End-User Order Flow and Exchange Rate Dynamics *

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Abstract

In this paper we provide evidence for Evans and Lyons' (2005b) model of an information aggregation process in FX markets using a German bank's end-user order flow from 2002 to 2003. Though customer order flow is unambiguously the vehicle incorporating non-public information into exchange rates over time, our empirical analysis does not support the widespread optimism in the market microstructure literature that customer order flow is the high-powered source of information easily exploitable for short-run speculation. Moreover, commercial customers' order flow produces negative coefficients in contemporaneous return regressions, stressing their role as liquidity providers.

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Keywords: foreign exchange; market microstructure; end-user order flow

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1 Introduction

In spite of many years of extensive research, short-run exchange rate fluctuations still remain difficult to explain, and standard macroeconomic models of exchange rates perform poorly particularly in terms of out-of-sample forecasting. As a baseline result, the random walk hypothesis can generally not be rejected at frequencies higher than one year (Meese and Rogoff, 1983, Cheung et al., 2005). Engel and West (2004, 2005) show that the unpredictability of short-run exchange rates may be due to some unobservable fundamentals following an I(1) process. In this case the discount factor in the present value equation approaches one, causing the exchange rate to exhibit time series properties similar to a random walk. If exchange rate dynamics are mainly driven by expectational surprises, there is obviously little room for forecasting based on fundamentals.[1]

The microstructure approach to foreign exchange suggests that the surprise part of the exchange rate equation, which by definition is orthogonal to public information can be explained by dealers' order flow (Evans and Lyons, 2005a). Order flow is defined as the net of buyer-initiated and seller-initiated currency orders submitted to a particular FX dealer. It may be interpreted as 'buying pressure' originating in shocks to costumers' hedging or liquidity demands, differential interpretation of public news, etc. Due to the intransparent structure of decentralized foreign exchange markets (Sager and Taylor, 2006), a dealer's order flow clearly represents private information. Thus, FX dealers are not uninformed market makers as in Kyle (1985), and may exploit this private information for future trades in the interdealer market. Evans and Lyons (2002a) develop a model that specifies how interdealer order flow maps information to exchange rates and find a strong positive correlation between the two variables. Alternatively, the trader may consider order flow information when quoting future spreads in the customer market, which is intensively investigated in the microstructure literature (eg. Huang and Stoll, 1997; Madhavan and Smidt, 1991). Independently of the dealer's decision on which market segment to choose in order to benefit from his private information, the logic of information aggregation on

[1] Some long-run forecastability seems to arise from nonlinearities in mean reversion of exchange rates; see - among others - Kilian and Taylor (2003).

FX markets implies that customer order flow will consistently be more important in the determination of exchange rates than interdealer flow (Sager and Taylor, 2005).[2] Indeed, Lyons (1995), Ito et al. (1998), and Bjønnes and Rime (2001) reveal that customer order flow is the primary source of private information in the FX market. Given that dealers maintain relationships with a broad range of different customers such as corporations, asset management firms, hedge funds, central banks, etc, it is natural to ask which group of customers provides the order flow that contains significant information (Evans and Lyons, 2005a).

Since the existence and structure of an information hierarchy across institutions shed light on the sources of private information in FX markets, it is surprising that only a few empirical contributions to the microstructure literature investigated FX data on the necessary level of disaggregation. Research using transaction data from different segments include Bjønnes et al. (2005), Carpenter and Wang (2003), Froot and Ramadorai (2005), Marsh and O'Rourke (2005), and Osler et al. (2006). A striking result is that order flow from financial customers is positively correlated with exchange rates whereas order flow from commercial customers tends to be negatively correlated, suggesting an alternative price discovery process in the foreign exchange market. Evans and Lyons (2005b) develop a new microstructure model that accounts for these puzzling findings. Distinguishing between different types of customers, who base their investment decisions on currently observable exchange rate fundamentals, and fundamentals which are observable only with a publication lag, allows for a realistic information aggregating process. In particular, financial customers engage in exchange rate research and receive a private (noisy) signal concerning the actual value of the unobservable fundamental. On the basis of their private signal and other publicly available information they submit orders to their FX dealer. Order flow from commercial customers is assumed to occur from international trade in goods and services. As such it is modeled as an AR(1) process that additionally accounts for correlation with exchange rate fundamentals and liquidity shocks. Dealers interpret the order flow from their customers as a noisy signal of the fundamental value of the exchange

[2] Moreover, order flow should have greater predictive power for exchange rates than fundamentals, at least in the short run.

rate and trade among each other. At the end of this trading process, the equilibrium exchange rate reflects that part of fundamental information that is common to all dealers.

