PRICE DISCOVERY IN CURRENCY MARKETS

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Abstract

This paper makes three contributions to our understanding of the price discovery process in currency markets. First, it provides evidence that this process cannot be the familiar one based on adverse selection and customer spreads, since such spreads are inversely related to a deal's likely information content. Second, the paper suggests three potential sources for the pattern of customer spreads, two of which are based on asymmetric information. Third, the paper suggests an alternative price discovery process for currencies, centered on inventory management strategies in the interdealer market, and provides preliminary evidence for that process. [*JEL F31, G14, G15. Keywords: Bid-ask spreads, foreign exchange, asymmetric information, microstructure, price discovery, interdealer, inventory, market order, limit order]*

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This paper investigates the price discovery process in the foreign exchange (FX) market. Though spot and forward trading averages over $800 billion per day (B.I.S. 2004) ─ over ten times daily trading on all NYSE stocks ─ the overall contours of price discovery in FX remain murky. Yet understanding exactly how information becomes embedded in exchange rates is central to current efforts to understand exchange-rate dynamics (see Evans and Lyons 2002, 2004, *inter alia*).

Our paper makes three contributions. First, it provides evidence that price discovery in FX cannot follow the familiar process based on adverse selection and customer spreads, since such spreads are inversely related to a deal's likely information content. Second, it suggests three potential sources for the pattern of customer spreads, two of which are based on asymmetric information. Finally, it proposes a price discovery process centered on dealers' inventory management strategies in the interbank market and provides evidence for that process. This introduction discusses each contribution in turn.

1. Does adverse selection matter in FX? The adverse-selection-based price discovery process, articulated in Glosten and Milgrom (1985) and Easley and O'Hara (1987), *inter alia*, asserts that dealers build into their price quotes the potential information revealed by a given customer transaction. When adverse selection dominates price discovery, spreads rise with the likelihood that a given customer has private information. This implies that spreads vary positively with trade size, since larger trades are more likely to carry information (Glosten and Milgrom 1985, Easley and O'Hara 1987, Glosten 1989). It also implies that spreads should be wider for relatively informed customers if dealing is not anonymous.

Though the original adverse-selection models were inspired by equity markets, adverse selection has been assumed to dominate price discovery in FX since Lyons (1995), which shows that deal size and spread were positively related for a particular interbank dealer during a week in 1992. Most subsequent research has instead concluded that currency spreads bear little or no relation to deal size (e.g., Yao 1998, Bjønnes and Rime 2005). Nonetheless, Bjønnes and Rime (2005) suggests that this is not necessarily inconsistent with adverse selection: spreads could be unrelated to deal size under adverse selection if it is only the direction of a deal that carries information, and the paper presents evidence consistent with this alternative hypothesis.

Most FX microstructure papers continue to draw on adverse selection as their primary interpretive framework. Marsh and O'Rourke (2005), for example, estimates Easley, Kiefer, and O'Hara's (1996, 1997) adverse-selection-based measure of private information on daily FX customer data. Similarly, Payne (2003) estimates a VAR decomposition of interdealer trades and quotes and interprets the results, following Hasbrouck (1991), through the lense of adverse selection. Indeed, it is common in this literature to assume that "price impact" is the same as "information content" (e.g., Lyons 2001, Luo 2002, Marsh and O'Rourke 2005) as implied by adverse selection.

Our evidence indicates that adverse selection may have limited practical relevance in the customer FX market. We show that customer spreads are widest for the deals least likely to carry information. More specifically, customer spreads are inversely related to deal size, and are narrower for the customers that dealers consider most informed. These reportedly informed customers are financial firms, meaning asset managers such as hedge funds and mutual funds; the other broad category of customers is commercial customers, meaning firms that import or export.[1] The resulting cross-sectional variation in customer spreads is substantial: baseline spreads in the euro-dollar market range from about four pips (or equivalently tics) on large financial deals to 13 pips on small commercial deals (in euro-dollar one pip is approximately one basis point).

2. What does drive currency spreads? Microstructure theory generally divides spreads into three or four components (e.g., Huang and Stoll 1997, Harris 2003): adverse selection, inventory risk, operating costs, and (occasionally) monopoly power. Researchers in currency microstructure generally assume the tripartite division (e.g., Rime 2003), since the intense competition among FX dealers rules out pure monopoly power. The three remaining components cannot fully explain the pattern of currency spreads, however. Adverse selection predicts the opposite pattern for both size- and customer-based variation, as noted above. Inventory risk also predicts the opposite size-based variation and it predicts zero customer-based variation. The last component, operating costs, cannot explain the customer-based variation in spreads, though it can explain the negative relation between deal size and customer spreads if some costs are fixed.

To explain why FX spreads are larger for commercial than financial customers we suggest that asymmetric information may operate through two important channels distinct from adverse selection. The first channel involves market power. As suggested in Green *et al.* (2004), dealers may quote the widest spreads when their market power is greatest, and market power in quote-driven markets depends on knowledge of current market conditions. In FX, commercial customers typically know far less about market conditions than financial customers so they might be expected to pay wider spreads, as they do.

The second channel through which asymmetric information might affect customer spreads in FX involves strategic dealing. Building on abundant evidence that customer order flow carries information (e.g., Evans and Lyons 2004, Daníelsson *et al.* 2002), we argue that rational FX dealers might strategically vary spreads across customers to gain information which they can then exploit in future trades. In standard adverse-selection models, by contrast, dealers passively accept the information content of order flow. We suggest that FX dealers effectively subsidize spreads on the transactions most likely to carry useful information, specifically large deals and the deals of financial customers. We also provide evidence consistent with the

[1] Our definition of a "customer" here follows the market definition as any counterparty that is not another dealer.

hypothesis that financial deals are indeed relatively informative and that large deals carry more information than small ones.

The idea that dealers strategically vary spreads to gather information was originally explored in Leach and Madhavan (1992, 1993), which show that dealers without access to an interdealer market might rationally vary customer spreads across time. However, our hypothesis concerns cross-section variation in a two-tier market, rather than time-series variation in a one-tier market. Naik *et al.* (1997), which also examines cross-sectional variation of spreads in a two-tier market, concludes that customer spreads will be narrower for trades with information, consistent with the pattern in FX. However, Naik *et al.* concludes that customer spreads will vary positively with deal size, contrary to the pattern in FX. Our strategic dealing hypothesis includes the possibility that dealers might narrow spreads for trades without any current information content, in order to enhance their order flow's future information content.

3. Price discovery in FX: An alternative interpretation. The paper's last contribution is to suggest a process through which information may become embedded in exchange rates. In contrast to adverse selection theory, in which the key mechanism involves spreads in the customer market, the mechanism at the core of our suggested process involves dealers' inventory management practices in the interdealer market.

The mechanism is this: After trading with an informed customer, a dealer's information and inventories provide strong incentives to place a market order in the interdealer market. An informed-customer buy would thus tend to trigger market buys in the interdealer market and thus higher interdealer exchange rates. In this way the information brought to the market by informed customers will generate appropriate changes in interdealer prices. By contrast, after trading with an uninformed customer a dealer has only weak incentives to place market orders. Thus dealer transactions with uninformed customers may be more likely to generate liquidity in the interdealer market than to drive exchange-rate returns.[2]

This view of dealer behavior differs in one critical way from that of the familiar "portfolio shifts" model of the FX market (Evans and Lyons 2002). In that model, there are three rounds of trading. In the first, dealers absorb inventory from end-users; in the second round dealers trade with each other; in the third round dealers sell their inventory to end-users. In that framework prices only adjust to reflect information during round three. We suggest, by contrast, tbat prices begin to reflect information during interbank trading.

Nonetheless, our view of dealer behavior predicts a number of the key stylized facts in FX microstructure. First, it predicts the positive correlation between interdealer order flow and exchange-rate returns documented in Lyons (1995), Payne (2003), Evans (2002), Evans and Lyons (2002), Hau, Killeen and Moore (2002), and Daníelsson *et al.* (2002), *inter alia*. If the dealer is correctly responding to fundamental information it also predicts that the relationship should be substantially permanent, consistent with evidence pre-

[2] We show in Section IV that a similar analysis applies if the dealer uses direct trades to unwind his inventory.

sented in Killeen *et al.* (2006), Bjønnes *et al.* (2005), and Section III of this paper. In addition, our view of dealer behavior predicts the positive relationship between exchange rates and financial order flow documented in Evans and Lyons (2004), Bjønnes *et al.* (2005), Marsh and O'Rourke (2005), and this paper. Finally, our view predicts that the relationship between exchange rates and financial order flow should be substantially permanent, as documented in Lyons (2001), Bjønnes and Rime (2005), and this paper.

We test two additional implications of our interpretation of price discovery in FX. First, dealers should be more likely to make outgoing transactions after financial transactions than after commercial transactions. Second, dealers should be more likely to make outgoing transactions after large incoming transactions than after small ones. Our evidence provides encouraging support for both implications.

Data: 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 most other tic-by-tic transactions datasets in FX: (i) they distinguish between financial and commercial transactions, and (ii) they cover a longer time period. Though the bank that provided our data is relatively small, there are a number of reasons why our conclusions should generalize to the overall currency market. First, the intense competition in major currency markets means that any bank's pricing practices should accurately represent practices at all banks. Second, market convention is the dominant determinant of spreads (Cheung and Chinn 2001). Third, traders from large banks tell us that their pricing policies conform to those described here (supporting statements from market participants are provided in Appendix A). Finally, our small bank behaves similarly to large banks in many other dimensions (as documented in Appendix B).

Outline: The rest of the paper has four sections and a conclusion. Section I describes our data. Section II shows that customer spreads in FX are narrowest for the deals most likely to carry information. Section III discusses how operating costs, market power, and strategic dealing can explain this pattern. This section also provides evidence that the information content of currency order flow varies in a manner consistent with the market power and strategic dealing hypotheses. Section IV presents our interpretation of the price discovery process in currency markets, along with supporting evidence. Section V concludes.

I. DATA

Our data comprise the complete USD/EUR transaction record of a bank in Germany over the 87 trading days from 11 July 2001 to 9 November 2001. Though the data technically refer to the overall bank, they are an accurate reflection of a single dealer's behavior because only one dealer was responsible for the bank's USD/EUR trading. For each transaction we have the following information: (1) the date and time;[3] (2) the direction (customer buys or sells); (3) the quantity; (4) the transaction price; (5) the type of counterparty –

[3] The time stamp indicates the time of data entry and not the moment of trade execution, which will differ slightly. Nevertheless, there is no allocation problem because all trades are entered in a strict chronological order.

dealing bank, financial customer, commercial customer, preferred customer; (6) the initiator; and (7) the forward points if applicable. Table 1 provides basic descriptive statistics.[4]

We include outright forward trades, adjusted to a spot-comparable basis by the forward points, as recommended by Lyons (2001). The bank's inventory position is inferred by cumulating successive transactions.[5] Following Lyons (1995), we set the daily starting position at zero. This should not introduce significant distortions since our dealer keeps his inventory quite close to zero, as shown Figure 1. The dealer's average inventory position is EUR 3.4 million during the trading day and only EUR 1.0 million at the end of the day.

