade in goods and services.

[1] Intraday trading in the major currency pairs is never constrained by supply because banks create deposits. During our sample period foreign exchange dealers were effectively the only intraday suppliers of liquidity, so there is no need to consider latent liquidity.

Our data comprise the complete USD/EUR transaction record of a bank in Germany over the 87 trading days from July 11, 2001, to November 9, 2001. As with all significant FX dealers, the bank offers the full range of FX products, including forwards and derivatives; it serves the full range of customers; and it participates in the interdealer market as both liquidity provider and liquidity demander. While the bank desires anonymity, we can state that it was included among the banks rated in Euromoney's annual FX poll for 2007, which places it among the top 10 percent of all dealing banks worldwide. Furthermore, in that same poll the bank was among those considered "best" in euro-dollar trading.

For each transaction, we have the following information: (1) date and time; (2) direction (counterparty buys or sells); (3) quantity; (4) transaction price; (5) type of counterparty – dealing bank, financial customer, corporate customer; (6) initiator; and (7) forward points if applicable. Our analysis relies on transaction time rather than clock time, and all trades are entered in strict chronological order. The data technically refer to the overall bank, but they are an accurate reflection of a single dealer's behavior because only one dealer was responsible for the bank's USD/EUR trading in spot and forward markets. We infer the dealer's inventory by cumulating the entire set of successive transactions. Our data do not distinguish among types of financial customers.

Table 1 provides basic descriptive statistics. The data include over 3,600 trades worth around €4.3 billion in aggregate, with mean trade size of €1.2 million.[2] The average financial-customer trade, at €2.4 million, is bigger than the average corporate-customer trade, at €0.8 million. Figure 1 shows the distribution of trades across the trading day. Financial-customer trades (Figure 1A) tend to cluster in the morning, dropping before lunchtime, while corporate-customer trades (Figure 1B) rise steadily during the morning, crest around lunchtime (when they also take a brief dip), and decline during the afternoon.

[Table 1 around here]

[Figure 1 around here]

We include outright forward trades adjusted to a spot-comparable basis by the forward points. This is appropriate, given the institutional structure of forward trading: the customer and the dealing bank first agree on a spot trade in exactly the same manner, and with exactly the same incentives, as they would for

[2] We exclude a few trades with tiny volumes (less than €1,000) and trades with apparent typographical errors.

regular spot trades. When they later adjust the trade to the appropriate maturity, the associated "forward points" are governed by market- and central-bank determined interest differentials so the bank's own influence on the forward price comes primarily through the spot quotes. We exclude the few transactions over $25 million, since such trades essentially represent a distinct market in which customers hire dealers to manage execution.[3] We also exclude trades with a few corporate customers who have cross-selling agreements with the bank, since the dealer's motivation when quoting to these customers is orthogonal to the strategic considerations on which we focus. According to the bank their quotes to these customers are not intended to be directly profitable but are instead intended to enhance the bank's overall relationship with the customer. The average trade size for these customers is only €0.18 million.

Our main qualitative conclusions should generalize beyond this one dealer for two reasons. First, during our sample period the largest dealer had market share of only about 10 percent. In FX, where the product is liquidity and the price is the bid-ask spread, dealers confirm their limited influence over spreads in surveys showing that their primary consideration is the spreads' "conventional level" (Cheung and Chinn, 2001). Our main conclusions should also generalize because our dealer behaves similarly to other dealers described in the literature. As shown in Table 2 our dealer is comparable to a NOK/DEM dealer at the large dealing bank examined in Bjønnes and Rime (2005) in terms of his daily trading value, average transactions per day, and mean absolute price change between transactions. More generally, our dealer was about average sized for the time (Bank for International Settlements, 2002).

[Table 2 around here]

Our dealer behaves similarly to other dealers in the way he manages his inventory, since inventory is strongly mean-reverting on an intraday basis. To evaluate the speed with which our dealer eliminates inventory, I_t, we estimate a standard regression: $I_t - I_{t-1} = \omega + \rho I_{t-1} + \varepsilon_t$, where time subscripts correspond to transaction time and we include all 3,534 transactions. If the dealer instantly eliminates unwanted inventories then $\rho \approx -1$; if he makes no effort to manage inventory then $\rho \approx 0$. We use GMM with a Newey-West weighting matrix to estimate standard errors that are robust to heteroskedasticity and autocorre-

[3] Fewer than 10 of the customer trades in our sample exceeded $25 million. These trades were not excluded when calculating inventory levels.

lation. The point estimate of ρ = -0.022 (standard error 0.007) implies a median inventory half-life of around two hours, well below estimated inventory reversion speeds for equities, which are measured in days (Madhavan and Smidt, 1993) or weeks (Hasbrouck and Sofianos, 1993).

Over the four months of our sample period, our measure of end-of-day inventory slowly gravitates away from zero and averages -€23 million. This raises the possibility of measurement error, since dealers assert consistently that they typically hold zero inventory overnight and it is possible that euro trades were handled by other traders at our bank if our dealer was away from his desk. This possibility is implicitly acknowledged by a common alternative approach to measuring FX inventory positions, in which inventories are reset to zero nightly (Lyons, 2001). When inventory is measured this way, the median inventory half-life is 17 minutes, similar to half-lives calculated in the literature for larger dealers.

The customers in our sample also behave consistently with those analyzed elsewhere in the literature. Cumulative financial and corporate order flow are both $I(1)$, like the exchange rate itself.[4] In addition, as shown in Table 3, cumulative financial (corporate) order flow is positively (negatively) cointegrated with the exchange rate. Qualitatively consistent results are reported in three studies of large banks – Lyons (2001), Marsh and O'Rourke (2005), and Evans and Lyons (2007) – as well as a study based on market-wide data for the Swedish krone (Bjønnes et al., 2005). This pattern is generally interpreted to mean that, on balance, corporate customers respond to price changes induced by financial-customer liquidity demand (Bjønnes et al., 2005; Osler, 2009). Since dealers' end-of-day inventory positions are usually close to zero, one customer group's net trading on a given day must be offset that same day by net trading in the other direction by a different group. The data suggest that financial net demand tends to induce exchange-rate changes which, in turn, induce trading by corporate customers.

[Table 3 around here]

Our sample period includes September 11, 2001, but that day's events do not materially affect our conclusions. Despite the extreme disruption of U.S. bond and stock markets, the FX market functioned smoothly overall. As would be expected in an efficient market subject to major news shocks, volatility and spreads were high on September 11, 2001. But they were indistinguishable from their normal levels

[4] Results available on request.

by the next day (Mende, 2006). This resilience stems in part from the large number of FX dealers and their wide geographical dispersion. In addition, Reuters and EBS, the two major electronic brokerages, both have servers in multiple locations around the world performing real-time replication of all functions.

3. Cross-sectional pattern of currency spreads

This section evaluates whether the cross-sectional pattern of customer spreads in FX is consistent with the predictions of adverse selection. This theory successfully explains the relation between spreads and trade size on the NYSE (see, for example, Bernhardt and Hughson (2002), Peterson and Sirri (2003)). Not only are NYSE spreads wider for larger trades, but some stock brokers pay for order flow from uninformed (retail) customers (Easley et al., 1996). Adverse selection theory also works well in explaining the pattern of price discrimination among specialists on the non-anonymous Frankfurt Stock Exchange (Theissen, 2003). There are, however, a number of markets where adverse selection cannot explain the behavior of customer spreads. A negative relationship between spreads and trade size has been documented in the London Stock Exchange (Hansch et al., 1999; Bernhardt et al., 2005) and the U.S. corporate bond market (Goldstein et al., 2007). A negative relationship between trade size and spreads has also been observed in the relatively illiquid U.S. municipal bond market (Green et al., 2007).

Our data comprise transaction prices, rather than quotes, so they do not permit us to calculate spreads directly. This difficulty, which is common in the literature, is typically solved by extracting measures of spreads from successive price changes. If spreads were constant across time and across customers and the mid-quote was stable as well, prices would change only when they switched from bid to ask or vice versa, so the spread could be estimated from price changes. In the absence of mid-quote stability the same conclusion still applies if there is no dominant trend. We estimate three familiar models that exploit this insight to extract the adverse-selection and other components of spreads: the Huang and Stoll (1997) model, the Madhavan and Smidt (1991) model, and the Glosten and Harris (1988) model. All three use transaction time rather than clock time. Throughout, we follow standard practice and use generalized method of moments (GMM) with a Newey-West weighting matrix that corrects covariance estimates for potential heteroskedasticity and autocorrelation in the residuals.

Each model produces model-specific tests for the presence of adverse selection and we also examine two general tests. First, with each model we examine whether larger trades are quoted relatively wide spreads, based on the familiar conclusion that the size of informed trades should vary positively with the likely magnitude of the traders' anticipated price move (Glosten and Milgrom, 1985; Easley and O'Hara, 1987). This seems relevant to foreign exchange markets since dealers observe that small trades are typically less informative than large trades. For example, William Clyde, formerly a trading-floor manager at First Chicago, asserts that, "Small trades, no matter what the source, do not contain much information."[5]

Second, with each model we examine whether financial customers are quoted wider spreads than corporate customers. Dealers claim that, on average, corporate order flow carries less fundamental information than financial order flow. According to Clyde: [6]

> Financial customers tend to get better spreads because their trades reflect their view of the market, and their views are often shared with other asset managers. … With corporates you're just seeing their core business activities – car building or whatever. Almost all of them will tell you "we're not in the business of speculating."