This paper provides evidence in favor of the Evans and Lyons (2005b) model using transaction data of a small German bank in a one-year period from October 2002 to September 2003. First, we estimate standard market microstructure models to characterize the trading behavior of the dealer. We find that order size and currency spreads are negatively correlated and commercial customers are faced with higher spreads than financial customers. This contrasts with to standard adverse selection theory, which suggests that dealers increase spreads with a rising likelihood of private information indicated by customer type or order size (Glosten and Milgrom, 1985; Easley and O'Hara, 1987). Moreover, our dealer refrains from quote shading, i.e. he does not quote currency prices in order to manage inventory. Instead, undesired inventory is uploaded in the interdealer market. The empirical results in this section are in line with other studies such as Bjønnes and Rime (2005) and Osler et al. (2006), implying that the end-user order flow investigated here is similar to other dealing banks. Second, we apply cointegration techniques to assess the information content of end-user order flow. In line with the price discovery process suggested by Evans and Lyons (2005b), we find that exchange rates and customer order flow are cointegrated. In the cointegration relationship exchange rates are positively related to financial customer orders and negatively related to commercial customer orders. In the short run, however, neither financial nor commercial customer order flow Granger-causes exchange rate returns; dealers may therefore find the practical value of order flow for forecasting purposes to be negligible. This is in line with Sager and Taylor (2005), who provide evidence that the practical value of end-user order flow for short-run prediction may be limited.

The remainder of the paper is organized as follows. In Section 2, we describe our dataset on foreign exchange transactions of a German bank from October 2002 to September 2003. In Section 3, the dealer behavior is characterized by estimating standard microstructure models. Section 4 assesses the information content of the bank's order flow via a cointegration analysis. In the final section, we present some concluding remarks.

2 The Data

Our data set consists of all FX transactions of a German bank that occurred between October 2002 and September 2003, covering a period of 251 trading days. While a large cross-section of dealers and currencies appears in the raw data, we examine the most active dealer in the EUR/USD market. One drawback of focusing on trades of one currency pair of a single dealer is that we are unable to calculate the bank's inventory position. The calculation of spot inventory involves the aggregation of spot transactions across dealers and across currencies. Since our dealers trade in different currencies, we cannot calculate their USD inventory from EUR/USD transactions. In addition, spot inventory is also affected by swap transactions or exercised currency options. However, the head of currency trading convinced us that, in line with common standards, the bank's overnight position aggregated over dealers and currencies is negligible. As such, it is reasonable to assume that our trader's inventory at the end of trading days coincides with the bank's desired levels. Thus, we follow Lyons (1995) and set the inventory equal to zero at the beginning of each trading day.

Our sample is similar to other proprietary data used in Lyons (1995), and Bjønnes and Rime (2005), with two distinct features. Like Carpenter and Wang (2003) and Osler et al. (2006), each counterparty has a unique customer code, which allows us to classify trades according to their origin. This contrasts with Lyons (1995), where the dealer has no customer order flow and earns profits by continually "shading" his quotes to induce interbank trades. Bjønnes and Rime (2005) only distinguish between customer trading and interbank trading. Second, the length of the sample is much longer than that of Lyons (5 days), Bjønnes and Rime (5 days), and Osler et al. (87 days). Each trade record contains the following information: (1) currency pair, (2) date and time stamp of the trade, (3) direction, (4) transaction price, (5) market price from the interdealer market (Reuters), (6) deal size, (7) counterparty, and (8) the initiator of the trade.

Incoming trades are generally initiated by customers for which the dealer will always be the supplier of liquidity. However, in interbank trades the dealer may also provide liquidity to other dealers. Outgoing trades, in contrast, are trades initiated by our dealer. On the one hand, they reflect his potential to exploit private information gathered from incoming customer trades; on the other hand, they may represent his liquidity demand resulting from inventory control. Outgoing trades are initiated by requesting quotes from other dealers or submitting market orders to brokers and are executed at prices set by other dealers. Consistent with existing literature, order flow variables are calculated from the perspective of the deal initiator, implying that customers' buy orders have a positive sign, and sell orders have a negative sign. For outgoing trades of the dealer, trades will have a positive sign when he is buying and a negative sign when he is selling foreign currency.

[Figure 1 about here]

Figure 1 shows the tick-by-tick transaction prices traded by the dealer in the USD/EUR market over the period between October 2002 and September 2003. All overnight changes are removed from the sample, so that all price effects are related to intraday order flow transacted by the dealer. Over the entire period, the euro appreciated against the US dollar, peaking at US$ 1.19, its highest value since the start of the European monetary union. The expansionary stance of Federal Reserve monetary policy in the aftermath of the New Economy hype caused interest rate disadvantage of US money market funds vis--vis their European counterparts. Besides the interest differential, concerns about the sustainability of US current account deficit could have led market participants to close long positions in the US dollar instruments.

[Table 1 about here]

Table 1 presents the composition of the bank's trading by counterparty. 49 percent of the bank's trades are with other interbank dealers, while 46 percent are with the bank's customers. As a matter of fact, the dealer in this study is quite similar to the dealer in Osler et al. (2006), who had considerable customer order flow as well, albeit with substantially less volume. The average trade size varies across counterparties. As expected, comparatively large trades are initiated by other banks and financial customers. The mean trade size of commercial customers is approximately 20 percent of the mean trade size across all counterparties.