Table 1. Descriptive statistics, currency dealing at a small bank in Germany

The table shows the complete USD/EUR trading activity of a small bank in Germany, except preferred customer deals, over the 87 trading days between July 11th, 2001 and November 9th, 2001.

A. All Business

	All Transactions	**Interbank**	**Customer**		
			All	**Financial**	**Commercial**
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 deals (€ 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

A preliminary comparison of our dealer with the large dealers described in the literature is provided in Table 2. Table 3 provides information on the size distribution of our dealer's transactions. The small size of our dealer is reflected in his total daily trading value, average transactions per day, average inventory position, and mean absolute price change between transactions.[6] Our dealer is comparable in size to a NOK/DEM dealer at the large dealing bank examined in Bjønnes and Rime (2004). Our bank is probably a

[4] We exclude trades with "preferred customers", typically commercial customers with multi-dimensional relationships with the bank, because these customers' spreads may reflect cross-selling arrangements and because their trades are typically very small (average size EUR 0.18 million). We also exclude a few trades with tiny volumes (less than EUR 1,000) or with apparent typographical errors.

[5] Though our dependent variable is sometimes restricted to a subset of deals, inventory calculations are based on all trades in all cases.

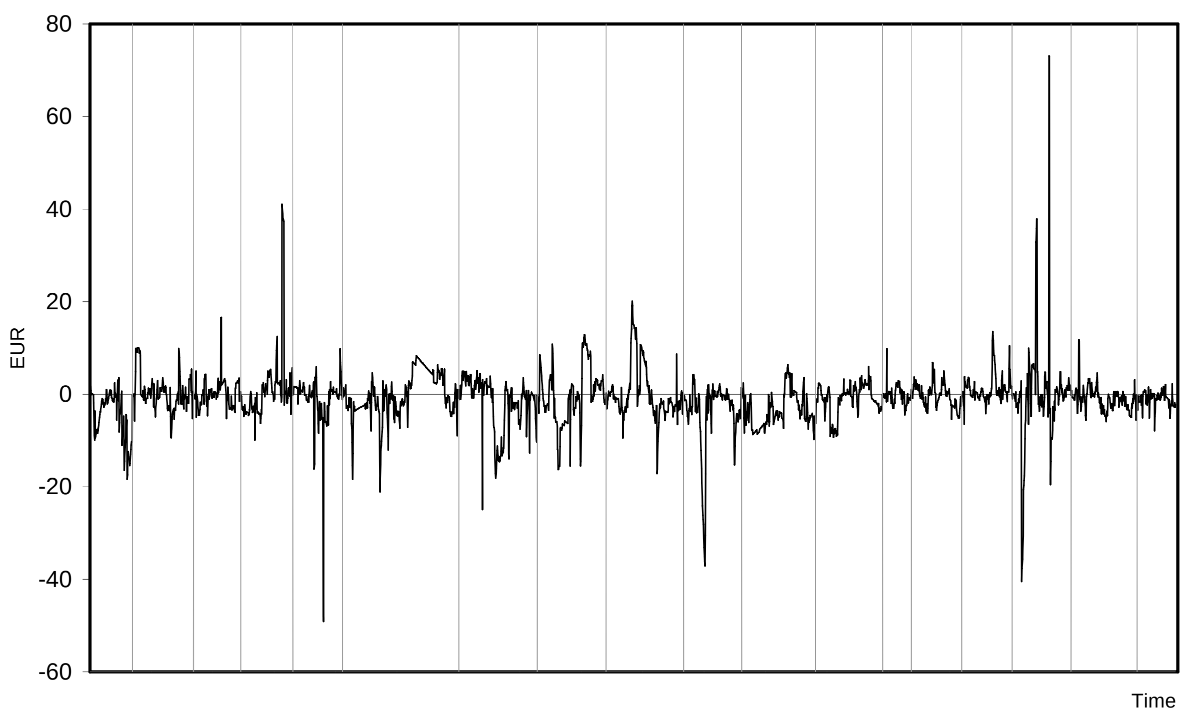
[6] The large mean absolute change in transaction price between successive deals, 10.7 pips, presumably reflects the relative infrequency of transactions at our bank as well as the high proportion of small commercial customer deals, which tend to have wide spreads (as we document below).

reasonably good representative of the average currency dealing bank because small dealing banks are far more common than large ones (B.I.S., 2002). Nonetheless, big banks dominate currency dealing.

Despite the small size of our bank, our main qualitative conclusions should generalize to the entire foreign exchange market for at least four reasons. First, the FX market is extremely competitive. Hundreds of banks deal in the major currency pairs and even the largest dealer's market share is only on the order of 10 percent. In such a market, the behavior of any (successful) dealer should accurately represent the behavior of all (successful) dealers. Second, evidence shows that market convention is the primary determinant of currency spreads (Cheung and Chinn 2001). Third, market participants consistently confirm that the pattern we identify is correct (see Appendix A). Finally, our small bank's behavior is broadly consistent in other dimensions with the behavior of large banks in recent years.

Figure 1. Overall inventory position (EUR millions)

Plot shows the evolution of a currency dealer's inventory position in EUR millions over the period July 11, 2001 through November 9, 2001. Data come from a small bank in Germany and include all USD/EUR spot and forward trades. The horizontal axis is transaction-time. Vertical lines indicate the end of each calendar week.



Appendix B provides an explicit, detailed comparison of our bank's pricing and inventory management practices with those of large banks analyzed in earlier studies. This statistical analysis suggests that the following statements about larger dealers are equally true for our dealer:

- The baseline spread for interbank deals is on the order of two pips
- The baseline spread for customer deals is a few times larger than the spread on interbank deals
- Existing inventories are not statistically related to quoted prices
- The dealer's central tendency for inventory is zero and inventories revert by the end of the trading day
- The dealer tends to bring inventory back to zero in a matter of minutes, a speed that is comparable with that of futures traders and lightning fast relative to equity and bond market makers.

These parallels and the arguments above suggest it is reasonable to generalize from this bank to the market.

Table 2. Comparison of small bank studied here with larger banks studied in other papers.

The table shows the complete USD/EUR trading activity of a small bank in Germany, except preferred customer trades, over the 87 trading days between July 11th, 2001 and November 9th, 2001. For comparison purposes we focus on statistics based exclusively on the small bank's spot deals.

	Small Bank in Germany	B.I.S. (2002) per Bank	Lyons (1995)	Yao (1998)	Bjønnes and Rime (2004)		
					Four Dealers, Range	DEM/USD Dealer	NOK/DEM Dealer
	87 Trading Days in 2001[a]	April 2001	5 Trading Days in 1992	25 Trading Days in 1995	5 Trading 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 ($ mil.)	**1.0**	---	4.5	8.4	1.6 - 4.6	2.2	4.6
Customer Share of Transaction value (in percent)	**23 (39)**	33	0	14	0 – 18	3	18
Average Inventory Level (in € or $ millions)	**3.4**		11.3	11.0	1.3 – 8.6	4.2	8.6
Average Transaction Size (in € or $ millions)	**1.2**		3.8	9.3	1.5 – 3.7	1.8	3.7
Average Price Change Btwn. Transactions (in pips)	**11**		3	5	5 - 12	5	12

[a] Values in parentheses refer to the data set including outright-forward transactions.

Table 3. Size distribution of individual deals

The table shows the size distribution of all USD/EUR spot and forward transactions, except those for preferred customers, at a small bank in Germany over the period July 11, 2001 through November 9, 2001.

	Interbank Deals	Financial Customer Deals	Commercial Customer Deals
Number	1,872	171	1,492
Share (%)			
1 below € 0.1 million	7	15	54
2 € 0.1 – 0.5 million	9	26	32
3 € 0.5 – 1.0 million	7	14	5
4 € 1.0 – 20 million	77	44	8
5 € 20 million and above	0	1	1

II. The Cross-Sectional Pattern of Currency Spreads

This section shows that currency spreads are wider for small deals than for large deals and that they are wider for commercial customers than for financial customers. Together these results imply that currency spreads are widest when customers are least likely to be informed, a pattern that is not predicted by adverse-selection theory. We begin the section by presenting the Madhavan-Smidt model (1991) and then use that model to examine the influence of deal size and customer type. We close the section by showing that our conclusions are sustained using the alternative model of Huang and Stoll (1997).

A. The Madhavan-Smidt Model

The Madhavan-Smidt model (1991), which is standard in transactions-based studies of currency spreads (e.g., Lyons 1995; Bjønnes and Rime 2005), assumes a representative dealer in a competitive market whose counterparty has private information about the asset's fundamental value. Agents are fully rational and there is a detailed information setting. Agent j calls dealer i requesting a quote on amount Q_{jt}, which is determined as $Q_{jt} = \xi(\mu_{jt} - P_{it}) + X_{jt}$. The term μ_{jt} represents agent j's expectation of the asset's true value, conditional on a noisy private signal of the asset's true value and on a noisy public signal. X_{jt} represents agent j's liquidity demand. Note that demand increases with the gap between the true value and the quoted price; this underlies the positive predicted relationship between deal size and spread.

Dealer i's regret-free price, P_{it}, is determined as $P_{it} = \mu_{it} + \zeta(I_{it} - I_i^*) + \chi D_t$. Here, μ_{jt} is dealer i's expectation of the asset's true value, conditional on the same noisy public signal; I_{it} is dealer i's inventory at the beginning of period t; I^*_i is his desired inventory; and D_t is the direction of trade [$D_t = 1$ (-1) if agent j is a buyer (seller)]. The model assumes that dealers shade prices to manage existing inventories (e.g., dealers lower prices in response to high inventory), which implies $\zeta < 0$. After solving for conditional expectations and taking first differences, one arrives at the following expression for the price change between incoming transactions, $\Delta P_{it} = P_{it} - P_{it-1}$:

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

Much of our discussion will focus on β_2, the coefficient on lagged direction, which according to the model is the negative of the "baseline" half-spread, meaning the spread that would apply before adjustment for deal size or existing inventories. The model also implies that $\beta_1 > |\beta_2| > 0 > \beta_2$. If the dealer shades prices in response to inventories then $\gamma_2 > 0 > \gamma_1$. Since large deals may reflect a big gap between the asset's true value and the dealer's quote, spreads should rise with deal size and the coefficient on deal size, δ, should be positive. In reality, however, a positive coefficient on deal size could also capture an inventory effect noted in Ho and Stoll (1981): larger deals leave market makers with higher inventory and thus greater inventory risk, so larger deals should carry wider spreads. Adverse selection and this inventory effect, which we will refer to as a "prospective" inventory effect, are observationally equivalent here.

We follow standard practice and estimate the model using generalized method of moments (GMM) with Newey-West correction for heteroskedasticity and autocorrelation (e.g., Yao 1998; Bjønnes and Rime 2005). Since the model operates on transaction time and concerns transactions in which the dealer sets the price, our dependent variable is the sequence of prices on incoming transactions. We exclude the few transactions over \$25 million because such deals essentially represent a distinct market: customers hire dealers to manage such deals by breaking them up into smaller interbank transactions.[7] Since our focus is the customer market we exclude interbank transactions for our baseline regressions. This also seems appropriate because interbank and customer trades may not strictly be comparable: the interbank market is dominated by order-driven trading through electronic brokers, while customer trading is carried out in a quote-driven market.