There is by now ample empirical support for the claim that financial customers in FX are informed, on average, while corporate customers are not (Fan and Lyons, 2003; Froot and Ramadorai, 2005; Frömmel et al., 2008; Menkhoff and Schmeling, 2008; Bjønnes et al., 2011). This would be surprising if non-financial corporate trades were dominated by capital issues, in which case the firms would presumably make an effort to guide their trades with informed forecasts of exchange-rate returns. In fact, however, the vast majority of corporate trades reflect mundane real-side concerns like the need to import inputs or pay taxes. One might likewise expect corporate trades to be informed if they rely on market-sensitive hedging strategies, but most non-financial firms review hedge ratios at most a few times yearly.

3.1 The Huang and Stoll model

Huang and Stoll (1997) observe that trade size is relatively unimportant for pricing in markets where large trades are routinely broken up into multiple smaller transactions, like FX. Even in such mar-

---

[5] Personal communication, August 18, 2004.
[6] Personal communication, August 18, 2004.

kets, however, the risk of trading with an informed counterparty remains. Huang and Stoll's model of a standard competitive dealership market analyzes the pricing decision of a representative dealer whose counterparties have private information that is revealed by their trade direction (buy or sell). Agents are fully rational. Dealer *i*'s quote to a customer, P_t, is determined by his expected true value of the asset, μ_t, the trade's direction, D_t [$D_t \equiv 1$ (-1) if the counterparty is a buyer (seller)], and the gap between the dealer's existing inventory and his desired inventory, I^*_t:

$$P_t = \mu_t + \frac{S}{2} D_t - \theta \frac{S}{2}\left(I_t - I_t^*\right) + \upsilon_t \ . \quad (1)$$

The term $S/2 > 0$ represents baseline half-spread, meaning the spread that would apply before adjustment for inventories, and υ_t is a mean-zero random disturbance. If dealers manage existing inventories by shading prices to customers (e.g., quoting lower prices when inventory is high), then $\theta > 0$.

Dealer *i* updates his expectation of the asset's fundamental value in light of the private information revealed by the direction of the previous trade and by public news, ε_t: $\mu_t - \mu_{t-1} = \lambda(S/2)D_{t-1} + \varepsilon_t$. The term $\lambda(S/2)$ captures the information effect of trade direction and is a direct manifestation of adverse selection. The public news shock, ε_t, is serially uncorrelated. Combining the pricing and updating rules gives the following expression for price changes between transactions:

$$\Delta P_t = \frac{S}{2}(D_t - D_{t-1}) + \lambda \frac{S}{2} D_{t-1} - \theta \frac{S}{2} \Delta I_t + e_t \ . \quad (2)$$

Here $e_t \equiv \varepsilon_t + \Delta\upsilon_t$. We measure $\Delta P_t \equiv P_t - P_{t-1}$ in pips, which are roughly equivalent to basis points.[7]

Our dependent variable is the sequence of prices on transactions initiated by customers. We follow Huang and Stoll (1997) in estimating separate coefficients for trades in various size and customer-type categories, which we achieve by interacting the key reight-hand-side variables with appropriate dummy variables. Dealers report that they informally divide normal-sized customer transactions into regular trades, which vary from €1 million to about €25 million; modest trades; and tiny trades. Though the line between the latter two categories is ambiguous, their treatment can vary substantially: tiny trades are often

[7] A pip is equivalent to a tick: one unit of the smallest significant digit in an exchange rate as conventionally quoted. In the euro-dollar market, where the exchange rate averaged \$1.1128/€ during our sample period, a one-pip change from that level would bring the rate to \$1.112**9**/€.

spread by formula rather than by dealers' discretion. We therefore assign the following size ranges: large trades (Lg): $\{|Q_t| \in [€1 \text{ million}, € 25 \text{ million})\}$; medium trades ($Md$): $\{|Q_t| \in [€0.5 \text{ million}, €1 \text{ million})\}$; and small trades ($Sm$): $\{|Q_t| \in (€0, € 0.5 \text{ million})\}$. Table 4 provides descriptive statistics on trade sizes, returns, inventory, and order flow disaggregated by customer type.

[Table 4 around here]

According to correspondents at large dealing banks, the correct customer disaggregation is between small corporate customers, on the one hand, and financial customers and large multinational (corporate) corporations, on the other. Though we cannot technically distinguish large multinationals from other corporate customers, large multinationals tend to trade through the biggest banks. Thus when our dataset distinguishes financial customers (*FC*) from corporate customers (*CC*), it roughly captures the distinction between informed and uninformed customers at our average-sized bank.

The results of estimating the Huang and Stoll (1997) model, shown in Table 5, provide no support for any of the implications of adverse selection. The first model-specific implication is that there is a positive relation between trade size and the estimated adverse-selection coefficients, λ, but for financial traders the point estimates imply the opposite. The other model-specific prediction is that λ should be higher for financial than customer trades, but the only significant value of λ is associated with corporate trades. Indeed, though the coefficients should all be positive under adverse selection they are jointly insignificant (chi-squared statistic 9.75, marginal significance 0.14).

[Table 5 around here]

The first general prediction of adverse selection is that baseline half-spreads should be positively related to trade size, but the results in Table 5 suggest the opposite. For financial customers, estimated baseline half-spreads are 10.8 pips for small trades, 5.4 pips for medium-sized trades, and 3.4 pips for large trades. Chi-squared statistics from the associated Wald tests confirm this pattern: for the small-vs.-medium comparison the test statistic is 4.06 with marginal significance 0.044; for the small-vs.-large comparison the test statistic is 6.10 with marginal significance 0.014. Corporate spreads also appear to be inversely related to trade size. Estimated baseline half-spreads are 13.5 pips for small trades, 11.2 pips for medium-sized trades, and 2.1 pips for large trades, and the inverse relation is again confirmed statistically. For the small-vs.-large comparison the chi-squared statistic is 46.1 with marginal significance 0.000; for the medium-vs.-large comparison the statistic is 8.8 with marginal significance 0.003.

The second general prediction of adverse selection is that financial customers should be quoted wider spreads than corporate customers. This, too, gets no support from the Huang and Stoll (1997) model. Indeed, corporate customers are quoted wider spreads for both small and medium trades and the difference is statistically significant for the medium-sized trades (chi-squared statistic of 4.01 with marginal significance 0.045). For large trades the estimated baseline half-spread is insignificant for both customer types.

The results of the Huang and Stoll (1997) model also suggest that dealers' inventory levels are not relevant to FX customer spreads, since none of the six inventory coefficients is significant; formal exclusion tests confirm their joint insignificance (chi-squared statistic is 3.64 with marginal significance 0.72). Similar results have been found for roughly contemporaneous data from other banks, which has led to a broad consensus that FX dealers preferred managing inventory via interbank trades rather than by shading prices to customers during our sample period (Bjønnes and Rime, 2005).

Table 5 presents three robustness tests, all of which support the qualitative conclusions outlined above. First, we rerun the regression with inventories reset to zero at the beginning of every day. Second, we include interdealer as well as customer trades to provide comparability with Bjønnes and Rime (2005), where customer transactions (as a single category) and interbank transactions are included in the main regressions. Reassuringly, our bank's baseline half-spread for normal-sized interbank transactions, 2.1 pips, is similar to those estimated for other banks. Third, we exclude forward transactions.

Our conclusion that adverse selection does not dominate the determination of customer spreads in the FX market is also robust to the following additional unreported modifications: excluding data for September 11, 2001; including additional lags of the dependent variable, with lag length of two suggested by the Akaike information criterion and other standard tests; and using a cutoff of €300,000 rather than €500,000 between small and medium trades.

3.2 The Madhavan and Smidt model

FX dealers consistently report that they consider large customer trades to be more informative than small ones, so the Huang and Stoll (1997) model's assumption that trade size is uninformative may be inappropriate in the FX customer market. Trade size *is* informative in the Madhavan and Smidt model (1991), which has frequently been applied in FX microstructure research (see, for example, Lyons (1995) and Bjønnes and Rime (2005)). In this model, agent *j* calls dealer *i* requesting a quote and chooses an amount Q_{jt} that is related to the gap between his expected value of the asset, μ_{jt}, and the price quoted by the dealer: $Q_{jt} = \xi(\mu_{jt} - P_t) + X_{jt}$, where $\xi > 0$ and X_{jt} represents agent *j*'s liquidity demand. In setting his regret-free price, P_t, dealer *i* considers his own expected value of the asset, μ_t, his inventory, and the direction of the trade: $P_t = \mu_t + \zeta(I_t - I_i^*) + \chi D_t$. In determining μ_i, dealer *i* rationally considers the customer's desired trade size. If the dealer shades prices to manage existing inventories, $\zeta < 0$.

Solving for conditional expectations and taking first differences gives the following expression for the price change between dealer *i*'s incoming transactions:

$$\Delta P_t = \alpha + \beta_1 D_t + \beta_2 D_{t-1} + \gamma_1 I_t + \gamma_2 I_{t-1} + \delta Q_{jt} + \eta_t \qquad (3)$$

The intercept, α, should be zero if the dealer's desired inventory is zero. If the dealer shades prices in response to inventories, then $\gamma_2 > |\gamma_1| > 0 > \gamma_1$. Our estimates of the Huang and Stoll model suggest that both γ_1 and γ_2 will be about zero.