3 Pricing Behavior of an FX Dealer in the Dollar-Euro Market

The microstructure literature generally suggests that market making is performed under information asymmetry, implying that spreads should include an adverse-selection component that compensates dealers for losses to privately informed counterparties (Glosten and Milgrom, 1985; Kyle, 1985). Based on this literature, it is now commonly accepted that adverse selection costs are the primary channel through which asymmetric information affects spreads. The adverse selection component of spreads would be expected to rise with the likelihood that a given counterparty has private information. In an anonymous trading framework, this spread component is supposed to vary positively with trade size, since larger trades should be associated with higher adverse selection costs (Easley and O'Hara, 1987; Glosten, 1989). In real-world currency markets, however, dealing is not completely anonymous, as dealers maintain business relationships with major customers (Sager and Taylor, 2006). Within the group of customers importers and exporters ("commercial customers") are considered less informed than other banks and hedge funds (jointly "financial customers"). Thus, the standard models for understanding spreads under information asymmetry indicate that, other things being equal, currency spreads should be widest on financial customers' large trades and narrowest on commercial customers' small trades. In this section, we empirically investigate this hypothesis about the cross-section of spreads. Though the focus of this paper is on the adverse selection component, spreads may be determined by operating costs and inventory risk premiums as well. Thus, an empirical analysis of currency spreads should include each of the three components.

As a starting point, we estimate the Madhavan and Smidt (1991) (MS) model, because its structural equations are consistent with agents' optimizing behavior and an informational setup is explicitly provided applying Bayesian expectations. The basic intuition may be revealed by referring to the two key equations of the model; the dealer's pricing equation and the informed trader's demand equation. The price set by the dealer i is a linear function of the dealer's expectation about the true value of the exchange rate μ_{it} conditional on a public signal, the deviation of current inventory from desired inventory at the beginning of period t ($I_{it} - I^*_{it}$), and execution costs:

$$P_{it} = \mu_{it} - \alpha(I_{it} - I^*_{it}) + \gamma D_t, \tag{1}$$

where D_t is a direction dummy that takes the value 1 if the dealer sells and -1 if the dealer buys. The term γD_t thus represents the fixed processing costs of a given trade such as labor and equipment costs. A non-zero coefficient α suggests price shading, which means that the dealer changes prices in response to undesired inventory. The price set by the dealer is regret-free in the sense that it reflects the dealer's expectations conditional on the information as to whether the calling agent is buying or selling foreign currency. The amount of foreign currency that agent j wants to trade is a linear function of the perceived mispricing ($\mu_{it} - P_{it}$) and his liquidity demand X_{jt}:

$$Q_{jt} = \theta(\mu_{jt} - P_{it}) + X_{jt} \tag{2}$$

where μ_{jt} is agent j's expectation of the true currency value conditional on the public signal as well as a private signal. The empirical exchange rate equation that results from the MS model is as follows:

$$\Delta P_{it} = \beta_0 + \beta_1 Q_{jt} + \beta_2 I_{it} + \beta_3 I_{it-1} + \beta_4 D_t + \beta_5 D_{t-1} + \epsilon_{it} \tag{3}$$

where ΔP_{it} is the change in the exchange rate between two incoming trades. Due to equation (1) the dealer is assumed to manage existing inventories by shading prices so that $\beta_2 < 0 < \beta_3$. Moreover, the model of anonymous currency trading predicts an asymmetric information effect on prices ($\beta_1 > 0$), because the dealer rationally infers the agent's private signal about the true asset value from deal size. Lastly, the structure of the model expects the dummy coefficients to satisfy $\beta_5 < 0 < \beta_4$ and $\beta_4 > |\beta_5|$, the difference between the absolute values of the coefficients increasing in line with the information content of the deal flow.[3] This provides us with a Wald-type test of whether or not our dealer indeed uses order flow to infer information about the true value of the currency.

Equation (3) is estimated using Hansen's (1982) Generalized Method of Moments, because it adjusts standard errors for heteroskedasticity and serial correlation with the Newey and West (1987) correction of the covariance matrix. Since the focus of this paper is to investigate the importance of cross-sectional differences in the customer order flow, the following table 2 provides estimation results of the baseline MS model, the MS model including deal size and counterparty-type dummies.

[Table 2 about here]

The estimation results of the baseline MS model reveal important insights into the dealer's trading behavior. In line with recent studies such as Bjønnes and Rime (2005) and Osler et al. (2006), we find that existing inventories do not influence the prices our dealer quotes to customers. This contrasts with earlier studies of interdealer trading, where evidence is provided that dealers did engage in inventory-based price shading towards other dealers (Lyons, 1995). Since the introduction of electronic brokerages in the mid-1990s, dealers have tended to control inventories via interbank trading instead of price shading (Bjønnes and Rime, 2005). Of course, our dealer reportedly used electronic brokered trades (EBS) to unload undesired inventory, because it is less expensive and faster than price shading. The insignificance of inventory effects on price changes remains robust when controlling for deal size and/or customer type.