We include three robustness tests for all our main results. First, we rerun the regressions excluding inventories, since existing inventories appear to have no influence on spreads. Second, we rerun the regressions using only spot transactions. Forward transactions account for 20 percent of all trades, so their inclusion could impede direct comparisons with earlier papers, which focus exclusively on spot trades. Finally, we also rerun the regressions including interdealer transactions. This provides comparability with Bjønnes and Rime (2001), where customer transactions (as a single category) and interbank transactions are included in the main regressions.[8] Our results consistently prove robust.

[7] Fewer than ten of the customer deals in our sample exceeded \$25 million.
[8] Since the interbank market in euros is largely order driven while the customer market is quote driven, it may not be meaningful to compare coefficients on the interbank and customer dummies. We provide these regressions primarily to provide results that are comparable with those in the literature.

B. Bilateral Relationships

In this subsection we derive some stylized facts about the average relationship between deal size and spreads, and about the average relationship between customer type and spreads. The next subsection analyzes the simultaneous variation of spreads across size and customer type.

Deal Size: Market participants tell us that they informally divide normal-sized customer transactions into three categories: regular deals, which vary from €1 million to about €25 million; modest deals; and tiny deals. Though the line between the latter two categories is ambiguous, their treatment can vary substantially: tiny deals are often spread by formula rather than by dealers' discretion, and three percent is not considered unreasonable. For estimation purposes we distinguish the following size ranges: Large deals: $\{|Q_{jt}| \in [€1 \text{ million}, € 25 \text{ million})\}$; medium deals: $\{|Q_{jt}| \in [€0.5 \text{ million}, €1 \text{ million})\}$; and small deals: $\{|Q_{jt}| \in (€0, € 0.5 \text{ million})\}$. To examine the bilateral relationship between deal size and spreads we interact the five spread determinants of the Madhavan-Smidt (1991) model with dummies for large (*LG*), medium (*MD*), and small deals (*SM*).

The results indicate that baseline half-spreads on large, medium, and small deals average 1.6 pips, 4.5 pips, and 11.5 pips, respectively (Table 4). This appears to be inconsistent with adverse selection. The consistent insignificance of the coefficients on inventory indicates that the level of existing inventory does not influence prices. The consistent insignificance of the coefficient on deal size indicates that there is no residual linear variation of spreads according to deal size.

The conclusion that deal size and FX spreads are negatively related differs from the results of earlier studies. The earliest study of FX transaction data found a positive relationship between deal size and interdealer spreads (Lyons 1995), and subsequent studies find little or no relationship (Yao 1998, Bjønnes and Rime 2005). Nonetheless, our result is statistically and economically strong and it is sustained across three robustness tests. It is also consistent with the negative relationship between deal size and spreads observed in other quote-driven markets. Such a relationship characterizes the U.S. municipal bond market, where muni spreads average 0.10 percent for on large deals and 2.23 percent for small deals (Harris and Piwowar 2004). A negative relationship has also been documented in the London Stock Exchange (Hansch *et al.* 1999), where average quoted spreads range from 165 basis points for the smallest stocks to 112 basis points for the largest stocks (similar results are provided in Bernhardt *et al.* 2004).[9] By contrast, spreads and transaction size do appear to be positively related in order-driven stock markets, as predicted

[9] We note in passing the relatively tiny size of FX spreads compared with those in these other markets. Hansch et al. (1999) shows that spreads on the London Stock Exchange are negatively related to the fraction of total trading carried out in the interdealer market. They comment, "This suggests that in stocks with a high degree of interdealer trading, market makers are able to share risk more easily and are willing to post tight quotes" (pp. 1821-22). Interdealer FX trading was most recently estimated at 53 percent of total FX trading volume (B.I.S. 2004). While this is substantially below its 64 percent share in 1995, it is still high by the standards of other markets. Reiss and Werner estimate, for example, that interdealer trading averages 25 percent of total trading on the London Stock Exchange.

by adverse selection (see, for example, Harris and Hasbrouck 1996; Bernhardt and Hughson 2002; Peterson and Sirri 2003).[10]

Table 4: Spread variation across deal size categories

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

The dependent variable is the change in price between two successive incoming deals 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_{it} 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 the three trade size categories, large trades (*LG*), medium trades (*MD*), and small trades (*SM*). Data include all incoming customer USD/EUR spot and forward deals of a small bank in Germany, except those with preferred customers, during the period July 11, 2001, through November 9, 2001. Estimation uses GMM and Newey-West correction. Significance at the 1, 5 and 10 percent levels indicated by ‡, † and *, respectively.

	Baseline Regression		Robustness Tests		
			No Inventories	Spot Trades Only	Interbank Trades Included
	Coefficient	***Std. Error***	**Coefficient**	**Coefficient**	**Coefficient**
Constant	0.378	0.31	0.461	1.194‡	-0.333
Direction					
$LG \times D_t$	3.726‡	*1.37*	4.839‡	0.789	4.404‡
$LG \times D_{t-1}$	-1.560†	*0.66*	-1.526†	-0.928	-1.358‡
$MD \times D_t$	17.455‡	*6.70*	17.548†	12.258	13.165†
$MD \times D_{t-1}$	-4.463‡	*1.55*	-4.424‡	-6.275‡	-3.739‡
$SM \times D_t$	12.250‡	*0.74*	12.245‡	10.275‡	11.367‡
$SM \times D_{t-1}$	-11.519‡	*0.59*	-11.557‡	-10.154‡	-9.903‡
Inventory					
$LG \times I_{it}$	0.436	*0.43*		-0.128	0.612†
$LG \times I_{it-1}$	-0.454	*0.44*		0.442	-0.688†
$MD \times I_{it}$	-2.098	*2.52*		-0.030	-2.142
$MD \times I_{it-1}$	1.856	*2.58*		-0.052	2.145
$SM \times I_{it}$	1.008*	*0.53*		-0.014	-0.200
$SM \times I_{it-1}$	-1.079†	*0.53*		-0.047	0.164
Deal Size					
$LG \times Q_{jt}$	0.158	0.47	-0.248	0.127	0.348
$MD \times Q_{jt}$	-13.163	9.59	-11.724	1.291	-9.980
$SM \times Q_{jt}$	4.968	3.45	3.807	7.841*	-2.329
Adjusted R^2	0.29		0.29	0.30	0.16
Observations	1,640		1,640	1,125	2,848

[10] The contrast between order-driven markets, where deal size and spreads seem to be positively related, and quote-driven markets, where they seem to be negatively related, certainly suggests that structural differences between markets affect the size-spread relationship. We defer further analysis of this interesting point to future work.

Customer Type: To examine the bilateral relationship between spreads and customer type we interact the key variables of the Madhavan-Smidt (1991) model with dummies for transactions with financial customers (*FC*) and commercial customers (*CC*) (Table 5). The results indicate that the baseline half-spread for financial customers is only 4.2 pips while the baseline half-spread for commercial customers is 10.8 pips. As usual, inventories do not appear to influence dealer quotes and our qualitative conclusions do not change if we exclude inventories, if we consider only spot trades, or if we include incoming interbank trades (*IB*). Thus it appears that dealers distinguish sharply between commercial and financial customers but not in the manner predicted by adverse selection.

Table 5. Spread variation across counterparty types

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

The dependent variable is the change in price between two successive incoming deals 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_{it} 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 both counterparty groups, financial customers (*FC*) and commercial customers (*CC*). Data include all incoming customer USD/EUR spot and forward deals of a small bank in Germany, except those with preferred customers, during the period July 11, 2001, through November 9, 2001. Estimation uses GMM and Newey-West correction. Significance at the 1, 5 and 10 percent levels indicated by ‡, † and *, respectively.

	Baseline Regression		Robustness Tests: No Inventories	Robustness Tests: Spot Trades Only	Robustness Tests: Interbank Trades Included
	Coefficient	***Std. Error***	**Coefficient**	**Coefficient**	**Coefficient**
Constant	0.031	0.32	0.159	0.718*	-0.597†
Direction					
FC X D_t	6.902‡	*1.48*	6.814‡	7.936‡	5.619‡
FC X D_{t-1}	-4.175‡	*1.32*	-4.216‡	-5.586‡	-2.090*
CC X D_t	11.876‡	*0.56*	12.278‡	11.137‡	12.386‡
CC X D_{t-1}	-10.758‡	*0.57*	-10.982‡	-10.183‡	-10.170‡
IB X D_t					2.987‡
IB X D_{t-1}					-1.578‡
Inventory					
FC X I_{it}	-0.255	*0.52*		-0.019	1.082
FC X I_{it-1}	0.168	*0.54*		-0.071	-1.150
CC X I_{it}	1.167†	*0.42*		-0.059	1.113‡
CC X I_{it-1}	-1.277†	*0.42*		-0.050	-1.259‡
IB X I_{it}					-0.274
IB X I_{it-1}					0.169
Deal Size					
FC X Q_{jt}	-0.366	0.59	-0.151	-0.645	0.656
CC X Q_{jt}	0.221	0.42	-0.919‡	-0.536†	0.076
IB X Q_{jt}					-0.217
Adjusted R^2	0.33		0.33	0.33	0.24
Observations	1,640		1,640	1,125	2,848

According to our correspondents at large dealing banks, the correct customer disaggregation is between small commercial customers, on the one hand, and financial customers and large multinational (commercial) corporations, on the other. Though we cannot technically distinguish large multinationals from other commercial customers, large multinationals are unlikely to do much business with a small bank. Thus the counterparty-based tiering identified here should be roughly accurate for our bank.

C. Deal Size and Counterparty Type

We now run the Madhavan-Smidt (1991) regressions interacting the key variables with dummies for both transaction size $\{LG, MD, SM\}$ and counterparty type $\{FC, CC\}$. This analysis reveals that currency spreads are influenced by both deal size and counterparty type (Table 6). The tiering of spreads by deal size is most pronounced for commercial customers, for whom estimated baseline half-spreads are 12.7 pips on small deals, 7.2 pips on medium deals, and 2.1 pips on large deals. For financial customers, estimate baseline half-spreads are 6.6 pips on small deals and roughly half that size – and insignificantly different from zero – for medium and large deals. These qualitative conclusions are sustained across our three robustness tests.

Market participants, whom we have questioned extensively, assert that the pattern just identified approximates common knowledge within the FX market: The pattern is known by virtually everyone who trades, and virtually everyone who trades knows that virtually everyone else who trades knows it, etc. Only rank beginners might find the pattern unfamiliar, they claim. Appendix A provides commentary from market participants who have had significant trading responsibilities at large banks.

Our empirical analysis indicates that spreads are positive for both commercial and financial customers, which in turn implies that both types of customers have a positive price impact. Lyons (2001) and Marsh and O'Rourke (2005) suggest, based on a negative correlation between commercial order flow and exchange rates in daily data, that commercial deals may have a negative price impact. Marsh and O'Rourke (2005) also suggest that the negative relationship may instead reflect feedback trading. Our evidence suggests that this second interpretation is more likely to be correct.