Adverse selection, if operative, has a number of model-specific implications. First, it implies that the coefficient on trade size, δ, should be positive. Large trades can reflect a big gap between the asset's true value and the dealer's quote, so a rational dealer in this model increases the spread with trade size. Adverse selection should also influence the relation between β_1 and β_2. The model implies that $\beta_1 = |\beta_2|/\phi > 0 > \beta_2$, where $0 < \phi < 1$ is a model-derived parameter capturing the extent to which dealers rely on their priors rather than the current trade in updating μ_t. Under adverse selection, the estimated value of ϕ should be closer to unity for uninformed trades. The model also implies that β_2 is the negative of the baseline half-spread and should thus be bigger (in absolute value) for informed trades.

The results of this analysis, presented in Table 6, are no more favorable to adverse selection than estimates from the Huang and Stoll (1997) regressions.[8] The first model-specific implication is that the coefficient on trade size, δ, should be positive for informed customers, but the estimates of δ are only positive for corporate customers and are insignificant for both customer types. The ratio between the coefficients on lagged and current direction, $\phi = |\beta_2|/\beta_1$, which should vary negatively with trade size, varies non-monotonically with size for the financial trades: the point estimates are 0.67, 0.99, and 0.66, respectively, for small, medium, and large financial trades. Similarly, though adverse selection predicts smaller values of ϕ for financial than corporate customers, estimates of ϕ for medium and large financial trades exceed corresponding estimates for corporate customers.

[Table 6 around here]

With respect to the general implications of adverse selection, the estimated baseline half-spreads once again vary negatively, rather than positively, with trade size. For financial customers the estimated baseline half-spreads are a statistically-significant 8.9 pips on small trades and roughly one-third that size – and insignificantly different from zero – for medium and large trades. For corporate customers, the estimated half-spreads are 13.2 pips on small trades, 5.7 pips for medium trades, and essentially zero for large trades. In this regression the small-vs.-large distinction for financial customers and all size distinctions for corporate customers are statistically significant.

Contrary to adverse selection, the point estimates for the baseline half-spreads are higher for corporate than for financial customers. Though the differences are not significant in the baseline regression, they are significant when we exclude the inventory and quantity variables. This exclusion is statistically appropriate since inventories and the trade quantity itself are jointly insignificant (chi-squared statistic 3.36 with marginal significance 0.34), as they were for the Huang and Stoll (1997) model.[9]

The constant term in the Madhavan and Smidt model is insignificant, implying that our dealer's preferred inventory level is about zero. The results are robust to numerous methodological modifications, the first three of which are reported in Table 6: calculating inventories with a daily starting value of zero;

---

[8] Co-linearity among instruments is not a problem, since the only pair with nontrivial correlation is *Fin* x Q_t and *Fin* x *LG* x D_t, and excluding the quantity variables does not change our qualitative conclusions.

[9] Results available upon request.

including interbank trades; excluding forward transactions; excluding September 11, 2001; including two lags of the dependent variable; or splitting small and medium trades at €300,000 rather than €500,000.

3.3 The Glosten and Harris model

Since the inventory coefficients have been consistently insignificant, it may be appropriate to consider the Glosten and Harris (1988) model, in which inventories play no role. This model is otherwise similar to the Madhavan and Shmidt (1991) model except that trade size influences the baseline spread as well as the adverse-selection component. The price set by dealer i is $P_t = \mu_t + (c_0 + c_1 V_t)D_t$, where $V_t \equiv |Q_{jt}|$ is the size of customer j's desired trade and $(c_0 + c_1 V_t)$ is the baseline half-spread. The dealer's current expected value of the asset is the previous period's expected value, μ_{t-1}, adjusted for V_t, to capture adverse selection, and by public news: $\mu_t = \mu_{t-1} + zD_tV_t + \varepsilon_t$.[10] The period-$t$ price change is:

$$\Delta P_t = c_0(D_t - D_{t-1}) + c_1(D_tV_t - D_{t-1}V_{t-1}) + zD_tV_t + \varepsilon_t. \tag{4}$$

The term c_0 should capture the baseline spread or, equivalently, fixed effects associated with trading; c_1 should capture any influence of trade size on spreads that is not driven by adverse selection; the adverse-selection term, $z,$ should be positive.

The results of this analysis, shown in Table 7, provide no more support for adverse selection than our previous results. The two adverse-selection coefficients, z, are both insignificant, and the hypothesis that they are jointly insignificant is not rejected (F-statistic 1.18, marginal significance 0.31). In addition, contrary to the prediction of adverse-selection theory the baseline spreads for corporate customers are significantly larger than those for financial customers. Indeed, while we can reject the hypothesis that the two coefficients are the same (F-statistic 18.64, marginal significance 0.00), we cannot reject the hypothesis that the baseline spread for corporate customers is twice the baseline spread for financial customers (F-statistic 0.05, marginal significance 0.42). The results also confirm our earlier finding that trade size and baseline spreads are inversely related: the estimated values of c_1 are negative and significant for both corporate and financial customers. When, as before, we rerun the regressions including interbank trades or excluding forward trades, our qualitative conclusions are sustained.

---

[10] We estimate the more general version of the two estimated in Glosten and Harris (1988), or their Equation 6. Since the tick sizes in FX are tiny (less than 1 basis point), rounding errors are incorporated in the disturbances.

[Table 7 around here]

4. Operating costs, market power, and strategic dealing

According to the evidence just presented, price discovery in FX cannot follow the standard adverse-selection based model of Glosten and Milgrom (1985) because dealers do not appear to adjust customer spreads to protect themselves against the likely information content of customer trades. Instead, the cross-sectional variation of FX customer spreads follows a pattern diametrically opposed to the one predicted by adverse selection: spreads are widest for the trades least likely to carry information.[11] This section highlights three factors that could drive this pattern: fixed operating costs, transitory market power, and strategic dealing.

4.1 Fixed operating costs

Per-unit processing costs fall as trade size rises, a point stressed by Angel (1996) and Hansch et al. (1999) as a potential source of the inverse relationship between spreads and trade size on the London Stock Exchange. While this also seems likely to help explain the negative relation between spreads and trade size in the FX customer market, it is unlikely to explain the gap between spreads paid by financial and corporate customers. Fixed costs do not vary in any evident way by customer type, and marginal costs are, if anything, higher for asset managers, who often require their trade proceeds to be split among numerous individual funds.

One might wonder whether the difference between financial- and corporate-customer spreads reflects a difference in the timing of the two groups' trades. Though there are differences in timing, as noted in Section 2, interdealer spreads in euro-dollar are fairly constant at low levels throughout our bank's regular trading hours (Ito and Hashimoto, 2006). In consequence, intraday trading patterns cannot predict the observed variation in customer spreads.

The rest of this section highlights two mutually consistent theories of dealing under asymmetric information that might explain the way FX spreads vary across counterparty types. The first theory suggests

[11] We stress that these results apply to the *customer* FX market. Quoted *interdealer* spreads should be invariant to counterparty type, since most interdealer trades benefit from pre-trade anonymity. While our results indicate that adverse selection does not dominate FX customer spreads, they also do not prove that adverse selection has zero influence on those spreads.

that information about current market conditions provides dealers with transitory market power relative to uninformed customers, allowing dealers to charge wider spreads to these customers. The second theory suggests that dealers strategically vary spreads across customers in an attempt to gather private information.[12] These information-based forces both imply that dealers will set wider spreads on smaller trades and on corporate trades, and we hypothesize that they operate simultaneously with fixed operating costs. The factors we highlight in this section do not exhaust the long list of factors dealers consider in setting spreads – though a longer list of factors could exhaust the patience of our readers.

4.2 Market power

Green et al. (2007) point out that dealership markets are opaque due to the dispersion of trading, so current market conditions – meaning real-time mid-quotes, spreads, volatility and the like – can be hard to ascertain. Asymmetric information about these conditions effectively creates bargaining power. As Angel (1996) describes it, "a dealer knows that an unsophisticated individual … may have higher search costs per share and is not in a good position to monitor the quality of a broker's execution. The broker has little incentive to spend time negotiating or shopping around for a better deal for a small order. Thus, a dealer may take advantage of this by quoting a wider market…" (p. 4). Duffie et al. (2004) develop this and related insights into a formal model and show that bargaining power in dealership markets partly reflects the alternatives to trading immediately.

This "market-power" hypothesis can be applied directly to explain why corporate FX customers pay wider spreads than financial customers. Currencies are traded in dealership markets with dispersed information, and there are numerous reasons why corporate customers might be less sophisticated than financial customers. Corporate trades are typically scattered across time and often across currencies, so the firms do not hire professional traders. Instead, they assign FX trading to administrators with many other responsibilities. It is difficult for these individuals to gain an intuitive understanding of the market, a difficulty often compounded during our sample period by a lack of real-time market information. Further, these individuals are rarely evaluated on execution quality, so they have little incentive to achieve better

[12] Huang and Stoll (1997) propose an explanation for the negative relationship between adverse selection costs and transaction size in equity market spreads, but it concerns block trades, which do not exist in foreign exchange.

spreads. In short, traders at corporate firms perceive that search is very costly and yet provides small benefits, making them ripe targets for wide spreads.

FX traders at financial firms, who are often professionals, perceive lower costs to search because they have plenty of real-time information and greater benefits from search because they are often evaluated on execution quality. Financial firms may also gain market power from their tendency to undertake larger trades (see Table 1). As shown in Bernhardt et al. (2005), customers who regularly trade substantial amounts may receive better spreads as dealers compete for their business.