The estimated coefficient of the lagged direction dummy implies an average half spread of 5.8 pips, which is quite large compared to those reported in Bjønnes and Rime (2005) (2.95 pips) or Lyons (1995) (0.92 pips). We suggest that this result reflects fixed processing costs in a dealing environment dominated by small deal sizes. Support for this interpretation can be provided by re-estimating the model using dummy variables for small and large deal sizes and dummy variables for counterparty types. In case of orders with a deal

[3] For details see Madhavan and Smidt (1991).

size smaller than EUR 0.5 million, the estimated half spread is 10.13 pips, while orders with a deal size greater than EUR 0.5 million were executed at an average half spread of 1.17 pips. If order flow is differentiated by counterparty type, the half spread is just 0.94 pips for financial customers, but 9.8 (14.3) pips if the counterparty is a commercial (internal) customer. These numbers appear to be reasonable when compared to those reported in previous studies.

The Wald test shows that the direction dummy coefficient is statistically significantly larger in absolute terms than the coefficient of the lagged dummy. From calculating the ratio $|\beta_5|/\beta_4$ we find that the average weight put on prior information is 0.89, while the average weight put on order flow information is 0.11. Though our dealer obviously perceives order flow to be generally informative regarding the fundamental value of the exchange rate, the average weight put on order flow is somewhat smaller than in other studies such as Madhavan and Smidt (1991). However, this is because a substantial part of the order flow is generated by small transactions with commercial customers, which our dealer appears to regard as mostly uninformative. This becomes obvious when calculating the weights put on order flow information resulting from large deals (0.45) as opposed to small deals (0.10). Regarding counterparty dummies the results indicate that deals from financial customers are perceived as very informative (0.54), unlike orders from internal customers (0.03) and commercial customers (-0.04).

The coefficient on deal size is statistically significant and has the appropriate sign in the baseline model. At first glance the data set seems to provide evidence in favor of the standard hypothesis that, due to asymmetric information, a dealer increases spreads in response to a larger order and moves prices accordingly. When disaggregating the order flow by means of deal size dummies and counterparty dummies, however, we find the relationship between deal size and price movements to be concentrated on small deals with commercial or internal customers.[4] Moreover, the statistical insignificance of deal size parameters within the group of large deals and within the group of financial customers indicates that there is no residual linear variation of spreads according to deal size. Con-

[4]This is surprising, because order flows from these types of customers are generally not regarded as very informative since these customers trade currencies for hedging and liquidity purposes.

sistent with the results reported in Osler et al. (2006) and Bjønnes and Rime (2005) our findings suggest that deal size is relatively unimportant for pricing in foreign exchange markets.

The statistically insignificant deal size parameters may be due to traders' response to the strategy of dealers inferring information from order flow (Huang and Stoll, 1997). As informed traders' profits would surely decrease in the presence of learning dealers, there is a strong incentive to camouflage private information by splitting up orders into a number of (smaller) standardized transactions. Thus, dealers have lost a source of information and the trade direction is the remaining variable to capture the price impact of asymmetric information. The current price change may then be written as:

$$\Delta P_t = \frac{S}{2}(D_t - D_{t-1}) + \lambda \frac{S}{2} D_{t-1} - \delta \frac{S}{2} \Delta I_t + e_t \tag{4}$$

where ΔP_t is the change in price between two incoming trades, D_t the direction indicator which takes the value 1 if the dealer sells and -1 if the dealer buys, ΔI_t the change in inventory, and e_t the error term, which contains a public information shock and measurement errors associated with price discreteness. The coefficients λ and δ represent the influence of adverse selection costs and inventory costs, respectively. Both are measured as a percentage fraction of the half spread $S/2$ (in pips). As before, we investigate the influence of deal size and counterparty type by using dummy variables to disaggregate the data set and compare the results with the modified Huang and Stoll (1997) (HS) model. GMM estimators with Newey-West standard errors are reported in Table 3.

[Table 3 about here]

The results broadly confirm our findings from the MS model estimations. The average half spread of large deals is lower than the half spread of small deals and financial customers obtain narrower margins than commercial or internal customers. This seems to be a robust feature of FX dealing even though large trades and trades from financial customers are perceived to be informative, as suggested by the estimated λs. When looking at the parameter δ, the results imply a moderate influence on exchange rates only if the recent change in inventory appears to be caused by large trades or financial customers.

In general, we conclude that our dealer's pricing behavior exhibits recently detected properties of market making in foreign exchange. Though our bank has to be regarded as a small player in the FX business the results suggest that this data set may reflect more market-wide dynamics. This provides us with the opportunity to address the important question of the extent to which customer order flow from a single bank can be regarded as a critical source of private information.