Table 6. Spread variation across deal sizes and counterparty types

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

The dependent variable is the change in price between two successive incoming deals, 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_{it} 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 commercial customers (*CC*). They are also interacted with dummies for deal size: *Lg*. = $\{Q_{jt} \in [1,\infty)\}$; *Med*. = $\{Q_{jt} \in [0.5,1)\}$; *Sm*. = $\{Q_{jt} \in (0,0.5)\}$. Data include all incoming customer USD/EUR spot and forward deals of a small bank in Germany, except those with preferred customers, over the period July 11, 2001, through November 9, 2001. Estimation uses GMM and Newey-West correction. Significance at 1, 5 and 10 percent levels indicated by ‡, † and *, respectively.

	Baseline Regression		Robustness Tests		
			No Inventories	Spot Trades Only	Interbank Trades Included
	Coefficient	***Std. Error***	**Coefficient**	**Coefficient**	**Coefficient**
Constant	0.094	0.31	0.174	0.799	-0.272
Direction					
FC X D_t *X Lg.*	2.397	*2.93*	2.788	4.013	-0.164
FC X D_{t-1} *X Lg.*	**-3.622***	*2.02*	**-3.100**	**-0.065**	**0.343**
FC X D_t *X Med.*	3.921	*2.69*	3.905	5.574	3.364
FC X D_{t-1} *X Med.*	**-2.972**	*2.99*	**-2.930**	**-4.679**	**-0.895**
FC X D_t *X Sm.*	10.456‡	*2.58*	10.419‡	12.924‡	9.034‡
FC X D_{t-1} *X Sm.*	**-6.615‡**	*2.39*	**-6.935‡**	**-13.236‡**	**-5.420‡**
CC X D_t *X Lg.*	4.682†	*2.31*	4.721†	1.010	6.296‡
CC X D_{t-1} *X Lg.*	**-2.064**	*1.76*	**-1.715**	**0.001**	**-3.189†**
CC X D_t *X Med.*	12.618‡	*1.56*	12.473‡	13.945‡	14.570‡
CC X D_{t-1} *X Med.*	**-7.199‡**	*1.86*	**-7.161‡**	**-5.607‡**	**-8.492‡**
CC X D_t *X Sm.*	13.329‡	*0.61*	13.327‡	11.403‡	12.934‡
CC X D_{t-1} *X Sm.*	**-12.681‡**	*0.64*	**-12.729‡**	**-11.100‡**	**-11.469‡**
IB X D_t *X Lg.*					3.450‡
IB X D_{t-1} *X Lg.*					**-1.122†**
IB X D_t *X Med.+Sm.*					2.027
IB X D_{t-1} *X Med.+Sm.*					**-3.757†**
Inventory					
FC X I_{it}	-0.464	*0.59*		-0.234	1.119
FC X I_{it-1}	0.365	*0.60*		0.169	-1.180
CC X I_{it}	**1.052†**	*0.41*		0.029	**1.012†**
CC X I_{it-1}	**-1.087‡**	*0.42*		-0.036	**-1.097‡**
IB X I_{it}					-0.263
IB X I_{it-1}					0.198
Deal Size					
FC X Q_{jt}	0.121	0.73	0.435	-0.263	1.597
CC X Q_{jt}	0.773*	0.47	-0.240	0.311	0.522
IB X Q_{jt}					-0.347
Adjusted R^2	0.33		0.33	0.32	0.24
Observations	1,640		1,640	1,125	2,848

D. The Huang and Stoll Model

Bjønnes and Rime (2005) find no evidence for adverse selection using the Madhavan-Smidt model but do find such evidence when they adopt (a modified version of) the Huang and Stoll model (1997). We close this section by showing that, when the trades of our dealer are disaggregated by customer type and size, the Huang and Stoll model provides little support for adverse selection though it does support the overall pattern of customer spreads identified above.

Huang and Stoll (1997) observes that deal size is relatively unimportant for pricing in markets, like foreign exchange, where large trades are routinely broken up into multiple smaller transactions. Even in such markets, however, the risk of trading with a better informed counterparty remains. Thus, Huang and Stoll's model assumes that prices are determined by a deal's direction and the market maker's existing inventories, but not by a deal's size.

In this model, dealer *i* sets his price, P_{it}, as $P_{it} = \mu_{it} + \frac{S}{2} D_t - \theta \frac{S}{2} I_{it} + \upsilon_t$. Once again, μ_{it} represents dealer *i*'s conditional expectation of the asset's fundamental value. The baseline half-spread is $S/2$ and the effect on price of existing inventory (through price shading) is $\theta S/2$. 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 as well as public news: $\mu_{it} - \mu_{it-1} = (\lambda S/2)D_{t-1} + \varepsilon_t$. The term $\lambda S/2$ captures the information effect of trade direction and ε_t is a serially uncorrelated public information shock. Combining the pricing and updating rules gives the following expression for price changes between incoming transactions:

$$\Delta P_{it} = \frac{S}{2}(D_t - D_{t-1}) + \lambda \frac{S}{2} D_{t-1} - \theta \frac{S}{2} \Delta I_{it} + e_t , \tag{2}$$

where $e_t \equiv \varepsilon_t + \Delta\upsilon_t$. We follow Huang and Stoll (1997) in estimating the model separately for various size categories. We also disaggregate deals according to counterparty. As earlier we use GMM with Newey-West standard errors. The results, shown in Table 7, broadly confirm our earlier findings: baseline spreads are wider for small deals than for large deals and are generally wider for commercial customers than for financial customers; also, spreads are little influenced by existing inventories.

However, estimates of λ, the adverse-selection coefficient, do not conform to adverse-selection theory. The theory predicts that λ should be larger for financial customers than commercial customers, but this is only true for one of the three size categories, and even there the difference is not statistically significant. The theory also predicts that λ should be largest for large deals, but the estimated coefficients for large deals are statistically insignificant for both financial and commercial customers.

Table 7. Modified Huang and Stoll (1997) model

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

ΔP_{it} is the change in price between two successive incoming trades measured in pips. D_t is +1 for buy-initiated trades and –1 for sell-initiated trades. I_{it} 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 commercial customers (*CC*). They are also interacted with dummies for trade size: *Lg*. = $\{|Q_{jt}| \in [1,\infty)\}$; *Med*. = $\{|Q_{jt}| \in [0.5,1)\}$; *Sm*. = $\{|Q_{jt}| \in (0,0.5)\}$. Data include all incoming USD/EUR spot and forward trades of a small bank in Germany, except those with preferred customers, over the period July 11, 2001, through November 9, 2001. Estimation uses GMM and Newey-West correction. Significance at 1, 5 and 10 percent levels indicated by ‡, † and *, respectively. Constant term suppressed.

	Baseline Regression		**Robustness 1: No Inventories**	**Robustness 2: Spot Deals Only**	**Robustness 3: Interbank Deals Included**
	Coefficient	**Std. Error**	**Coefficient**	**Coefficient**	**Coefficient**
Half-Spread, *S*/2					
S/2 X *FC* X *Lg.*	4.202†	1.94	4.214†	0.998	1.597
S/2 X *FC* X *Med.*	5.354†	2.39	4.125	2.763	4.918†
S/2 X *FC* X *Sm.*	10.538‡	2.55	10.606‡	7.807‡	9.304‡
S/2 X *CC* X *Lg.*	3.804†	1.65	3.480†	6.505†	4.478‡
S/2 X *CC* X *Med.*	11.621‡	2.74	12.298‡	13.561‡	12.963‡
S/2 X *CC* X *Sm.*	13.478‡	0.59	13.436‡	11.346‡	12.805‡
S/2 X *IB* X *Lg.*					3.934‡
S/2 X *IB* X *Med.+Sm.*					0.817
Adverse Selection					
λ X *FC* X *Lg.*	0.266	0.57	0.346	-3.360	1.965
λ X *FC* X *Med.*	0.457	0.52	0.330	-0,395	0.802*
λ X *FC* X *Sm.*	0.319	0.21	0.333*	0.529*	0.391†
λ X *CC* X *Lg.*	0.513	0.46	0.534	0.489	0.364
λ X *CC* X *Med.*	0.393†	0.18	0.426‡	0.614‡	0.348†
λ X *CC* X *Sm.*	0.056†	0.02	0.048†	0.197‡	0.101‡
λ X *IB* X *Lg.*					0.717‡
λ X *IB* X *Med.+Sm.*					-2.729
Inventory					
θ X *FC* X *Lg.*	0.003	0.05		0.152	0.05
θ X *FC* X *Med.*	-0.512	0.42		-1.315	0.42
θ X *FC* X *Sm.*	0.038	0.18		0.116	0.18
θ X *CC* X *Lg.*	-0.011	0.02		-0.017	0.02
θ X *CC* X *Med.*	0.081	0.27		-0.003	0.27
θ X *CC* X *Sm.*	-0.078*	0.04		-0.002	0.04
θ X *IB* X *Lg.*					-0.077
θ X *IB* X *Med.+Sm.*					4.814
Adjusted R^2	0.33		0.33	0.35	0.23
Observations	1,651		1,651	1,129	2,859

III. Operating Costs, Market Power, and Strategic Dealing

The cross-sectional pattern of currency spreads just documented is not consistent with adverse selection, despite the widespread acceptance of that hypothesis in the FX microstructure literature. This section examines possible alternative explanations for the pattern of spreads.

We begin by considering the components of the standard paradigm beyond adverse selection, which are: monopoly power, inventory risk, and operating costs. Pure monopoly power is unlikely to be important in FX, where hundreds of dealers compete intensely. Inventory risk can also be ruled out as a determinant of our pattern, since the prospective inventory effect implies a positive relationship between spreads and deal size (Ho and Stoll, 1981). In addition, inventory risk is invariant across customers, so this element cannot explain the relationship between spreads and customer type.

The remaining component of the standard paradigm is operating costs. In discussing the negative relationship between spreads and deal size on the London Stock Exchange, Angel (1996) and Hansch *et al.* (1999) note that such a relationship could arise if per-unit processing costs are smaller for large trades, or equivalently if processing costs are largely fixed. Fixed costs certainly exist in FX and, in conversation, foreign exchange dealers themselves suggest that they are relevant. However, operating costs are invariant across customers, so this component cannot explain customer-based variation in spreads. In short, the standard paradigm can explain the relationship between FX customer spreads and deal size but not the relationship between spreads and customer type.

We highlight two mutually consistent theories of dealing under asymmetric information that might explain how FX spreads vary across counterparty types. One theory suggests that information about current market conditions provides market power which, in turn, affects spreads. The other theory suggests that dealers strategically vary spreads across customers in an attempt to gather private information about near-term exchange-rate returns.[11] It is our view, based on discussions with dealers and on the evidence presented below, that both of these information-based forces operate simultaneously with operating costs.