4.3 Strategic dealing

The gap between corporate and financial spreads may also reflect the strategic efforts of dealers to attract informed order flow by selectively setting attractive quotes. The importance of gathering information from customers is indicated by comments from William Clyde, the former trading-floor manager:

> Banks will want to make good quotes on large, potentially information-bearing amounts for two reasons. First, it gets them better access to the current information: in addition to getting the directional information won by being dealt on, the caller will sometimes share a little additional information with the bank. With this information you don't get caught out and you can make better trading decisions. Second, it ensures that institutions with large amounts continue to call whenever they have something going on.

The two-tier structure of FX makes it logical for FX dealers try to capture informative customer order flow, since they can exploit the information in subsequent interdealer trading.[13] Evidence that the order flow of large currency dealing banks is informed is provided in Evans and Lyons (2007) and Rime et al. (2009), inter alia. Bjønnes et al. (2011) provide evidence that the interdealer trades of relatively small banks even carry information, on average, though they carry less information than the trades of big banks.

The insight that market makers might strategically manipulate spreads to increase the information value of incoming order flow was originally explored in Leach and Madhavan (1992). That work uses an equity-market inspired model to demonstrate that market makers in one-tier markets may adjust prices early in a trading session to enhance later profitability. Flood et al. (1999) present evidence for such intertemporal manipulation of spreads in an experimental setting similar to the FX interdealer market. Our evidence, however, concerns cross-sectional rather than intertemporal variation in spreads. Naik et al.

[13] Strategic dealing may be more relevant in FX than in the municipal or corporate bond markets. Most such bonds trade relatively infrequently, so the information value of any trade may be negligible.

(1999) presents a model of strategic dealing in a two-tier market in which some customers are informed. They conclude that customer spreads will be narrower for more informed customers, consistent with the pattern we document for FX. Hansch and Neuberger (1996) present evidence consistent with this type of strategic dealing on the London Stock Exchange.

Our bank's order flow need not be hugely informative for strategic dealing considerations to influence its customer spreads. Since dealers are largely price takers with respect to spreads (Cheung and Chinn, 2001), strategic dealing will indirectly influence spreads at moderate-sized banks as long as it directly influences spreads at the largest banks.[14]

Evidence for strategic dealing in FX is presented in Ramadorai (2008), who analyzes the transactions of asset managers. He finds that spreads are narrower for managers that produce higher (risk-adjusted) FX returns and are therefore presumably better informed. Reitz et al. (2009) provide evidence for the broader claim, implied by both the market power and the strategic dealing hypotheses, that financial customers have more bargaining power than corporate customers vis-à-vis their dealers.

5. Price discovery in foreign exchange

The evidence presented here suggests that spreads in the FX customer market are not positively related to a trade's information content. Indeed, the price moves *more* when uninformed customers trade than when informed customers trade, on average. This raises a logical follow-up question: If adverse selection is not the basis for price discovery in currency markets, what is? This section first proposes an alternative price discovery process that reflects the FX market's two-tiered structure. It then shows that this process predicts many of the stylized facts of currency market microstructure. The section finishes by providing new evidence consistent with the alternative process.

According to our proposed price discovery process, information moves from customers to market prices in three stages. In the first stage, an informed customer trades with a dealer, but the customer's information is not reflected in the dealer's quoted price. In the second stage, the information moves inter-

[14] This preoccupation with standard practice may bring to mind the issues of collusion on the NASDAQ raised in Christie and Schultz (1994). However, there are literally hundreds of dealers in the major currency pairs, and they are spread across the globe; it seems unlikely that collusion could maintain FX spreads for decades.

dealer prices when dealers trade with each other. In the third stage, the information finally affects customer prices when dealers trade with more customers.

Any comprehensive formalization of this process awaits the resolution of technical constraints in the literature. The dynamics of limit-order markets with asymmetric information are so complex that models only yield closed-form solutions under highly constrained assumptions. But the complexities of our hypothesis exceed even these, since it involves the interaction of an order-driven (interdealer) market with a quote-driven (customer) market, both under asymmetric information. Fortunately, all the key conceptual elements of our proposed process have been formally elaborated in the literature: our contribution is to articulate a synthesis appropriate for FX.

5.1 The mechanism

This section describes in greater detail the three stages of our proposed price discovery process.

Stage 1. An informed customer contacts his dealer to trade. In contrast to the Glosten and Milgrom (1985) model, the FX customer's market-relevant information is not immediately impounded in the dealer's quotes.

Stage 2. A customer's information influences the interdealer price. The dealer infers some or all of the customer's information and uses it to guide his own trades. Our key hypothesis is that dealers have a stronger tendency to place market orders after informed-customer trades than after uninformed-customer trades. This hypothesis draws on existing theoretical analyses of order choice and the institutional structure of FX markets.

Consider a dealer whose inventory begins at zero and then rises because a customer decides to sell. Since FX dealers prefer to have zero inventory, this dealer will likely try to offload the new inventory to another dealer. As described in Section 2, dealers can trade through the limit-order markets run by the interdealer brokers or they can trade directly in the OTC market. Our analysis carries through regardless of this choice, as described below.

Suppose first that our dealer trades through a broker. In this case he submits either a market sell or a limit sell. Market orders provide immediate execution with certainty, while limit orders provide better prices but uncertain execution (Harris, 1998; Foucault, 1999). This choice depends on whether the customer is informed (Reiss and Werner, 1998). If so, the dealer has three incentives to exploit the immediacy offered by market orders: (i) he has information and might rationally speculate, other things equal; (ii) he has inventory with its inherent risk; and (iii) his information indicates that his inventory could soon bring a loss. Our dealer therefore seems likely to place a market sell order and earn the lower bid price. The amount sold could exceed the new inventory if the dealer chooses to open a speculative short position. The structure of the interdealer market itself matches in critical respects the one analyzed in Glosten and Milgrom (1985), so regret-free interbank prices should reflect the dealer's information. If the customer is considered uninformed, the dealer has only one incentive to place a market order – the inherent riskiness of his inventory, so the dealer is more likely to place a limit order.[15]

Putting the pieces together, we see that after an informed customer sale the interdealer prices is likely to fall and after an uninformed customer sale the interdealer price is not likely to fall. The connection to price discovery is direct: brokered interdealer prices tend to move in the direction indicated by informed trades.[16]

If our dealer chooses to trade in the over-the-counter market, this analysis changes only superficially. Calling another dealer, like placing a market order, produces a quick, certain trade at a relatively undesirable price; waiting for someone else to call, like placing a limit order, could bring a better price but could instead bring no trade at all. A dealer has strong incentives to call another dealer after buying from an informed customer, in which case he sells at the lower bid price. After trading with an uninformed customer, the dealer is more likely to wait for incoming calls and the price is less likely to fall.

Stage 3. Market-relevant information influences customer prices. Once the interdealer quotes reflect the new information, subsequent customer trades with other dealers will also reflect that information.

The price discovery process just outlined could theoretically lead to a no-trade equilibrium in the interdealer market in which all market orders would be placed by dealers with information, uninformed dealers would have no source of profits, and trading would cease. Such an equilibrium would require

[15] The choice between limit and market orders will also hinge on market conditions, such as the width of the bid-ask spread and the depth of the book (Menkhoff et al., 2010).

[16] Our conclusion that dealers will place aggressive/market orders after trading with informed customers is consistent with the finding of Bloomfield et al. (2005) that informed traders provide liquidity when the value of their information is high.

three conditions to be satisfied, however, and none of them hold true. First, speculation must be the only motive driving trades; in reality, however, many dealer trades are driven instead by the need to offload inventory. (Indeed, customer service – not speculative interbank trading – is the main source of profits for small and mid-sized bank dealers, as shown in Mende and Menkhoff (2006).) Second, customer identity must be the only factor determining whether a dealer makes an aggressive trade; in reality, however, this choice is influenced by many other factors, including volatility and depth (Menkhoff et al., 2010). Third, customer identity must indicate flawlessly whether and when a customer is informed, but in reality informed customers sometimes trade for liquidity reasons.

5.2 Explaining the stylized facts

Our proposed price discovery process predicts a number of the stylized facts in FX microstructure. First, it predicts that the relatively-informed financial order flow will be positively related to upcoming exchange-rate returns. Evidence for such a relationship is provided in Bjønnes et al. (2005), Marsh and O'Rourke (2005), and Evans and Lyons (2007). If the information in question is fundamental, then our analysis also predicts that this relationship is substantially permanent, evidence for which is provided in Lyons (2001) and in Bjønnes et al. (2011).

Our proposed price discovery process also predicts a positive and largely permanent relationship between exchange rates and interdealer order flow. Consistent with this prediction, substantial evidence indicates a strong and positive contemporaneous correlation between interdealer order flow and exchange-rate returns at the daily and weekly horizons, and a substantial portion of this relationship is permanent (Osler (2009) provides a survey).

Our proposed price discovery process also answers a natural question regarding the strategic dealing hypothesis: If dealers quote narrower spreads to attract informed customers, how do the dealers benefit from that information? We answer: they benefit via enhanced interdealer trading. The information permits them to reduce their inventory risk and/or to take informed speculative positions.

5.3 Additional evidence

Our proposed price discovery process has four additional testable implications. First, it predicts that interdealer prices are the best measure of “the market” at any instant. Abundant institutional evidence confirms this implication. Most critically, dealers' standard practice is to base their customer quotes on the interdealer market's current best bid and offer. Second, our proposed price discovery process predicts that dealers with the most financial customers should be best informed and should profit the most from interdealer trading, consistent with the findings in Bjønnes et al. (2011).