4 The Information Content of End-User Order Flow

The discussion surrounding the information content gained momentum with the seminal paper by Evans and Lyons (2002a). Regressing exchange rate returns on interdealer order flow and the change in interest differentials, the authors find that 64% of daily mark-dollar returns and 45% of daily yen-dollar returns can be primarily explained by (interdealer) order flow. This striking result is confirmed by Evans and Lyons (2002b), who use the US dollar exchange rates of European currencies (though R^2 statistics vary substantially), and Killeen, Lyons and Moore (2006), who apply Johansen cointegration procedures to daily data from the Electronic Banking System (EBS). In general, there is now a broad consensus among researchers that order flow is the central mechanism by which private information is carried over to exchange rates. While this has proven to be very important from a theoretical perspective, the practical value of order flow considerations remains unclear. As pointed out by Sager and Taylor (2005) the ability of order flow data available to market participants to improve forecasting performance seems to be generally weak. The authors analyze the relationship between order flow and *subsequent* exchange rate returns using different data sets, including the one used in Evans and Lyons (2002a), and find that R^2 statistics fall virtually to zero. When additionally considering Granger-causal relationships running from exchange rate returns to order flow, it has to be concluded that the practical value of (publicly available) order flow information for decision making in FX markets seems to be limited. Bjønnes and Rime (2001) and Sager and Taylor

(2005) conclude that, at best, for dealers who are able to sample order flow at very high frequencies (including on a tick-by-tick basis) and in a raw unmanipulated form, these data may represent an important, and profitable, source of private information.

Against the background of Evans and Lyons (2005b), even dealers who are able to sample order flow at very high frequencies, including on a tick-by-tick basis, may not benefit in the simple way as suggested by earlier models. The order flow data of a single dealer are unlikely to significantly predict next period's order flow in the interdealer market, where exchange rates are actually set. However, dispersed information about unobservable fundamentals is slowly compounded in every dealer's customer order flow. Thus, a single dealer's customer order flow has long-run forecasting power, because it is correlated with future market-wide information flow that dealers use to set prices. To provide evidence for this complex mechanism we first test for the equilibrium relationship by means of cointegration analysis and Granger-causality tests. Second, the adjustment process of deviations from equilibrium is investigated by estimating the related error correction model.[5]

Before analysing cointegration relationships we test for stationarity of the order flow variables and the exchange rate. Note that the microstructure models of section 3 are estimated using 'dealt' spot rates, whereas in this section the 'market' spot rate received from Reuters is used to investigate the information transmission of customer order flow. As Table 4 shows, the results of the Augmented Dickey-Fuller tests suggest non-stationarity of cumulative incoming order flow as well as the level of the exchange rate. The time series of cumulative incoming order flows do not coincide with the dealer's inventory, which was made stationary by setting it equal to zero at the beginning of each trading day. We follow the Johansen procedure in order to test for cointegration of the exchange rate and the different types of order flow. First, the unrestricted VAR models

$$\begin{pmatrix} P_t \\ X_{i,t} \end{pmatrix} = \begin{pmatrix} \beta_0^P \\ \beta_0^{X_i} \end{pmatrix} + \begin{pmatrix} \beta_1^P \\ \beta_1^{X_i} \end{pmatrix} trend_t + \sum_{j=1}^{4} \Gamma_j \begin{pmatrix} P_{t-j} \\ X_{i,t-j} \end{pmatrix} + \begin{pmatrix} u_t^P \\ u_t^{X_i} \end{pmatrix} \tag{5}$$

are estimated, where t is an event time observation counter and i represents the coun-

[5]VAR analysis has been applied to market microstructure models by - inter alia - Hasbrouck (1991a,b), Payne (2003) and Killeen et al. (2006).

terparty type, i.e. $i \in \{Internal, Financial, Comercial, Financial + Commercial\}$. The lag order of the system is set to four according to the recommendation of the Schwarz and Hannan-Quinn information criteria. Second, Maximum Eigenvalue statistics and trace statistics are calculated to test the null hypothesis of no-cointegration. The numbers in table 4 indicate that no cointegration with the exchange rate is rejected for financial and commercial customers, while no cointegration of the exchange rate and the order flow from internal customers cannot be rejected at standard levels. Thus, we skip order flow from internal customers from the subsequent analysis. In order to compare our results with earlier studies, we construct an aggregated order flow consisting of incoming trades of financial and commercial customers.