A. Market Power

Green *et al.* (2004) shows that variations in market power between dealers and their customers may explain why spreads are inversely related to deal size in the U.S. municipal bond market. That paper points 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 – are hard to ascertain. The customers who make smaller municipal bond deals tend to know the least about current market conditions, so they have the least market power relative to the dealers and are charged the widest spreads.

[11] Huang and Stoll (1997) propose yet another explanation for the negative relationship between adverse selection costs and transaction size in their analysis of equity market spreads. We pass over this explanation since it relies on the special properties of block trades, and there are no block trades in currency markets.

The market-power hypothesis can be applied directly to explain why commercial FX customers pay wider spreads than financial customers. Currency markets are also dealership markets with dispersed information. What little market information is available to customers is expensive. Financial customers typically purchase real-time information and hire professional traders who know how to interpret it. By contrast, most commercial customers do not purchase that information and do not hire sophisticated traders, so their traders are usually considered relatively uninformed about market conditions.

Information about market conditions is not the only potential source of financial customers' market power. In discussing the NYSE, Angel (1996) notes that

> a dealer knows that an unsophisticated individual who places a small order 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 for small orders (p. 4).

Duffie *et al.* (2004) provides a formal treatment for this insight, showing that bargaining power in OTC markets partly "reflects each investor's or market maker's alternatives to immediate trade" (p. 1), which in turn is determined by the relative costs and benefits of further search. In currency markets, the benefits to search are smaller at commercial customers than financial customers.[12] FX traders at commercial firms are not always rewarded for finding better prices; for them, trading is typically just one of many administrative responsibilities. By contrast, FX traders at financial customers are often explicitly evaluated on execution quality. Since FX traders at financial firms perceive greater benefits to search, they are more likely to keep at it until they find a narrow spread. Knowing this, dealers may not even try to quote them a wide spread. Financial customers' market power may also come from their tendency to undertake large trades (see Table 3). As shown in Bernhardt *et al.* (2004), customers who regularly provide a dealer with substantial amounts of business may receive better spreads as dealers compete for their business.

B. Strategic Dealing

The counterparty-based tiering of currency spreads may also reflect dealers' strategic attempts to learn customers' private information about upcoming returns. Order flow at large banks includes information about upcoming high-frequency currency returns. This predictive relationship is documented statistically in Evans and Lyons (2004) and Daníelsson *et al*.(2002). Evidence from equity markets confirms that access to real-time order flow information can provide an informational advantage (Anand 2004). Thus it seems at least possible that FX dealers might try to capture a larger share of the most informative deal

[12] As interpreted here, asymmetric information has two roles in the Duffie et al. (2004) model. First, dispersed/asymmetric information about current prices generates the need to search in OTC markets. Second, information asymmetries determine the agency relationships between customer firms and their traders that determine whether execution is rewarded or not.

flow, since the information could help increase returns and/or lower risk through better inventory management, better pricing on upcoming deals, and better speculative positioning.[13]

Indeed, the importance of such information for FX dealers can hardly be overstated. In Clyde (1996), a Ph.D. economist who worked as a dealer before entering academe provides a microstructural depiction of FX dealing. He asserts:

> Bank foreign exchange dealing rooms are set up with at least two things in mind: 1) to optimize the flow of information into the room, and 2) to ease the execution, recording, and settlement of a large number of trades. Information flow comes from the constantly updating quotation, news, charting, and other screens, on each trader's desk, from live price action being quoted across "open boxes" by brokers (more about brokers later), *from constantly nurtured information exchanging phone relationships, and from the size and direction of the bank's customer business,* among other places (p. 6, italics added).

Additional quotes from FX dealers, confirming that they seek to learn the size and direction of important customers' foreign exchange needs, are presented in Appendix A. Consistent with this, Reiss and Werner (2004) report that "[d]uring the period of our sample, London [Stock Exchange] dealers were known to solicit large customer orders, even if the terms were unfavorable. The explanation most often given for this behavior was that dealers were 'purchasing' information …" (p. 625).

Large currency orders matter in part because of the way they are broken into many smaller interbank transactions.[14] As noted in Madhavan (1995), when customers break up large deals, "trading information is valuable because large traders tend to trade on the same side of the market [across periods]. Thus reversals are less likely than continuations" (p. 588). Sager and Taylor (2006) provide a description rich in institutional detail:

> To the extent that a [FX] dealer sees order flow from large, active, informed currency customers it is generally reasonable to assume that this is only a small part of the total trade being executed, and that the remaining orders are likely to be fed into the market throughout the current trading session (in the case of hedge funds) or several trading sessions (currency overlay managers, for instance). This knowledge will allow the dealer either to "piggy-back" on the trade, committing some of his own risk capital to the same trade, or to net off trades from other customers" (p. 13).

The tendency for large customer orders to be broken up generates but one of the many reasons why an FX dealer might be wise to quote narrow spreads to informed customers. According to dealers, a few financial customers have measurable ability to predict exchange rates, so dealers can benefit from knowing whether those customers are buying or selling. A given dealer may only learn this if the customer actually chooses to trade with him.

An FX dealer might also be wise to subsidize a trade that appears to carry no information at all. FX dealing is a relationship business, so dealers can use narrow spreads to enhance a relationship that may

[13] Strategic dealing may be more relevant in FX than the municipal bond market, since most municipal bonds trade just a few times and the information value of any trade may be negligible.
[14] The optimality of breaking up big orders is demonstrated in Bertsimas and Lo (1998).

bring useful information in the future. More specifically, quoting attractive spreads increases the odds of being asked to manage the customer's future large currency needs, a privilege that provides a clear information advantage relative to the rest of the market. In addition, quoting a narrow spread increases the odds that a customer will in the future place take-profit and stop-loss orders with the dealer, both of which help predict exchange rates (Osler 2003, 2005).[15,16]

The insight that market makers might strategically manipulate spreads to increase the information value of order flow is not new, though we have not found previous academic discussion of the idea as applied to the customer market in FX. Leach and Madhavan (1992, 1993) use equity-market inspired models to demonstrate that market makers may adjust prices early in a trading session to enhance profitability later on. The first of these papers shows that a specialist might rationally raise the signal-to-noise ratio of order flow on early trades by quoting narrower spreads, effectively driving informed trades in. The second shows that dealers might achieve the same goal by quoting wider spreads in early trades, effectively driving uninformed trades out. This general insight motivates the empirical tests of Hansch and Neuberger (1997), which "provide[s] evidence that dealers [on the London Stock Exchange] do act strategically, and that they deliberately accept losses on some trades in order to make superior revenues on others" (p. 1). Evidence for this type of strategic dealing in an experimental market that shares many properties with the FX interdealer market is presented in Flood *et al.* (1999).

Our strategic dealing hypothesis concerns cross-sectional variation in spreads, rather than variation across time. An equity-inspired strategic dealing hypothesis that overlaps more substantially with our own is presented in Naik *et al.* (1997), whose analysis of a two-tier market indicates that customer spreads will be narrower for more informed customers, consistent with the pattern we document for FX. The motivation for this conclusion is similar to the first two outlined above: after gleaning the information included in the current customer trade, dealers can profit more in subsequent trading. However, the Naik *et al.* model also concludes that customer spreads vary positively with deal size, while our hypothesis fits the opposite pattern observed in the data. Our perspective also differs from the one offered by Naik *et al.* (1997) insofar as we highlight the potential value of future information that may be gained by enhancing a relationship with a potentially informative customer.

C. Empirical Support for Strategic Dealing

Our strategic-dealing hypothesis incorporates three properties of currency order flow consistently

[15] Stop-loss and take-profit orders are conditional market orders where the conditioning variable is market price. A stop-loss order instructs a dealer to buy (sell) a specific amount at market prices if and only if the market price rises (falls) to a certain pre-specified level. A take-profit order instructs a dealer to sell (buy) a specific amount at market prices if and only if the market price rises (falls) to a certain pre-specified level. Orders are distinct from deals, in which a market maker provides a two-way quote and the counterparty chooses whether to deal at those prices.

[16] Information about stop-loss orders is also valuable indirectly, as it is one of the major commodities traded in the informal market for information among dealers and their better customers.

asserted by FX dealers: (1) order flow carries information; (2) order flow carries more information when it comes from financial customers than when it comes from commercial customers; (3) large trades are more informative than small trades. This section provides empirical evidence for all three properties.

1. Order flow carries information

Earlier studies confirm that the order flow of individual large dealing banks carries information (Evans and Lyons 2002, Daníelsson *et al.* 2002, Evans and Lyons 2004). But the question remains: Does the limited order flow of a *small* bank carry information? To address this question we estimate cointegrating relationships between exchange rates and our three types of cumulative incoming order flow:

$$P_{it} = \omega_i + \phi_i trend + \kappa_i CumDF_{it} + \nu_{it}\ , \qquad (3)$$

where $CumDF_i$, $i \in \{IB, FC, CC\}$. We include other banks among the counterparties to provide results for later discussion. If incoming order flow of type i is associated with a currency appreciation, κ_i will be positive. The results, shown in Table 8, show that the residuals, ν_{it}, are stationary as required for cointegration. We conclude that even a small bank's order flow can be informative.

2 Information and Counterparty Type

Dealers claim, and our strategic-dealing hypothesis requires, that financial order flow is more informative than commercial order flow. Consistent with this, the information half-life of financial deals exceeds three days, while that of commercial deals is only about five hours.[17]

There may seem to be an inconsistency between the idea that commercial order flow is less informative for dealers than financial order flow, on the one hand, and certain other prominent conclusions in the literature, on the other. Pasquariello, Yun, and Zhu (2006) shows that commercial firms are wise in their timing of ADR issues, in terms of both stock and currency markets, which certainly suggests that such firms are informed about these markets. The analysis of Evans and Lyons (2004) may also bring to mind an image of "informed" traders more consistent with commercial than financial firms. This paper discusses how order flow in aggregate may convey information about economic fundamentals dispersed among myriad agents in the market. The concept of a "fundamental" is typically associated with real economic activity, and the illustrative model they provide focuses on information about the real economy. With this in mind one's image of the "informed" trader might naturally be someone involved in real economic activity – that is, a commercial customer.

The idea that commercial trades carry the most information may well be correct with respect to *long-term* exchange-rate dynamics. As shown in Fan and Lyons (2003), non-financial flows seem to be

[17] To calculate these half-lives we first find, based on the relevant ECM coefficient, the number of periods until the effect of a given cointegrating residual has been reduced by half. We then multiply this number by the median number of minutes between transactions.

most strongly related with multi-year exchange-rate dynamics. More broadly, it is widely appreciated that PPP, a relationship driven by the activity of international goods and services traders, is approximation correct over long horizons (Rogoff 1996).