The last two testable implications of our proposed price discovery process concern the likelihood of aggressive interbank transactions. Under our proposed price discovery mechanism, dealers should be more likely to place interdealer market orders after trades with financial customers than after trades with corporate customers. Similarly, dealers should be more likely to place interdealer market orders after large trades than after small ones, other things equal. If our hypothesis is not correct – and information from individual customers is not critical to the dealers' decision to make or take liquidity – then customer type and trade size should not matter after controlling for the dealer's inventory level and other factors.

We test these last two implications using a probit analysis of the conditional probability that a given transaction is aggressive in the interbank market, given the nature of the previous trade:

$$Prob(Trade_t = IB^{out}) = P(FC_{t-1},\ CC_{t-1},\ 10mio_{t-1}, |I_t|,\ I_t^2,\ |Q_t|)\ . \tag{5}$$

The first three variables are dummies indicating that the previous trade was with a financial customer, FC_{t-1}, or with a corporate customer, CC_{t-1}, and a dummy set to one if the value of the previous transaction exceeds €10, $10mio_{t-1}$. We conjecture that the coefficient on FC_{t-1} will exceed the coefficient on the corporate dummy and the coefficient on $10mio_{t-1}$ will be positive.

The last three terms in Equation (5) capture other factors relevant to the decision to place a market order. The coefficient on absolute inventory, $|I_t|$, should be positive, since higher inventory brings higher inventory risk. The influence of inventory seems likely to diminish as inventories get larger, so we follow Bjønnes and Rime (2005) by including squared inventory, I_t^2. The absolute size of the current transaction, $|Q_t|$, is included because our dealer's customer transactions are often smaller than $1 million, the minimum size for brokered trades. Since our dealer prefers to carry out interbank trades on EBS, a broker, rather than by dealing directly, he seems likely to collect inventory from small customer transactions and then square his position by submitting one relatively substantial market order.

The results of estimating Equations (5), shown in column one of Table 8, support our view that the likelihood of an aggressive interbank transaction is higher when the previous transaction is considered informed. Aggressive interbank transactions are significantly more likely when the previous transaction involves a financial customer than when it involves a corporate customer. They are also significantly more likely after trades over €10 million.

[Table 8 around here]

The economic magnitudes of these effects can be gauged by calculating the probability of an aggressive interbank trade for different types of previous trades, with other variables evaluated at sample means. After a normal-sized corporate trade the estimated probability of an aggressive interbank transaction is 9.6 percent; after a similarly sized financial trade, that probability is roughly twice as large, at 18.9 percent. After a corporate trade over €10 million, the probability of an aggressive interbank transaction is 26.3 percent. After a similarly sized financial trade, this probability reaches 41.6 percent.

Our analysis has the further implication that the likelihood of an aggressive aggressive trade is higher when the direction of the aggressive trade is similar to the direction of the previous incoming trade. For example, if the previous trade was a financial-customer purchase, then the likelihood that the dealer responds aggressively is higher if the dealer is also choosing to make a purchase.[17] To capture this insight, we run an expanded version of the regression outlined above, in which dummy variables capture whether the current trade has the same direction as the previous trade. One same-direction dummy applies to financial customers ($SD\text{-}FC_{t-1}$), and the other applies to corporate customers ($SD\text{-}CC_{t-1}$):

$$Prob(Trade_t{=}IB^{out}) = P(FC_{t-1}, CC_{t-1}, SD\text{-}FC_{t-1}, SD\text{-}CC_{t-1}, 10mio_{t-1}, |I_t|, I_t^2, |Q_t|)\ . \qquad (6)$$

The results of this regression, shown in column 2 of Table 8, indicate as before that dealers are more likely to make aggressive interbank trade after informed trades with others. As expected, the results indicate that the likelihood is far higher when the current trade is in the same direction as the previous trade. For large corporate trades the likelihood of an aggressive same-direction trade, 56 percent, is over twice the likelihood of an aggressive other-direction trade, 22 percent; for large financial trades these probabilities are 77 percent and 32 percent.

[17] We are grateful to an anonymous referee for pointing out this implication.

In the baseline results, the inventory terms are statistically insignificant. Since Bjønnes and Rime (2005) find inventories significant in related regressions, we also run the regression using our other measure of inventory – sometimes preferred in currency microstructure – in which each day's starting value is set to zero. This modification leaves our main conclusions unaffected but inventories themselves become statistically significant. As anticipated, inventories have a positive and concave relation to the likelihood the dealer trades aggressively in the interbank market.

Our proposed process implies that our dealer should also tend to trade more aggressively after incoming trades by other dealers. Existing evidence suggests that our bank is likely to consider other banks to be better informed, on average (Bjønnes et al., 2011). Banks of all sizes have information, but banks with the most customers are best informed, and our bank has a relatively modest customer base compared with the likes of Citibank and Deutsche Bank. To test whether our bank tends to view other banks as informed, we include incoming interbank trades as a determinant of order aggressiveness. As expected, the results indicate that our bank trades more aggressively after incoming trades by other dealers than it does after corporate trades (Table 8, column 4). Other properties of the regression are unaffected. Our main conclusions are also insensitive to the inclusion of forward trades (Table 8, column 5), and to the exclusion of September 11, 2001 (unreported).

6. Conclusions

This paper examines the process of price discovery in FX markets. Our benchmark is the standard model of spread determination in equity markets (Glosten and Milgrom, 1985), in which adverse selection concerns lead dealers to set wider spreads when they expect customers to be informed. Using the complete USD/EUR trading record of a bank in Germany over a period of four months, the paper first provides evidence that the spreads quoted to foreign-exchange end users/customers do not behave as predicted by adverse selection. Instead, FX customer spreads *narrow* with the likelihood that a customer is informed: they are wider for small trades than for large trades and they are wider for the relatively uninformed corporate customers than for financial customers. Other implications of adverse selection are also not supported for customer FX trades. We infer that the standard adverse selection model does not adequately describe the price discovery process in FX.

The paper then highlights three hypotheses from the broader microstructure literature that can help explain the cross-sectional variation of currency spreads. First, since dealers' operating costs are largely fixed, it would be natural for spreads to be larger for small trades. The wider spreads paid by corporate customers cannot be explained by operating costs but could be explained in part by Green et al.'s (2007) market-power hypothesis. This asserts that spreads in quote-driven markets vary positively with a dealer's transitory market power relative to a given customer, and that such market power derives in part from knowledge of market conditions. Corporate customers tend to know the least about current market conditions, so this theory correctly predicts they pay the widest spreads. The customer-based variation in spreads could also reflect dealers' attempts to strategically gather information (Leach and Madhavan, 1992; Naik et al., 1999). Dealers may narrow spreads to attract informed customers and extract information from their trades, information from which the dealers can benefit in subsequent interdealer trades. Dealers consider financial order flow to be relatively informative, so this theory correctly predicts that financial customers pay the narrowest spreads.

The final section of the paper proposes a new price discovery process that incorporates the FX market's two-tiered structure. The pattern of spreads shows that a customer's information is not immediately embedded in the prices quoted to it by dealers, which means that price discovery must take place in the interdealer market. We suggest that price discovery is driven by a difference in how dealers trade after providing liquidity to informed and uninformed customers. After trades with informed customers they tend to make parallel aggressive trades in the interdealer market – placing a market buy order after an informed customer buy, for example – which moves the interdealer price in a direction consistent with the customer's information. After trading with uninformed customers, by contrast, dealers are more likely to place parallel limit orders or to wait for incoming calls, leaving the interdealer price relatively unaffected. Because later customer quotes are based on the new interdealer prices, the information spreads to all prices once it is affects the interdealer price.

Our theory predicts some key stylized facts in FX, specifically the positive and substantially permanent relation between cumulative financial order flow and exchange rates, as well as the positive and substantially permanent relation between interdealer order flow and exchange rates. Our theory also predicts that dealers are more likely to place aggressive interdealer trades after informed customer trades, and we provide evidence consistent with this implication.

Customer spreads are known to vary inversely with trade size in other liquid two-tier markets, including the U.S. Treasury market, the U.S. corporate bond markets, and the London Stock Exchange. Future research could investigate the extent to which the price discovery process proposed here applies in these markets.

Acknowledgements: We are deeply grateful to the bankers who provided the data and to William Clyde, Pete Eggleston, Keith Henthorn, Valerie Krauss, Peter Nielsen, Peter Tordo, and other bankers who discussed dealing with us. We thank, without implicating, Geir Bjønnes, Alain Chaboud, Yin-Wong Cheung, Thomas Gehrig, Michael Goldstein, Joel Hasbrouck, Rich Lyons, Albert Menkveld, Bruce Mizrach, Anthony Neuberger, Paolo Pasquariello, Tarun Ramadorai, Dagfinn Rime, Erik Theissen, Dan Weaver, and participants at the European Finance Association Annual Conference in Zurich, the Second Annual Microstructure Conference in Ottawa and at the NBER microstructure meeting for insightful comment.

References

Angel, J., 1996. Who gets price improvement on the NYSE? Georgetown University Working Paper FINC-1377-12-694.

Bank for International Settlements, 2010. Triennial Central Bank Survey, Foreign Exchange and Derivatives Market Activity in 2010. B.I.S., Basel.

Bank for International Settlements, 2002. Preliminary Global Results, Triennial Central Bank Survey, Foreign Exchange and Derivatives Market Activity in 2002. B.I.S., Basel.

Bernhardt, D., Hughson, E., 2002. Intraday trade in dealership markets. European Economic Review 46, 1697-1732.