Third, we estimate the related vector error-correction model

$$\begin{pmatrix} \Delta P_t \\ \Delta X_{i,t} \end{pmatrix} = \begin{pmatrix} \alpha^P \\ \alpha^{X_i} \end{pmatrix} \begin{pmatrix} 1 & \beta_{i0} & \beta_{i1} & \beta_{i2} \end{pmatrix} \begin{pmatrix} P_{t-1} \\ 1 \\ trend_{t-1} \\ X_{i,t-1} \end{pmatrix} + \sum_{j=1}^{3} \Gamma_j \begin{pmatrix} \Delta P_{t-j} \\ \Delta X_{i,t-j} \end{pmatrix} + \begin{pmatrix} \varepsilon_t^P \\ \varepsilon_t^{X_i} \end{pmatrix} \tag{6}$$

for the different types of incoming order flow. The coefficients of the cointegrating vector - constituting the equilibrium relationship between the two variables - are statistically significant and have the expected sign. In case of financial customers, the β_{i2} parameter confirm the standard result in market microstructure that cumulative order flow is positively correlated with the exchange rate. Interestingly, this is not true for order flow from commercial customers. As predicted by Evans and Lyons (2005b) and consistent with Marsh and O'Rourke (2005), Bjønnes et al. (2005), and Osler et al. (2006), we find that buying pressure from commercial customers increases when the spot rate decreases and vice versa. Osler (1998) suggests that the negative correlation is due to the role of commercial customers as the ultimate liquidity suppliers in the FX market. If financial customers buy foreign exchange on average, dealers clearly will provide the necessary liquidity in the first place. However, as these market participants try to limit their open positions, they pass on undesired order flow to counterparties outside their own circle. To quote from Osler et al. (2006): "Whoever they are, these ultimate liquidity providers have cumulative order flow that must, by definition, be negatively correlated with exchange rates, and information about their order flow would not have incremental value once one knew about financial customers' order flow." In practice, commercial customers act as liquidity suppliers by submitting conditional market orders, so-called take-profit orders, which trigger buy orders when the exchange rate falls to a pre-specified level and vice versa (Osler 2003, 2005), or they try to exploit intra-day exchange rate movements by applying a buy low/sell high strategy. The above interpretation of parameter signs suggests that, indeed, financial customers drive prices of foreign exchange, whereas commercial customers react to price changes. The dominating role of financial customers is confirmed by the fact that the positive correlation between order flow and exchange rate is preserved in case of aggregated incoming orders.

Finally, the adjustment dynamics of the above cointegrated system is investigated. In particular we are interested in which variable provides the adjustment to equilibrium. The answer to this question comes from the error correction (ECM) coefficients, coefficients of lagged changes in spot price and order flow, and various test statistics summarized in Table 5. The estimated coefficients might also be used to evaluate how rapidly this system reverts to its equilibrium, i.e. to measure information half lifes. Remember, however, that the order flow comes from customers of a single bank, whereas the exchange rate is driven by market-wide order flow. Hence, the reported price-impact coefficients are based on a noisy signal of the market-wide order flow and tend to overestimate the influence of order flow on exchange rates. At best, they may be viewed as a qualitative characterization of market-wide patterns.

The estimated ECM coefficients differ substantially between customer groups. In case of financial customers, 0.1 percent of departures from equilibrium is dissipated each incoming trade. The adjustment is significantly driven by both the spot price and the order flow; this is confirmed by the rejection of both the weak and strong exogeneity hypothesis.[6] The reported average half lives of 81 hours and 67 hours reflect the fact that private signals of FX end-users are slowly processed into the information aggregation mechanism

[6]While tests for weak exogeneity focus on statistically significance of the ECM coefficient, strong exogeneity comprises weak exogeneity and Granger causality.

(Evans and Lyons, 2005b).[7]

In case of commercial customers, weak and strong exogeneity of the spot price cannot be rejected at least at the 5% level, which implies that commercial customer order flow is the variable that reacts to deviations from the equilibrium. Again, this is consistent with Evans and Lyons (2005b) and the hypothesis that commercial customers are the ultimate providers of liquidity in FX markets. The estimated average half-life is shorter than that of financial customers, but longer than those reported in Osler et al. (2006). The latter difference in the results might be due to the fact that our data set contains very few take-profit orders, which react immediately to price changes.

Concerning aggregated order flow, the ECM coefficient in the exchange rate equation is statistically significant, but is of lower magnitude than the ECM coefficient in the exchange rate equation of financial customers. The reason for the weaker adjustment of exchange rates to the equilibrium level, which is mirrored in a longer half life of deviations, is the tendency of commercial customers to smooth the impact of financial customers by selling foreign currency when the exchange rate rises and vice versa.

Regarding the hypothesis that dealers subsidize trades with financial customers in order to gain an informational advantage exploitable in future trades originally proposed by Leach and Madhavan (1992) and applied to foreign exchange markets by Osler et al. (2006) is not supported by our data. First, adjusted R^2 statistics do not exceed 14 percent, implying that the error correction model explains only a minor fraction of total return variance. Second, statistically insignificant coefficients of lagged order flow leads to a rejection of the hypothesis that order flow Granger-causes spot rate changes. One might argue that these regressions cannot fully assess forecasting ability, because the model only fails to provide significant point estimates. Clearly, traders do not care much about the exact amount of order flow necessary for a given spot return. Therefore, we rerun the model using a cumulative trade indicator instead of cumulative incoming orders, but the results do not change qualitatively.[8] Obviously, deals initiated by financial

[7] Remaining serial correlation at higher lags in the residuals of order flow equations, as documented by the Q statistics, may also be interpreted as the outcome of slow learning processes.