Table 8. Tests of cointegration between exchange rates and cumulative deal flow

Table reports ordinary least squares estimates of the following cointegrating relationship between exchange rates and cumulative deal flow:

$$P_{it} = \omega_i + \phi_i trend_t + \kappa_i \sum_{j=0}^{t} CumulativeDealFlow_{ij} + \nu_{it},$$

where i represents the counterparty type, $i \in \{IB, CC_{All}, FC_{All}, FC_{Small}, FC_{Med\text{-}Lg}\}$. Preliminary statistical tests indicate that the variables are not stationary, so t-values on the coefficients are not reliable and are not reported. ADF-test is a standard augmented Dickey-Fuller test on the regression residuals. PP-test is a Phillips-Perron test on the regression residuals. The number of lags included is calculated from the sample size (Newey-West automatic truncation lag selection). The tests do not include a constant since a constant is included in the original regression equation. Significance at the 1, 5 and 10 percent levels is indicated by ‡, † and *, respectively. Flow and trend coefficients are multiplied by 10^3.

	Commercial Customers	Financial Customers: All Deals	Incoming Interbank	Financial Customers	
				Med. & Lg. Deals	Small Deals
Constant **Trend**	0.884‡ 0.008‡	0.885‡ 0.167‡	0.871‡ 0.010‡	0.891‡ 0.167†	0.875‡ 0.553‡
Cumulative Order flow	-0.301‡	0.150*	0.417‡	0.255†	4.330
ADF-test **PP-test**	(-2.72)‡ (-3.10)‡	(-1.63)* (-1.46)†	(-2.40)† (-2.67)‡	(-1.64)* (-2.62)‡	(-1.55) (-2.40)†
ECM coeff.	-.012‡	-0.051†	-0.012‡	-0.098†	-0.132†
Information Half-life	4.8 hours	78.7 hours	32.7 hours	7.8 hours	NA
Adjusted R^2	0.59	0.30	0.50	0.20	0.479
Observations	1,492	171	1,269	70	101

There is strong evidence, however, that it is financial trades that carry the most information with respect to *high-frequency* exchange-rate dynamics. Fan and Lyons (2003) notes that "extreme exchange-rate movements at high frequency are generally associated with large net flows from financial institutions" (p. 160), but not from commercial institutions. More generally, that paper suggests that financial trading dominates short-run exchange-rate dynamics. Additional evidence that financial institutions' currency deals provide exchange-rate relevant information is provided in Froot and Ramadorai (2005).

If commercial order flow is informative about long-run dynamics while financial order flow is relevant to short-run dynamics, it will be the dealers' horizon that determines which type of order flow is most informative for them. And currency dealers are usually interested in very short horizons – typically a few minutes or a few hours, rarely more than a day (in part because they typically end the day with minimal inventory: see Appendix B). Dealers will thus have little use for information about long-run fundamentals, since such information has essentially no forecasting power for short-run dynamics (Meese and Rogoff, 1983). Indeed, dealers report that they generally believe that high-frequency exchange rate dynamics are not driven by fundamentals (Cheung and Chinn, 2001).

Dealers themselves report that the information they seek concerns short-run phenomena. This is the conclusion of Gehrig and Menkhoff (2004), a survey that covers foreign exchange dealers and fund managers in Germany and Austria. Evidence for the same conclusion is presented in Oberlechner (2004), in which dealers in North America were asked to rate, on a scale of 1 to 6, the importance to their profitability of short-term, medium-term, and long-term price forecasts. Of the 400-plus respondents, 68 percent indicated that short-term forecasts were in the top two categories of importance, while only 27 percent of respondents made that claim for long-term forecasts.

Since dealers care about short horizons and financial order flow seems to carry the most information relevant to such horizons, it would seem likely that dealers consider financial order flow most informative. They consistently claim that this is true (as illustrated in Appendix A), and empirical support for their claim comes from Carpenter and Wang (2003). That paper finds that dealers widen their interdealer spreads after transactions with financial customers but leave those spreads unchanged after transactions with commercial customers, and interprets this as evidence that financial order flow is informative to dealers while commercial order flow is not.

The positive and significant coefficients on cumulative financial order flow in Table 8 suggest that this component of order flow is informative in the familiar way: net buying demand from such customers is associated with an appreciation of the commodity currency. The negative coefficient on commercial order flow is puzzling, however, since it seems to suggest that such order flow is not only informative, contrary to the views of dealers, but informative in the "wrong" way. The result is not an artifact of our small bank's relatively limited trading activity. Qualitatively consistent results are reported in Lyons (2001), Evans and Lyons (2004), and Marsh and O'Rourke (2005), all of which examine larger banks, and Bjønnes *et al.* (2005), which examines marketwide data on trading in SEK/EUR.

To better understand why commercial order flow might be considered uninformative, despite its negative relationship with exchange rates, we consider the structure of liquidity in FX. Suppose that financial customers drive short-run exchange-rate returns. If so, some other set of participants must be providing the necessary liquidity – if financial customers are, say, buying and driving the price up, some other group must be selling. Dealers are obviously the immediate source of that liquidity. But dealers would not readily provide immediate liquidity if they did not anticipate that they could soon pass on their inventory to counterparties outside their own circle. Whoever they are, these ultimate liquidity providers must, by definition, have cumulative order flow that is negatively correlated with exchange rates, and at the same time information about their order flow will have zero incremental value once one knows about financial customers' order flow. In short, if commercial customers are the ultimate providers of liquidity in FX, their trades could simultaneously have a statistically significant negative relationship with exchange rates and yet have no incremental information value for dealers.

Direct support for this interpretation of the evidence comes from Bjønnes *et al.* (2005), which carefully examines the structure of liquidity using ten years of comprehensive data for the market between Swedish krone and the euro. In addition to showing that cumulative financial (resp. commercial) order flow is positively (resp. negatively) cointegrated with exchange rates, this study shows that "changes in net positions of non-financial customers are forecasted by changes in net positions of financial customers." The authors conclude that "non-financial customers are the main liquidity providers in the overnight foreign exchange market" (p. 1). Further evidence consistent with this view comes from Marsh and O'Rourke's (2005) analysis of daily customer flows from the Royal Bank of Scotland. This paper finds a strong negative relationship between commercial order flow and lagged returns in most major currency pairs, consistent with the liquidity hypothesis outlined here.

The positive sign of the cointegration coefficient for cumulative interbank order flow (Table 8) provides further support for our hypothesis that commercial customers are net liquidity providers. Cumulative order flow from the bank's liquidity suppliers must have a negative relationship with the exchange rate, and only commercial order flow satisfies this requirement.

In practice, how do commercial customers provide liquidity in FX? We highlight two relevant institutional practices. First, commercial customers are relatively heavy users of take-profit orders, conditional market orders in which dealers are instructed to buy (sell) a specific amount of currency at the market price immediately after its value falls (rises) to a certain level (Osler 2003, 2005). Of all the euro-dollar, dollar-yen, and dollar-GBP orders placed by commercial customers at the Royal Bank of Scotland between June 2001 and September 2002, 72 percent were take-profits. This structure generates the quick negative-feedback trading found empirically. Second, large exporters with inventories of foreign currency are often alert to intraday exchange-rate movements and will sell when the rate reaches intraday targets.[18]

[18] For example, market participants often discuss the day's trigger rates of "Japanese exporters." This practice can be understood in terms of options (Osler 2006).

3. *Information and Deal Size*

Are there systematic differences in the information content of large and small transactions? That is, could the strategic-dealing hypothesis be a second explanation, beyond fixed operating costs, for the inverse relationship between deal size and currency spreads? The value of learning when a customer is about to trade an amount over $25 million has already been discussed, but these large amounts are usually broken up into many smaller transactions. As a result, large regular-sized deals need not carry more information than small ones. Indeed, Chakravarty (2001) shows that the most informative trades on the NYSE are not large but medium-sized. On the other hand, Biais *et al.* (1995) finds that large trades on the Paris Bourse seem to carry more information than small ones.[19] Similarly, Kurov and Lasser (2004) provides evidence that large futures trades seem especially informative on the Chicago Mercantile Exchange.[20]

The relative information value of large versus small individual FX transaction is thus an empirical question. We focus this analysis on financial transactions, since commercial transactions apparently carry little information. We partition financial transactions into two size categories, small and medium-and-large, as suggested by the results in Table 6. Cointegration tests, reported in Table 8, show that the link between cumulative financial customer order flow and exchange-rate levels is significant for medium-and-large deals but insignificant for small deals. This is consistent with the hypothesis that medium-and-large financial deals are quoted the tightest spreads in part because they have the highest information value.

To summarize: This section has provided three explanations for the cross-sectional pattern of currency spreads, one based on fixed operating costs and two based on asymmetric information. In the game between dealers and their commercial customers, dealers gain market power from their knowledge of market conditions on the basis of which they extract wider spreads. In the game between dealers and their financial customers, both sides are well informed about market conditions but financial customers also have private information relevant to near-term exchange-rate dynamics. Dealers strategically set small spreads to increase their business with these privately informed customers and learn their information.

IV. PRICE DISCOVERY IN FOREIGN EXCHANGE

The evidence presented so far shows that spreads in the FX customer market are inversely related to a deal's information content, the opposite of the pattern predicted by adverse selection. But, if adverse selection is not the basis for price discovery in currency markets, what is? This section provides an alter-

[19] Biais *et al.* (1995) show that after large sales (purchases) there are more cancellations of limit bids (offers). Similarly, after large sales (purchases) relatively many new ask (bid) orders are placed within the quotes.

[20] Kurov and Lasser (2004) show that large trades on the CME trigger position-taking by locals in electronic E-mini futures contracts on the same commodities, which may explain why the E-mini futures' apparent price leadership

native interpretation of the price discovery process in FX, along with preliminary evidence in support of that interpretation. Asymmetric information is the centerpiece of our story, as it must be, but we suggest that information influences inventory management and order choice in the interdealer market rather than spreads in the customer market. Our interpretation thus reflects institutional features of the FX market, such as its two-tiered structure and the importance of the interdealer market for inventory management.

Our interpretation differs in a key way from the familiar “portfolio shifts” model of the FX market articulated in Evans and Lyons (2002). In that model, dealers first absorb inventory from end users, then trade that inventory among themselves, and finally sell the inventory to other end users. The exchange rate moves to reflect information only during the customer trading of round three. If one were to graft our price discovery framework to the Evans and Lyons model, however, one would conclude that the exchange rate moves to reflect information during the interbank trading of round two. Nonetheless, our interpretation creates a coherent picture from disparate stylized facts from FX microstructure.

A. The Mechanism

Our suggested mechanism involves dealers' interbank trading in response to customer trades. We focus on the interbank market because the evidence presented above implies that a given trade's potential information content is not embedded in customer prices. We infer that price discovery does not happen in the customer market and must therefore happen in the interdealer market.[21] Interdealer markets are crucially important for inventory management in FX (Lyons 1996) as in other two-tier markets (Manaster and Mann 1996, Reiss and Werner 1998, Lyons 1996).

Consider a dealer whose inventory rises abruptly in response to an incoming customer call. Since FX dealers prefer to have zero inventory, other things equal (this is documented for our dealer in Appendix B and for large dealers in Bjønnes and Rime (2005)), our dealer will most likely try to offload the new inventory to another dealer. In FX the dealer must choose between "indirect" trading in the order-driven broker market or "direct" trading in the regular quote-driven market.