Bernhardt, D., Dvoracek, V., Hughson, E., Werner, I.M., 2005. Why do larger orders receive discounts on the London Stock Exchange? Review of Financial Studies 18, 1343-1368.

Bjønnes, G.H., Osler, C., Rime, D., 2011. Asymmetric information in the interbank foreign exchange market. Brandeis University Working Paper.

Bjønnes, G.H., Rime, D., 2005. Dealer behavior and trading systems in foreign exchange markets. Journal of Financial Economics 75, 571-605.

Bjønnes, G.H., Rime, D., Solheim, H.O.Aa., 2005. Liquidity provision in the overnight foreign exchange market. Journal of International Money and Finance 24, 175-196.

Bloomfield, R., O'Hara, M., Saar, G., 2005. The "make or take" decision in an electronic market: Evidence on the evolution of liquidity. Journal of Financial Economics 75, 165-199.

Burnside, C., Eichenbaum, M., Rebelo, S., 2009. Understanding the forward premium puzzle: A microstructure approach. American Economic Journal: Macroeconomics 1, 127-154.

Cheung, Y.-W., Chinn, M.D., 2001. Currency traders and exchange rate dynamics: Asurvey of the U.S. market. Journal of International Money and Finance 20, 439-471.

Christie, W.G., Schultz, P.H., 1994. Why do NASDAQ market makers avoid odd-eighth quotes? Journal of Finance 49, 1813-1840.

Duffie, D., Garleanu, N., and Pedersen, L. H., 2004. Over-the-counter markets. Econometrica 73, 1815-1847.

Dunne, P. G., Hau, H., Moore, M., 2008. A tale of two platforms: Dealer intermediation in the European sovereign bond market. C.E.P.R. Discussion Papers: 6969.

Easley, D., O'Hara, M., 1987. Price trade size and information in securities markets. Journal of Financial Economics 19, 69-90.

Easley, D., Kiefer, N., O'Hara, M., 1996. Cream skimming or profit sharing? The curious role of purchased order flow. Journal of Finance 51, 811-833.

Easley, D., Kiefer, N., O'Hara, M., 1997. One day in the life of a very common stock. Review of Financial Studies 10, 805-835.

Euromoney, May 2007. Euromoney FX Poll 2007: http://www.euromoney.com/article.asp?PositionID=polls&ArticleID=1330478

Evans, M., Lyons, R.K., 2002. Order flow and exchange rate dynamics. Journal of Political Economy 110, 170-180.

Evans, M., Lyons, R.K., 2006. Understanding order flow. International Journal of Finance and Economics 11, 3-23.

Evans, M., Lyons, R.K., 2007. Exchange-rate fundamentals and order flow. NBER Working Papers: 13,151.

Fan, M., Lyons, R.K., 2003. Customer trades and extreme events in foreign exchange. In: Paul Mizen (Ed.), Monetary History, Exchange Rates and Financial Markets: Essays in Honour of Charles Goodhart. Edward Elgar, Northampton, 160-179.

Flood, M.D., Huisman, R., Koedijk, K.G., Mahieu, R.J., 1999. Quote disclosure and price discovery in multiple-dealer financial markets. Review of Financial Studies 12, 37-59.

Foucault, T., 1999. Order flow composition and trading costs in a dynamic limit order market, Journal of Financial Markets 2, 99-134.

Frömmel, M., Mende, A., Menkhoff, L., 2008. Order flows, news, and exchange rate volatility. Journal of International Money and Finance 27, 994-1012.

Froot, K.A., Ramadorai, T., 2005. Currency returns, intrinsic value, and institutional investor flows. Journal of Finance 60, 1535-1566.

Glosten, L., Harris, L. 1988. Estimating the components of the bid/ask spread. Journal of Financial Economics 21, 123-42.

Glosten, L., Milgrom, P., 1985. Bid, ask, and transaction prices in a specialist market with heterogeneously informed agents. Journal of Financial Economics 14, 71-100.

Goldstein, M.A., Hotchkiss, E.S., Sirri, E.R., 2007. Transparency and liquidity: A controlled experiment on corporate bonds. Review of Financial Studies 20, 235-273.

Green, R.C., Hollifield, B., Schurhoff, N., 2007. Financial intermediation and the costs of trading in an opaque market. Review of Financial Studies 20, 275-314.

Hansch, O., Neuberger, A., 1996. Strategic trading by market makers on the London Stock Exchange. The Institute for Financial Research, Birkbeck College, Working Papers.

Hansch, O., Naik, N., Viswanathan, S., 1999. Preferencing, internalization, best execution, and dealer profits. Journal of Finance 54, 1799-1828.

Harris, L., 1998. Optimal dynamic order submission strategies in some stylized trading problems. Financial Markets, Institutions, and Instruments 7, 1-75.

Hasbrouck, J., 1991. Measuring the information content of stock trades. Journal of Finance 46, 179-207.

Hasbrouck, J., Sofianos, G., 1993. The trades of market makers: An empirical analysis of NYSE specialists. Journal of Finance 48, 1565-1593.

Huang, R.D., Stoll, H.R., 1997. The components of the bid-ask spread: A general approach. Review of Financial Studies 10, 995-1034.

Ito, T., Hashimoto, Y., 2006. Intraday seasonality in activities of the foreign exchange markets: Evidence from the Electronic Broking System. Journal of Japanese International Economics 20, 637-664.

King, M., Osler, C., Rime, D., 2012. Foreign exchange market structure. In: James, J., Marsh, I., Sarno, L. (Eds), Handbook of Exchange Rates. Wiley and Sons, New York and London.

Leach, J.C., Madhavan, A.N., 1992. Intertemporal price discovery by market makers: Active versus passive learning. Journal of Financial Intermediation 2, 207-235.

Lyons, R.K., 1995. Tests of microstructural hypotheses in the foreign exchange market. Journal of Financial Economics 39, 321-351.

Lyons, R.K., 2001. The microstructure approach to exchange rates. MIT Press, Cambridge, MA, U.S.A.

Madhavan, A.N., Smidt, S., 1991. A Bayesian model of intraday specialist pricing. Journal of Financial Economics 30, 99-134.

Madhavan, A.N., Smidt, S., 1993. An analysis of changes in specialist inventories and quotations. Journal of Finance 48, 1595-1628.

Marsh, I., O'Rourke, C., 2005. Customer order flow and exchange rate movements: Is there really information content? Presented at the Norges Bank/Norwegian School of Management Conference on Equity and Currency Market Microstructure, September 2005.

Mende, A., 2006. 09/11 on the USD/EUR exchange market. Applied Financial Economics 16, 213-222.

Mende, A., Menkhoff, L., 2006. Profits and speculation in intra-day foreign exchange trading. Journal of Financial Markets 9, 223–245.

Menkhoff, L., Schmeling, M., 2008. Local information in foreign exchange markets. Journal of International Money and Finance 27, 1383-1406.

Menkhoff, L., Osler, C., Schmeling, M., 2010. Limit-order submission strategies under asymmetric information. Journal of Banking and Finance 24, 2665-2677.

Naik, N.Y., Neuberger, A., Viswanathan, S., 1999. Trade disclosure regulation in markets with negotiated trades. Review of Financial Studies 12, 873-900.

Osler, C., 2009. Foreign exchange microstructure: A survey of the empirical literature. In: Robert A. Meyers (Ed.), Encyclopedia of Complexity and System Science. Springer, New York.

Osler, C., Vandrovych, V., 2009. Hedge funds and the origins of private information in the foreign exchange market, presented at the Third Annual Microstructure Workshop, Emerging Markets Group, Cass Business School, London, May 1, 2009.

Payne, R., 2003. Informed trade in spot foreign exchange markets: An empirical investigation. Journal of International Economics 61, 307-329.

Phylaktis, K., Chen, L.., 2010. Asymmetric information, price discovery, and macroeconomic announcements in fx market: Do top trading banks know more? International Journal of Finance and Economics 15, 228-246.

Peterson, M.A., Sirri, E.R., 2003. Order preferencing and market quality on U.S. equity exchanges. Review of Financial Studies 16, 385-415.

Ramadorai, T., 2008. What determines transaction costs in foreign exchange markets. International Journal of Finance and Economics 13, 14-25.

Reiss, P.C., Werner, I.M., 1998. Does risk sharing motivate interdealer trading? Journal of Finance 53, 1657-1703.

Reiss, P.C., Werner, I.M., 2004. Anonymity, adverse selection, and the sorting of interdealer trades. Review of Financial Studies 18, 599-636.

Reitz, S., Schmidt, M., Taylor, M., 2009. Financial intermediation and the role of price discrimination in a two-tier market, presented at the Fifth Annual Central Bank Workshop on the Microstructure of Financial Markets, Zurich, Switzerland, October 9, 2009.

Rime, D., Sarno, L., Sojli, E., 2009. Exchange-rate forecasting, order flow, and macroeconomic information. Journal of International Economics 80, 72-88.

Theissen, E., 2003. Trader anonymity, price formation and liquidity. European Finance Review 7, 1-26.

Yao, J.M., 1998. Market making in the interbank foreign exchange market. Working paper S-98-3, Stern School of Business, New York University.

Table 1. Descriptive statistics, currency dealing at a small bank in Germany over the 87 trading days between July 11, 2001, and November 9, 2001.