[8] The results are available from the authors on request.

customers seem to be unable to predict current spot price changes in the short run (Sager and Taylor, 2005). It might be argued that the data set at hand comes from a small German bank, which probably does not maintain strong business relationships with major players in the FX markets. While containing idiosyncratic elements, even a data set from a small bank may be correlated with those from other banks, because the FX market is extremely competitive and large orders from informed investors are split across multiple banks.

If the strategic dealing hypothesis is unlikely to be the major dealing mechanism, the question is what forces our dealer to quote narrower spreads to financial customers than to commercial customers. Green et al. (2006) argue that opaque markets allow dealers to exploit market power vis-à-vis market participants who are endowed with little knowledge about current market conditions. In contrast, dealers earn lower markups on trades with informed customers, even though these trades are likely to bear more inventory risks. From this point of view, the bargaining power of our dealer seems to be weak vis-à-vis financial customers.

5 Conclusions

In a recent paper, Evans and Lyons (2005b) developed a new microstructure model for understanding end-user order flow in FX markets. Distinguishing between different types of customers, who base their investment decisions on concurrently observable exchange rate fundamentals and those which are not immediately observable, allows for a more realistic aggregating process of end-user (private) information. In particular, financial customers are supposed to engage in exchange rate research and receive a private (noisy) signal concerning the actual value of the unobservable fundamental. Order flow from commercial customers is modeled as an AR(1) process that additionally accounts for correlation with exchange rate fundamentals and liquidity shocks. Dealers interpret the order flow from their customers as a noisy signal of the fundamental value of the exchange rate and trade among each other. At the end of this trading process the equilibrium exchange rate reflects that part of fundamental information that is common to all dealers.

This paper provides strong empirical evidence in favor of this complex information aggregation process. Using a tick-by-tick FX data set of a small German bank, we first show that the trading activities of our dealer are consistent with the standard behavior of FX dealers by estimating standard market making models. By means of cointegration and vector error correction analysis of the different counterparty types and the exchange rate, we then empirically investigate the major propositions of Evans and Lyons' (2005b) model. The results are encouraging. First, commercial customers' order flow produces negative coefficients in contemporaneous return regressions, stressing their role as liquidity providers. Second, customer order flow is cointegrated with exchange rates, suggesting a stable relationship between end-user order flow and market-wide information flow used by dealers to set prices. Third, small error correction coefficients confirm that exchange rates react very slowly to shocks stemming from customer order flow. Moreover, low R^2 statistics indicate that order flow data of a single dealer (bank) explains only a minor fraction of concurrent exchange rate variation.

Though customer order flow is unambiguously the vehicle incorporating non-public information into exchange rates, our analysis does not support the widespread optimism in the market microstructure literature that customer order flow is the high-powered source of information easily exploitable for speculative purposes. In contrast, we strengthen the notion that in the short run the "... knowledge of customer or interdealer order flow cannot help improve the quality of exchange rate forecasting or the profitability of investment portfolio decision-making" (Sager and Taylor, 2005, p. 24).

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Table 1: Trading activity of a small German bank

254 trading days between October 1, 2002 and September 30, 2003

	Financial Cust.	Commercial Cust.	Internal Cust.	Interbank Cust.	All Cust.
Incoming transactions	189	5,229	639	5,773	11,83
Percent	1.6%	44.2%	5.4%	48.8%	100.0%
per trading day	0.8	20.8	2.5	23	47.1
Turnover (EUR million)	841	1,118	1,044	9,049	12,052
Mean size spot (EUR million)	4.4	0.2	1.6	1.6	1.2

Table 2: Spread variation across deal size and counterparty type

254 trading days between October 1, 2002 - September 30, 2003 (11,830 obs.)

	Baseline MS	Size Dummies		Counterparty Dummies	
Constant	0.21 (0.11)*		0.15 (0.11)		0.08 (0.11)
Deal Size Q_{it}	0.34 (0.13)**	Large	0.06 (0.08)	Commercial	0.94 (0.17)***
		Small	20.2 (2.10)***	Financial	0.09 (0.09)
				Internal	0.29 (0.14)**
Inventory I_t	0.01 (0.07)	Large	0.03 (0.07)	Commercial	0.04 (0.07)
		Small	0.03 (0.07)	Financial	0.04 (0.07)
				Internal	0.03 (0.09)
Lagged Inventory I_{t-1}	0.001 (0.07)	Large	0.04 (0.07)	Commercial	0.03 (0.07)
		Small	0.02 (0.07)	Financial	0.05 (0.07)
				Internal	0.16 (0.12)
Direction D_t	6.48 (0.20)***	Large	2.13 (0.21)***	Commercial	9.47 (0.19)***
		Small	11.5 (0.26)***	Financial	2.04 (0.21)***
				Internal	14.8 (1.08)***
Lagged Direction D_{t-1}	5.82 (0.18)***	Large	1.17 (0.15)***	Commercial	9.84 (0.20)***
		Small	10.3 (0.26)***	Financial	0.94 (0.15)***
				Internal	14.3 (1.50)***
R^2	0.23		0.33		0.34

Notes: The dependent variable is the change of the currency price measured in pips between two incoming deals. The set of instruments equals the set of regressors implying that the parameter estimates parallel OLS estimates (see Bjønnes and Rime, 2005). * (**, ***) denote significance at the 10% (5%, 1%) level.