Assume for now that our dealer chooses to trade through an interdealer broker, in which case he must decide whether to submit a market sell or a limit sell. Harris (1998) and Foucault (1999) highlight a central trade-off between market orders, which provide immediate execution with certainty, and limit orders, which can provide better prices but have uncertain execution. Since FX dealers can identify their customers, this order choice could depend on the type of customer providing the inventory (Reiss and Werner 2004).

[21] We are not the first to note that some price discovery happens in the interdealer market (Evans and Lyons 2006), but to our knowledge we are the first to note that price discovery *cannot* happen in the customer market, and that therefore *all* price discovery must happen in the interdealer market.

Suppose the customer is informed. In this case the dealer has three incentives to exploit the immediacy offered by market orders: He has information, he has inventory with its inherent risk, and 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. Suppose instead the customer is uninformed. In this case the dealer has only one incentive to place a market order: the inherent riskiness of his inventory. Thus our dealer might be more likely to place a limit order which, if executed, would earn him the higher offer price. In short, we suggest that dealers using the brokers market to manage inventory will have a stronger tendency to place market orders after informed customer trades than after uninformed customer trades.[22] The connection to price discovery is direct: brokered interdealer prices will tend to move in the direction indicated by informed trades.

If our dealer chooses to deal directly, a modified version of this cost-benefit analysis still applies. Calling another dealer produces a quick, certain trade at a relatively undesirable price, like placing a market order; waiting for someone else to call could bring a better price but could instead bring no trade at all, like placing a limit order. Thus, a dealer who chooses the direct interdealer market has strong incentives to call another dealer after trading with an informed customer and may be more likely to wait for incoming calls after trading with an uninformed customer.

The overall conclusion is consistent regardless of whether a dealer chooses to manage his inventory via brokered or direct deals. After trades with informed customers a dealer will be more likely to make a (parallel) outgoing deal than after trades with uninformed customers. As a result, interdealer prices will tend to move in the direction required by the information contained in customer trades.

B. Explaining the Stylized Facts

This analysis predicts a number of the stylized facts in FX microstructure. For example, it predicts that financial order flow, which dealers assert is relatively informed, will be positively related to exchange-rate returns. Evidence for this relationship is provided in Table 7 above and in Evans and Lyons (2004), Bjønnes *et al.* (2005), and Marsh and O'Rourke (2005). Our analysis also predicts that the positive relationship between financial order flow and exchange rates will be substantially permanent, evidence for which is provided in Table 8 above and in Lyons (2001) and Bjønnes *et al.* (2005).

Our analysis predicts a positive and largely permanent relationship between exchange rates and interdealer order flow, which is defined as buy-initiated interdealer transactions minus sell-initiated transactions. (In the order-driven (brokered) portion of the interdealer market the initiator of a transaction is considered to be the dealer placing the market order; in the quote-driven (direct dealing) portion of that market the initiator is the dealer that calls out. In both cases the initiator makes an “outgoing trade.”) And

[22] 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 (Biais *et al.* 1995, Goettler *et al.* 2005, Lo and Sapp 2005).

indeed, there is a strong and positive contemporaneous correlation between interdealer order flow and exchange-rate returns at the daily and weekly horizons (see Lyons (1995), Payne (2003), Evans (2002), Evans and Lyons (2002), Killeen, Lyons, and Moore (2002), and Daníelsson *et al.* (2003), *inter alia*). Furthermore, a substantial portion of this relationship is permanent (Evans and Lyons 2002, Payne 2003, Killeen *et al.* 2005, Bjønnes *et al.* 2005).

C. New Evidence

Our interpretation of price discovery in FX has three 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 universally base their customer quotes on the interdealer market's current best bid and offer. In a large dealing room, salespeople construct the quote actually given to a customer from a preliminary quote provided at that moment by the relevant interdealer trader. Those preliminary quotes are in turn anchored on the best bid and offer in the interdealer market. In electronic communication networks (e.g., Currenext, FXAll) the connection between interdealer prices and customer quotes is programmed directly into the pricing algorithm.

Our conjecture also has the testable implication that dealers should be more likely to make outgoing interbank transactions after deals with financial customers than after deals with commercial customers. Finally, our conjecture implies that dealers should also be more likely to make outgoing interbank transactions after larger deals, since large deals apparently carry more information than small ones.

We test these last two implications via a probit analysis of the conditional probability that a given transaction is outgoing in the interbank market:

$$Prob(Trade_t = IB^{out}) = P(FC_{t-1}, CC_{t-1}, 10mio_{t-1}, |I_{it}|, I_{it}^2, |Q_{jt}|) \quad . \tag{4}$$

Our hypothesis concerns the first three variables; FC_{t-1} and CC_{t-1} have already been defined; $10mio_{t-1}$ is a dummy set to one if the previous transaction was worth €10 million or more. Our conjecture suggests that the coefficient on the financial dummy will be higher than the coefficient on commercial dummy, and the coefficient on $10mio_{t-1}$ will be positive. The last three terms capture other factors relevant to the decision to place a market order. The coefficient on absolute inventory, $|I_{it}|$, should be positive since higher inventory brings higher inventory risk.[23] Following Bjønnes and Rime (2005) we include squared inventory, I_{it}^2, to capture potential nonlinearities in this relationship. The absolute size of the current transaction, $|Q_{jt}|$, is included because our dealer's customer transactions are often smaller than the $1 million 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 large market order.

[23] A more general framework would replace $|I_{it}|$ with $|I_{it}-I^*_t|$, the gap between actual and desired inventory. However, currency dealers' desired inventory is usually zero.

Table 9. Probit regression of choice of outgoing interbank deals

We estimate this equation, $Prob(Trade_t{=}IB^{out}) = P(FC_{t-1}, CC_{t-1}, |I_{it}|, I_{it}^2, |Q_{jt}|)$, as a probit regression. Incoming (outgoing) interbank deals 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 commercial customers and other banks. *I* represents inventories, in millions of euros; $|Q_{jt}|$ represents the absolute size of the current deal, measured in EUR millions; *10 mio*$_{t\text{-}1}$ is a dummy set to one if the size of the previous transaction was €10 million or larger. Significance at the 1, 5 and 10 percent levels indicated by ‡, † and *, respectively.

	Baseline Regression			Robustness Tests	
				Spot Trades Only	Interbank Trades Included
	Coefficient	Std. Error	*z*-Statistic	Coefficient	Coefficient
Constant	-0.875‡	*0.044*	-19.92	-0.893‡	-0.728‡
FC_{t-1}	-0.116	*0.116*	-1.00	-0.091	-0.256*
CC_{t-1}	-0.531‡	*0.055*	-9.60	-0.409‡	-0.672‡
IB_{t-1}					-0.214‡
10 mio$_{t-1}$	0.650‡	*0.190*	3.43	0.770‡	0.657‡
$\|I_{it}\|$	0.030‡	*0.011*	2.85	0.051‡	0.028‡
I_{it}^2	-0.001‡	*0.000*	-2.64	-0.002‡	-0.001†
$\|Q_{jt}\|$	0.029‡	*0.008*	3.58	0.070‡	0.028‡
McFadden's R^2	0.041			0.044	0.044
Observations	3,534			2,894	3,534

The results of estimating Equation (4), shown in Table 9, support our view that the likelihood of an outgoing interbank transaction is higher when the most recent transaction is considered informed. Outgoing interbank transactions are statistically significantly more likely when the previous transaction involves a financial customer than when it involves a commercial customer. They are also statistically significantly more likely after deals over €10 million. The results are economically meaningful, as well. After a commercial deal below €10 million the estimated probability of an outgoing interbank transaction is 9.5 percent; after a similarly-sized financial deal that probability is roughly twice as large, at 18.5 percent. After commercial deal over €10 million the probability of an outgoing interbank transaction is 25.4 percent. After a similarly-sized financial deal this probability reaches a lofty 40.2 percent. (In these calculations all other independent variables are taken at sample means.) These results, like our earlier results, are consistent across robustness tests.

The rest of the results from estimating Equation (4) also make sense. The likelihood of an outgoing deal rises with the absolute value of existing inventory and the relationship is concave. The positive relationship between absolute deal size and the likelihood that the deal itself is outgoing indicates that outgoing brokered transactions tend to be larger than the dealer's average incoming transaction, as expected.[24]

To summarize: This section suggests a mechanism through which price discovery may occur in FX. We first note that price discovery must happen in the interdealer market since customer spreads vary inversely with a deal's likely information content. We then show both conceptually and empirically that dealers are more likely to make outgoing interbank deals after trading with informed customers than after trading with uninformed customers. This could be the force that drives interdealer prices in the direction consistent with information brought to the market by informed customers.

V. CONCLUSIONS

This paper investigates the process through which information becomes embedded in exchange rates. Our data comprise the complete USD/EUR trading record of a bank in Germany over four months in 2001. In addition to covering a relatively long span of time for tic-by-tic FX transactions data, these data have the advantage of distinguishing between transactions with financial and commercial customers.

The paper's first contribution is to show that spreads on normal-sized currency deals varied inversely with deal size and are wider for commercial customers than for financial customers. Both components of the pattern are inconsistent with the hypothesis that adverse selection dominates currency spreads, since FX dealers consider large trades to be more informative than small trades and financial customers to be more informed than commercial customers. Dealers report that the pattern we identify approximates common knowledge within the market (though it has become less extreme since 2001 as competition has intensified as a result of the introduction of new electronic communication networks). One potentially important implication of the pattern is that a trade's price impact is not necessarily equivalent to its information value.

The paper's second contribution is to highlight three hypotheses that help explain the cross-sectional pattern of currency spreads. We first note that operating costs are largely fixed in FX, which could help explain the negative relationship between deal size and spreads. The customer-based variation in spreads could be explained by Green *et al.*'s (2004) market-power hypothesis. This hypothesis asserts that spreads in quote-driven markets vary positively with a dealer's market power relative to a given customer, and that such market power derives in part from knowledge of market conditions. Commercial customers tend to know the least about current market conditions, so they pay the widest spreads. The customer-based variation in spreads could also reflect dealers' attempts to strategically gather information about near-term returns (Leach and Madhavan 1992, 1993, Naik *et al.* 1997). Dealers may subsidize

[24] Like other aspects of our dealer's behavior, these inventory management practices are consistent with practices at large banks (Bjønnes and Rime, 2004).

trades with informed customers in order to learn information immediately or to increase the odds of learning information in the future by managing the customer's future large deals or the customer's future price-contingent order flow. Dealers consider financial order flow to be relatively informative, so financial customers pay the narrowest spreads.

The paper's third contribution is to create a coherent picture of the FX price discovery process by fusing (a) our own evidence, (b) empirical evidence from other FX microstructure research, and (c) insights from mainstream microstructure. We first note that, since customers' information is not immediately reflected in the prices they pay, price discovery must take place entirely in the interdealer market. We focus our analysis, therefore, on dealer behavior in the interdealer market, a market that is important for inventory management (Lyons 1996).