A. The table shows the size and nature of euro-dollar trades.

	All transactions	Interbank	Customer		
			All	Financial	Corporate
Number of transactions	3,609	1,919	1,690	171	1,519
(percent)	(100)	(44)	(56)	(5)	(42)
Of which, forward	646	114	532	60	472
Value of trades (€ mil.)	4,335	2,726	1,609	405	1,204
(percent)	(100)	(61)	(39)	(9)	(28)
Of which, forward	999	87	912	226	686
Mean size (€ mil.)	1.20	1.42	0.95	2.37	0.79
Mean size, forwards (€ mil.)	1.55	0.76	1.71	3.77	1.45

B. The table shows the size distribution of euro-dollar spot and forward euro-dollar transactions in the sample.

	Financial-customer trades	Corporate-customer trades	Interbank trades
Number	171	1,492	1,872
Share			
Below € 0.1 million	15%	54%	7%
€ 0.1 – 0.5 million	26%	32%	9%
€ 0.5 – 1.0 million	14%	5%	7%
€ 1.0 – 20 million	44%	8%	77%
€ 20 million and above	1%	1%	0%

Table 2. Comparison of bank studied here with other banks

The table shows the euro-dollar trading activity of a bank in Germany over the 87 trading days between July 11, 2001, and November 9, 2001. To enable comparisons with related papers, most figures cover the spot trades of the bank in Germany. Values in parentheses refer to the data set including outright-forward transactions.

Study, dealer	Bank in Germany	B.I.S. (2002) per bank	Lyons (1995)	Yao (1998)	Bjønnes and Rime (2005) Four dealers, range	Bjønnes and Rime (2005) DEM/USD dealer	Bjønnes and Rime (2005) NOK/DEM dealer
Time period	**87 days in 2001[a]**	April 2001	5 days, 1992	25 days, 1995	5 days in 1998		
Transactions per day	**40 (51)**	---	267	181	58 - 198	198	58
Transaction value per day (in $ millions)	**39 (52)**	50 - 150	1,200	1,529	142 - 443	443	270
Value per transaction ($ millions)	**1.0**	---	4.5	8.4	1.6 - 4.6	2.2	4.6
Customer share of transaction value (%)	**23 (39)**	33	0	14	0 – 18	3	18
Average transaction size ($ millions)	**1.2**		3.8	9.3	1.5 – 3.7	1.8	3.7
Average price change between trades (pips)	**11**		3	5	5 - 12	5	12

[a] .

Table 3. Customer order flow and exchange rates

The table shows results from OLS regressions of the exchange-rate level on a constant, a linear trend, and cumulative order flow, along with associated ECM coefficients. If incoming order flow of type *i* is associated with a currency appreciation, the coefficient in the cointegration regression will be positive. Johansen tests with these three variables reject zero cointegrating relations and reject the existence of more than one cointegrating relation: regressions involving just one type of order flow are provided for comparison with earlier studies. The number of lags is calculated from the sample size (Newey-West automatic truncation lag selection). Order flow coefficients multiplied by 10^3. Significance at the 1, 5, and 10 percent levels is indicated by ‡, †, and *, respectively.

Dependent variable: Exchange rate level	**Standardized coefficients**		
Cointegrating relation			
Financial-customer order flow	0.107	0.150*	
Corporate-customer order flow	-0.370‡		-0.301‡
ECM for exchange rate return	-0.010‡	-0.051†	-0.120‡

Table 4. Descriptive statistics for main regression variables

The table shows the euro-dollar trading activity of a bank in Germany over the 87 trading days between July 11, 2001, and November 9, 2001. Price changes are measured in pips; quantity traded (Q) and inventories are measured in millions of euros. There are 2,859 observations.

	ΔP_t	ABS(ΔP_t)	Q_t	ABS(Q_t)=V_t	Inventory	|Inventory|	ΔInventory	|ΔInventory|
Mean	0.2	10.78	0.02	1.08	-23.8	24.0	-0.02	1.25
Median	0.0	6.00	0.04	0.35	-20.2	20.3	-0.04	0.44
Maximum	99.7	99.7	76.4	76.4	32.8	84.0	76.32	76.43
Minimum	-91.0	0.00	-76.3	0.01	-84.0	0.00	-76.43	0.00
Std. Dev.	17.3	13.6	3.5	3.33	15.6	15.2	3.64	3.41
Skewness	0.07	2.09	0.6	13.0	-0.19	0.32	-0.38	12.0
Kurtosis	7.43	8.94	206	234	2.27	1.93	177	209

Table 5. Huang and Stoll (1997) model

We estimate this model: $$\Delta P_t = \frac{S}{2}(D_t - D_{t-1}) + \lambda \frac{S}{2} D_{t-1} - \theta \frac{S}{2} \Delta I_t + e_t .$$

ΔP_{it} is the change in price between two successive customer trades measured in pips. D_t is +1 for buy-initiated trades and –1 for sell-initiated trades. I_t is the dealer's inventory, measured in EUR millions. These variables are interacted with dummy variables for trades with financial customers (*FC*) and trades with corporate customers (*CC*). They are also interacted with dummies for trade size: *Lg.* = $\{|Q_{jt}| \in [1,\infty)\}$; *Md.* = $\{|Q_{jt}| \in [0.5,1)\}$; *Sm.* = $\{|Q_{jt}| \in (0,0.5)\}$. The table shows the euro-dollar trading activity of a bank in Germany over the 87 trading days between July 11, 2001, and November 9, 2001. Estimation uses GMM and Newey-West standard errors. Significance at 1, 5 and 10 percent levels indicated by ‡, † and *, respectively. Constant term suppressed. Estimates of the baseline half-spread are highlighted in bold.

	Baseline regression		Robustness tests		
	Coefficient	**Std. error**	**Inventory reset daily**	**Interbank trades included**	**Spot trades only**
Half-spread, *S*/2					
S/2 x *FC* x *Sm.*	**10.76‡**	*2.30*	**10.54‡**	**7.93‡**	**7.66‡**
S/2 x *FC* x *Md.*	**5.35***	*2.41*	**5.35†**	**4.00***	**-5.46**
S/2 x *FC* x *Lg.*	**3.41***	*1.95*	**4.20†**	**4.93‡**	**2.09**
S/2 x *CC* x *Sm.*	**13.46‡**	*0.61*	**13.48‡**	**11.98‡**	**11.38‡**
S/2 x *CC* x *Md.*	**11.21‡**	*2.60*	**11.62‡**	**12.46‡**	**16.12‡**
S/2 x *CC* x *Lg.*	**2.11**	*1.54*	**3.80†**	**5.44‡**	**5.34†**
S/2 x *IB* x *Sm.+ Md.*				**-0.97**	
S/2 x *IB* x *Lg.*				**2.11‡**	
Adverse selection, λ					
FC x *Sm.*	0.39	*0.20*	0.32	0.45†	0.48
FC x *Md.*	0.33	*0.65*	0.46	0.49	1.74*
FC x *Lg.*	0.19	*0.74*	0.27	0.65*	-1.14
CC x *Sm.*	0.03	*0.03*	0.06†	0.12‡	0.20‡
CC x *Md.*	0.35*	*0.19*	0.39†	0.35†	0.69‡
CC x *Lg.*	0.51	*0.81*	0.51	0.34	0.30
IB x *Sm.+ Md.*				0.03	
IB x *Lg.*				0.58†	
Inventory, θ					
FC x *Sm.*	0.10	*0.17*	0.04	0.02	0.21
FC x *Md.*	-1.00	*0.71*	-0.51	-0.65	0.82
FC x *Lg.*	0.01	*0.06*	0.00	-0.01	-0.21
CC x *Sm.*	-0.05	*0.04*	-0.08*	-0.05	0.01
CC x *Md.*	0.08	*0.29*	0.08	0.06	0.05
CC x *Lg.*	0.01	*0.05*	-0.01	-0.02	0.07
IB x *Sm +Md.*				0.70	
IB x *Lg.*				-0.06	
Adjusted R^2	0.34		0.33	0.25	0.34
Observations	1,644		1,651	2,857	1,131

Table 6. Madhavan and Smidt (1991) model

We estimate this equation: $\Delta P_t = \alpha + \beta_1 D_t + \beta_2 D_{t-1} + \gamma_1 I_t + \gamma_2 I_{t-1} + \delta Q_{jt} + \varepsilon_t$.

The dependent variable is the change in price between two successive incoming trades, measured in pips. D_t is an indicator variable picking up the direction of the deal, positive for purchases (at the ask) and negative for sales (at the bid); I_t is the dealer's inventory at time t, and Q_{jt} is order flow measured in millions of euros. These variables are interacted with dummy variables for financial customers (*FC*) and corporate customers (*CC*). They are also interacted with dummies for trade size: $Lg. = \{Q_{jt} \in [1,\infty)\}$; $Md. = \{Q_{jt} \in [0.5,1)\}$; $Sm. = \{Q_{jt} \in (0,0.5)\}$. The table shows the euro-dollar trading activity of a bank in Germany over the 87 trading days between July 11, 2001, and November 9, 2001. Estimation uses GMM and Newey-West correction. Significance at 1, 5 and 10 percent levels indicated by ‡, † and *, respectively. Estimates of the (negative of the) baseline half-spread are highlighted in bold.

	Baseline regression		**Robustness tests**		
	Coefficient	**Std. error**	**Inventory reset daily**	**Incl. interbank trades**	**Spot trades only**
Constant	0.14	0.49	0.03	0.028	0.33
Direction, β					
FC x Sm x D_t.	13.58‡	*2.68*	10.46‡	6.94‡	6.60‡
FC x Sm x D_{t-1}	**-8.93‡**	*2.82*	**-6.62‡**	**-4.05‡**	**-3.44**
FC x Md. x D_t	3.18	*2.58*	3.92	2.98	1.18
FC x Md. x D_{t-1}	**-3.14**	*3.08*	**-2.97**	**-1.82**	**-3.18**
FC x Lg. x D_t	3.87	*1.94*	2.40	5.20‡	1.97
FC x Lg. x D_{t-1}	**-2.58**	*1.97*	**-3.62***	**-1.62**	**-1.08**
CC x Sm. x D_t	13.30‡	*0.64*	13.33‡	11.87‡	11.26‡
CC x Sm. x D_{t-1}	**-13.24‡**	*0.62*	**-12.68‡**	**-10.43‡**	**-9.08‡**
CC x Md. x D_t	10.82‡	*1.49*	12.62‡	12.34‡	13.55‡
CC x Md. x D_{t-1}	**-5.73‡**	*2.15*	**-7.20‡**	**-7.97‡**	**-5.29‡**
CC x Lg. x D_t	1.43	*1.51*	4.68†	5.80‡	6.56‡
CC x Lg. x D_{t-1}	**0.59**	*1.81*	**-2.06**	**-3.52‡**	**-4.25**
IB x Md.+Sm.x D_t				-0.96	
IB x Md.+Sm.x D_{t-1}				**-0.01**	
IB x Lg. x D_t				2.22‡	
IB x Lg. x D_{t-1}				**-0.88***	
Inventory, γ					
FC x I_{it}	-0.58	*0.50*	-0.46	-0.32	0.28
FC x I_{it-1}	0.65	*0.51*	0.37	0.30	-0.28
CC x I_{it}	0.47	*0.42*	1.05†	0.65	-0.13
CC x I_{it-1}	-0.51	*0.42*	-1.09‡	-0.64	0.14
IB x I_{it}				0.01	
IB x I_{it-1}				0.00	
Trade size, γ					
FC x Q_{jt}	-0.60	*0.52*	0.12	-0.41	0.10
CC x Q_{jt}	0.52	*0.43*	0.77*	0.53	-0.13
IB x Q_{jt}				-0.18	
Adjusted R^2	0.32		0.33	0.33	0.35
Observations	1,644		1,651	2,857	1,131

Table 7. Glosten and Harris (1988) model

We estimate this model: $\Delta P_t = c_0(D_t - D_{t-1}) + c_1(D_t V_t - D_{t-1}V_{t-1}) + zD_t V_t + \varepsilon_t$.

The dependent variable is the change in price between two successive incoming trades, measured in pips. D_t is an indicator variable picking up the direction of the deal, positive for purchases (at the ask) and negative for sales (at the bid); V_{jt} is the absolute value of order flow measured in millions of euros. These variables are interacted with dummy variables for financial customers (*FC*) and corporate customers (*CC*) and other banks (*IB*). The table shows the euro-dollar trading activity of a bank in Germany over the 87 trading days between July 11, 2001, and November 9, 2001. Estimation uses GMM with Newey-West standard errors. Significance at 1, 5 and 10 percent levels indicated by ‡, † and *, respectively.

	Baseline regression		**Robustness tests**	
	Coefficient	**Std. error**	**Interbank trades included**	**Spot trades only**
Baseline spread, c_0				
$(CC_t*D_t-CC_{t-1}*D_{t-1})$	10.79‡	0.54	10.77‡	7.43‡
$(FC_t*D_t-FC_{t-1}*D_{t-1})$	5.12‡	1.17	4.92‡	5.64‡
$(IB_t*D_t-IB_{t-1}*D_{t-1})$			0.39	
Volume, c_1				
$(CC_t*V_{jt}*D_t-CC_{t-1}*V_{jt-1}*D_{t-1})$	-0.32‡	0.12	-0.29‡	-0.71†
$(FC_t*V_{jt}*D_t-FC_{t-1}*V_{jt-1}*D_{t-1})$	-0.46‡	0.13	-0.33‡	-0.15*
$(IB_t*V_{jt}*D_t-IB_{t-1}*V_{jt-1}*D_{t-1})$			0.23	
Adverse selection, z				
$CC*D_t*V_{jt}$	-0.18	0.16	-0.22	0.33
$FC*D_t*V_{jt}$	0.24	0.23	0.15	0.33
$IB*D_t*V_{jt}$			0.19	
Adjusted R^2	0.33		0.24	0.06
Observations	1,645		2,853	1,129

Table 8. Probit regression of choice of aggressive interbank trades

We estimate this model: $Prob(Trade_t{=}IB^{out}) = P(FC_{t\text{-}1}, CC_{t\text{-}1}, SDFC_{t\text{-}1}, SDCC_{t\text{-}1}, 10mio_{t\text{-}1}, |I_{it}|, I_{it}^2, |Q_{jt}|)$, as a probit regression. Incoming (aggressive) interbank trades are coded 0 (1). $FC_{t\text{-}1}$ is a dummy coded 1 if the previous counterparty was a financial customer, $CC_{t\text{-}1}$ and $IB_{t\text{-}1}$ are defined similarly for corporate customers and other banks. *SDFC* (*SDCC*) is a dummy coded 1 if the current dealer trade has the same direction as the previous financial-customer (corporate-customer) trade. $10\ mio_{t\text{-}1}$ is a dummy coded 1 if the size of the previous transaction was €10 million or larger. *I* represents inventories, in millions of euros; $|Q_{jt}|$ represents the absolute size of the current deal, measured in EUR millions; Significance at the 1, 5 and 10 percent levels indicated by ‡, † and *, respectively.

	Baseline regressions		**Robustness tests**		
	No direction	**With direction**	**Inventory reset daily**	**Interbank trades included**	**Spot trades only**
$FC_{t\text{-}1}$	-0.115	-0.441‡	-0.441‡	-0.588‡	-0.408†
$CC_{t\text{-}1}$	-0.537‡	-0.754‡	-0.748‡	-0.901‡	-0.621‡
Samedirection FC		1.221‡	1.219‡	1.221‡	1.108‡
Same direction CC		0.928‡	0.930‡	0.928‡	1.065‡
$10\ mio_{t\text{-}1}$	0.668‡	0.736‡	0.719‡	0.740‡	0.450‡
$IB_{t\text{-}1}$				-0.223‡	
$\lvert I_{it}\rvert$	-5.28 E-3	-0.005	0.031‡	-4.4E-3	-5.03E-3
I_{it}^2	9.19 E-5	8.40E-5	-0.001‡	7.55E-5	9.76E-5
$\lvert Q_{jt}\rvert$	0.024‡	0.025‡	0.029‡	0.024‡	0.014
Constant	-0.740‡	-0.741‡	-0.879‡	-0.600‡	-0.938‡
McFadden's R^2	0.038	0.069	0.072	0.072	0.084
Observations	3,534	3,534	3,534	3,534	2,894

Figure 1: Intraday distribution of trades
The charts below show the average number of trades during each five-minute period of the trading day. Data come from a small bank in Germany and include all USD/EUR spot and forward trades during four months in 2001.

Figure 1A: Financial-customer trades

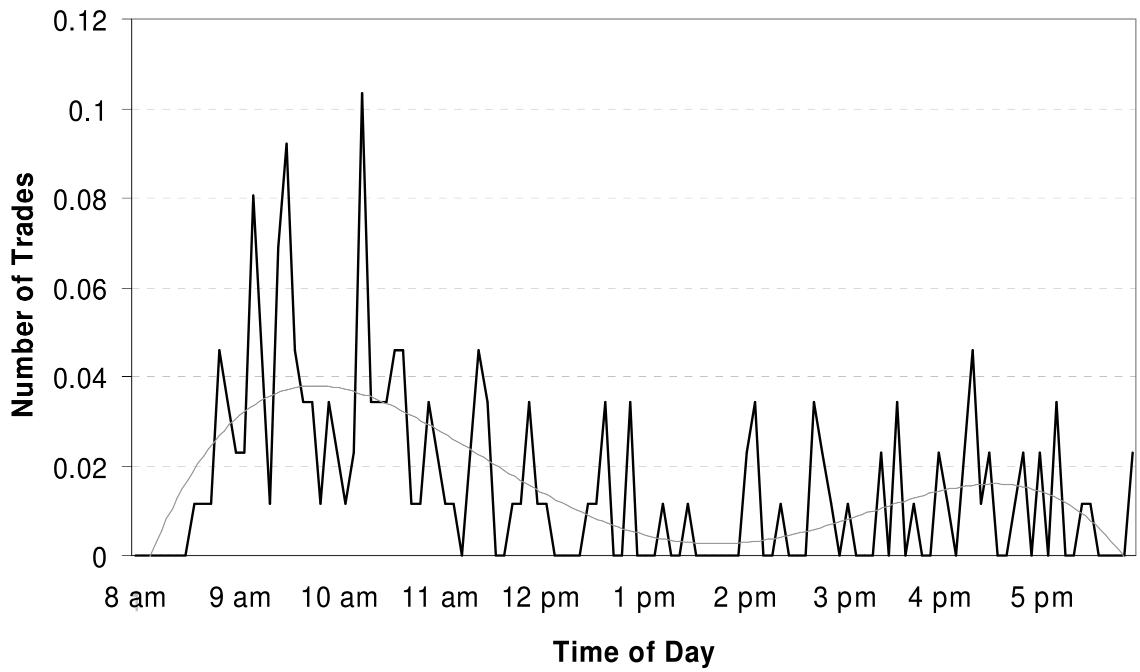

Figure 1B: Corporate-customer trades