The key mechanism behind our suggested price discovery process involves the dealer's response to individual customer trades. We suggest that after transactions with informed customers dealers will tend to make parallel outgoing interdealer trades – placing a market order at a broker, for example – motivated by their inventory as well as by their newly-acquired information. In this way the information from customer trades will be reflected in interdealer prices. After transactions with uninformed customers, by contrast, dealers will be relatively likely to place parallel limit orders or to wait for incoming calls. This picture predicts some key stylized facts in FX: the positive and substantially permanent relation between cumulative interdealer order flow and exchange rates, as well as the positive and substantially permanent relation between financial order flow and exchange rates. We show empirically that the dealer studied here was substantially more likely to place outgoing interdealer trades after informed customer trades.

In future research it would be appropriate to develop formal models of the price discovery process outlined in the text and of strategic dealing when dealers seek to enhance the future information content of their order flow by building relationships. It would also be appropriate to delve more deeply into the ways in which structural differences between order-driven and quote-driven markets affect pricing and inventory management practices among market makers.

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Appendix A: Market Participants Weigh In

While writing this paper we corresponded frequently with currency market participants. There was no question among our correspondents that our broad conclusions accurately represent the cross-sectional pattern of currency spreads. We provide comments from two individuals.

Peter Nielsen is currently Global Head of Foreign Exchange, Currency Options, Equities & Futures at the Royal Bank of Scotland, the world's largest dealer in U.K. pounds and one of the larger foreign exchange dealing banks overall. He states:

> "Large customers tend to get better prices than smaller customers as they generally have more banking relationships, thereby providing a greater facility for price discovery than smaller customers who may only have one banking counterparty. In addition, in general, larger transactions are quoted with tighter spreads than smaller transactions, although the large customers tend to receive best pricing for all business due to the buying power associated with their overall size and volume of business." (Personal correspondence, April 8, 2004)

William Clyde, Ph.D., was Vice President and Manager of overnight trading at First Chicago Corp. and is now Professor of Finance at Quinnipiac University. He states:

> 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.
>
> Small trades, no matter what the source, do not contain much information. They are valuable only for either relationship building (which could result in very tight spreads – I've even quoted zero spreads on small trades to important relationships), or as sources of profit due to large spreads. In fact, it is common for someone asking for a price on a small trade to 'give up their side' and only ask for the bid or the offer (the one they want), in which case the spread implied by the price could be quite large without actually being quoted as a large spread.
>
> 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. So when you see a lot of financial institutions doing one thing you're sometimes getting a sense of a broad opinion. 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.' And the trades they're executing now don't tell you much about what other corporates are doing because their current trades reflect business deals done a long time ago, driven by lots of different things. (Personal correspondence, August 18, 2004)

Appendix B: Small Banks and Large Banks Behave Similarly

This Appendix documents that our small-bank dealer behaves very similarly to large-bank dealers in terms of pricing and inventory management. The analysis is based on the Madhavan-Shmidt model outlined in Section II, with all customers aggregated for comparability with earlier studies.

Baseline spreads: As shown in Table A1, our bank's average baseline half-spread for interbank transactions is about 1.5 pips, which is similar to estimates from other studies. For example, Goodhart et al. (2002) finds that the average spread for USD/EUR transactions on the Electronic Brokerage Service (EBS, one of the two major electronic brokerage systems for interbank trading) was 2.8 pips about one year after the euro was introduced. Our bank's average half-spread for customer deals, 9.2 pips, is much higher than its average interdealer spread of 1.6 pips. Bjønnes and Rime's (2001) NOK/DEM dealer also sets sharply higher spreads for customers than for other dealers. These figures imply that currency spreads average less than 0.1 percent; for comparison, average municipal bond spreads were 180 basis points in 2003 (Harris and Piwowar, 2004) and average spreads on the London Stock Exchange were 110 basis points in 1991 (Reiss and Werner 2004).

Influence of existing inventories: Our results indicate that existing inventories have no influence on the prices our dealer quotes to other dealers, consistent with recent studies of large banks (Yao, 1998; Bjønnes and Rime, 2004). Survey-based evidence confirms that inventories are of minimal importance when dealers set spreads, and that the dominant concern is whether spreads conform to market convention (Cheung and Chinn, 2001). Lyons (1995) provides evidence that his dealer did engage in inventory-based price shading towards other dealers in 1992. This may reflect the unusual character of Lyons' dealer who, as a jobber, dealt exclusively with other dealers at extremely high frequency. Yao (1998) claims that his dealer avoided such shading because it would reveal information about his inventory position.

Bjønnes and Rime (2004) argue that any shift away from inventory-based price shading in recent years may reflect the interbank market’s rapid shift to a heavy reliance on electronic brokerages after their introduction in the mid-1990s (Melvin and Wen, 2003). Our dealer reports that for interbank trades he generally uses EBS because it is less expensive and faster than direct interbank dealing.[25] Together, these observations imply that our dealer controls inventories via interbank trading instead of price shading, a conclusion we support empirically later in this section. Studies from other markets also show that dealers in two-tier markets with access to brokerage services prefer to manage their inventory through interdealer transactions (Reiss and Werner 1998).

The estimates in Table 4 seem to provide slight evidence of inventory-based price shading in the “wrong” direction with respect to transactions with customers. Reassuringly, this can be traced to one deal carried out in the first month of our sample period. If that deal is excluded, the coefficients on inventory are insignificant.

Deal size and spreads: The coefficient on deal size is statistically insignificant for interbank deals, suggesting that neither information asymmetries nor prospective inventories cause large interbank deals to be priced less attractively than small ones. This is consistent with the large dealing bank examined in Bjønnes and Rime (2004), for which spreads on brokered interbank transactions seem independent of deal size. That paper also finds that spreads rise with deal size for direct interbank transactions, a distinction that makes economic sense. Dealers have limited control over the relationship between deal size and spread for brokered transactions, but they have full control for direct deals. Notably, the earliest study of currency dealers (Lyons, 1995; Yao 1998), which did not control for the distinction between direct and

[25] This preference is supported by the transactions data. Our dealer's mean interbank transaction size was only €1.42 million (Table 1), the maximum interbank trade size was only € 16 million, and the standard deviation of these trade sizes was only €1.42. These small values are consistent with heavy use of EBS, where the mean USD/EUR transaction size in August 1999 was €1.94 million and the standard deviation of (absolute) transaction sizes was €1.63 million. By contrast, interbank deals averaged closer to $4 million prior to the emergence of electronic brokerages (Lyons, 1995).

brokered trades, found that interbank spreads do rise with deal size, consistent with standard models. This could reflect the fact that interbank trading was mostly carried out through direct transactions until the late 1990s.

The coefficient on deal size is also insignificant for customers in our baseline regression. Note that this coefficient is negative and significant when inventories are excluded: Section II shows that the overall relationship between spreads and deal size is indeed negative for customer transactions.

2. Inventory Management

Our dealer's tendency to keep inventories close to zero (Figure 1) is itself similar to inventory management practices at large banks. As Table 1 shows, currency dealers of all sizes tend to keep minimal inventories. A more rigorous description of our dealer's approach to inventory management comes from estimating the following regression:

$$I_t - I_{t-1} = \omega + \rho I_{t-1} + \varepsilon_t. \quad (4)$$

If the dealer instantly eliminates unwanted inventories, then $\rho \approx -1$. If the dealer allows his inventory to change randomly, then $\rho = 0$. The time subscript corresponds to transaction time, and only incoming transactions, for which our dealer quotes the price, are included (giving 2,858 observations). Results from estimating Equation (4), once again using GMM with Newey-West standard errors, confirm that our small bank consciously strives to keep inventories close to zero. Our point estimate of $\rho = -0.20$ has a standard error of 0.008 and is thus highly statistically significant. Thus the dealer on average eliminates 20 percent of an inventory shock in the next trade, which implies a median inventory half-life of 19 minutes.

Our estimated inventory half-life is quite close to the 18-minute median inventory half-life for Bjønnes and Rime's (2004) NOK/DEM dealer. The speed of adjustment faster in futures markets, where dealers eliminate almost half of any inventory shock in the next trade (Manaster and Mann 1994). Adjustment speeds are also faster of the large DEM/USD dealers at the bank studied by Bjønnes and Rime, for which inventory half-lives range from 0.7 to 3.7 minutes. Nonetheless, our dealer's adjustment speed is lightning fast, and hardly differs from the others just reported, when compared with inventory adjustment lags elsewhere. On the NYSE they average over a week (Madhavan and Smidt 1993) and can extend beyond a month (Hasbrouck and Sofianos 1993).[26] Even on the London Stock Exchange, which is a dealership market like FX, inventory half-lives average 2.5 trading days (Hansch *et al.* 1998).

Overall, this analysis shows that the dealer from which we take our data behaves much like large dealers despite his small volume.

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[26] We note in passing that inventory adjustment speed appears to be related to market structure. Adjustment lags in futures markets are comparable to those in FX (Manaster and Mann 1999), while those on the London Stock Exchange average only 2.5 days (Hansch et al. 1998).

Table A1. Baseline Madhavan-Smidt model

We estimate this equation: $\Delta P_{it} = \alpha + \beta_1 D_t + \beta_2 D_{t-1} + \gamma_1 I_{it} + \gamma_2 I_{it-1} + \delta Q_{jt} + \varepsilon_t$.
The dependent variable is the change in price between two successive incoming trades measured in pips. Q_{jt} is order flow measured in EUR millions, I_{it} is the dealer's inventory at time *t,* and D_t is an indicator variable picking up the direction of the trade, positive for purchases (at the ask) and negative for sales (at the bid). These variables are interacted with dummy variables for the two counterparty groups, other dealers (*IB* for "interbank") and all customers (*CU*). Data include all incoming customer USD/EUR spot and forward trades of a small bank in Germany, except those with preferred customers, over the period July 11, 2001 through November 9, 2001. Estimation uses GMM and Newey-West correction. Significance at the 1, 5 and 10 percent levels indicated by ‡, † and *, respectively.

	Baseline Regression		**Robustness Tests**		
			No Inventories	**Spot Trades Only**	**Interbank Trades Excluded**
	Coefficient	***Std. Error***	**Coefficient**	**Coefficient**	**Coefficient**
Constant	-0.590†	*0.23*	-0.426*	-0.383	0.070
Direction					
$CU \times D_t$	11.467‡	*0.50*	11.327‡	10.988‡	11.548‡
$CU \times D_{t-1}$	-9.206‡	*0.45*	-9.186‡	-8.864‡	-10.025‡
$IB \times D_t$	2.817‡	*0.69*	2.753‡	0.706	
$IB \times D_{t-1}$	-1.579‡	*0.48*	-1.555‡	-1.025†	
Inventory					
$CU \times I_{it}$	1.125‡	*0.38*		-0.064	0.855†
$CU \times I_{it-1}$	-1.264‡	*0.38*		-0.046	-0.974†
$IB \times I_{it}$	-0.259	*0.35*		-0.191	
$IB \times I_{it-1}$	0.133	*0.35*		0.187	
Deal Size					
$CU \times Q_{jt}$	0.126	*0.39*	-1.001‡	-0.840‡	-0.001
$IB \times Q_{jt}$	-0.152	*0.40*	0.055	0.590	
Adjusted R^2	0.23		0.23	0.23	0.32
Observations	2,848		2,848	2,212	1,640