Table 3: Modified Huang and Stoll (1997) model

254 trading days between October 1, 2002 September 30, 2003 (11,830 obs.)

	Baseline HS	Deal Size Dummies		Counterparty Dummies	
Half-spread ($S/2$)	6.19 (0.14)***	Large	3.70 (0.12)***	Financial	3.56 (0.12)***
		Small	8.41 (0.18)***	Commercial	7.72 (0.14)***
				Internal	11.98 (0.69)***
Information (λ)	2.25 (2.82)	Large	115.70 (5.07)***	Financial	116.65 (5.30)***
		Small	39.56 (2.57)***	Commercial	42.01 (2.41)***
				Internal	56.48 (9.98)***
Inventory (δ)	4.95 (1.45)***	Large	6.75 (1.45)***	Financial	3.42 (1.30)***
		Small	1.60 (0.92)*	Commercial	3.91 (2.23)*
				Internal	2.37 (1.23)*
$Adj.R^2$	0.29		0.40		0.42

Notes: The dependent variable is the change of the currency price measured in pips between two incoming deals. The set of instruments equals the set of regressors implying that the parameter estimates parallel OLS estimates (see Bjønnes and Rime, 2005). * (**, ***) denote significance at the 10% (5%, 1%) level.
The half spread $S/2$ is in pips. The coefficient λ and δ are measured in percent of the half spread.

Table 4: Cointegration relationship between exchange rates and cumulative incoming orders

254 trading days between October 1, 2002 and September 30, 2003

	Internal Customers	Financial Customers	Commercial Customers	Fin. and Com. Cust.
Unit-root test (ADF) tStatistic	2.10	1.74	1.52	1.97
Max. Eigenvalue statistics	10.47	16.54†	18.50†	18.54†
Trace test statistics	12.71	18.54	19.48	20.82

Notes:

Unit root test: The number of lags included is calculated from the sample size (Newey-West automatic truncation lag selection).

The t - Statistic of the level of the exchange rate is 2.79. DF 10% critical value for unit root test with constant and trend: 3.13.

Max. Eigenvalue test: 5% critical value of the unrestricted cointegration rank test (Maximum Eigenvalue): 14.26 (†denotes significance).

Trace test: 5% critical value of the unrestricted cointegration rank test (trace): 15.49 (†denotes significance).

Table 5: Cointegration relationship between exchange rates and cumulative incoming orders

254 trading days between October 1, 2002 and September 30, 2003

	Financial Customers		Commercial Customers		Fin. and Com. Customers	
Dependent variable	ΔP_t	ΔX_t	ΔP_t	ΔX_t	ΔP_t	ΔX_t
ECM coefficient	0.10 (2.46)**	-0.12 (3.38)***	0.19 (1.90)*	0.21 (3.95)***	0.05 (2.25)**	0.15 (3.70)***
Half life	80.8 hours	67.3 hours	42.5 hours	38.5 hours	161.6 hours	50.5 hours
ΔP_{t-1}	0.41 (39.43)***	22.87 (1.73)*	0.41 (39.21)***	2.53 (0.50)	0.41 (39.44)***	26.81 (1.88)*
ΔP_{t-2}	0.15 (13.90)***	6.50 (0.46)	0.15 (13.77)***	3.40 (0.62)	0.15 (13.91)***	10.64 (0.70)
ΔX_{t-1}	0.12 (1.43)	0.13 (12.57)***	0.23 (1.09)	0.01 (0.48)	0.13 (1.75)*	0.11 (10.36)***
ΔX_{t-2}	0.01 (1.11)	0.11 (10.55)***	0.17 (0.80)	0.01 (0.01)	0.10 (1.34)	0.08 (7.77)***
$Adj.R^2$	0.04	0.14	0.001	0.14	0.03	
Q(10)	1.16 (0.31)	3.55 (0.00)	1.05 (0.40)	2.00 (0.03)	1.12 (0.34)	3.03 (0.00)
Weak exogeneity	6.07**	11.40***	3.77*	15.59***	5.06**	13.66***
Strong exogeneity	10.07**	15.93***	5.71	17.57***	10.62**	17.99***

Notes:

ECM coefficient in the ΔP_t equation is multiplied by 100 and order flow variables are in EUR million; t-statistics in brackets.

* (**, ***) denote significance at the 10% (5%, 1%) level.

$Q(10)$ is the Breusch-Godfrey F-test of residual autocorrelation up to ten lags, p-value in brackets.

Weak exogeneity: χ^2-test statistic (1 df).

Strong exogeneity: χ^2-test statistic (4 df).

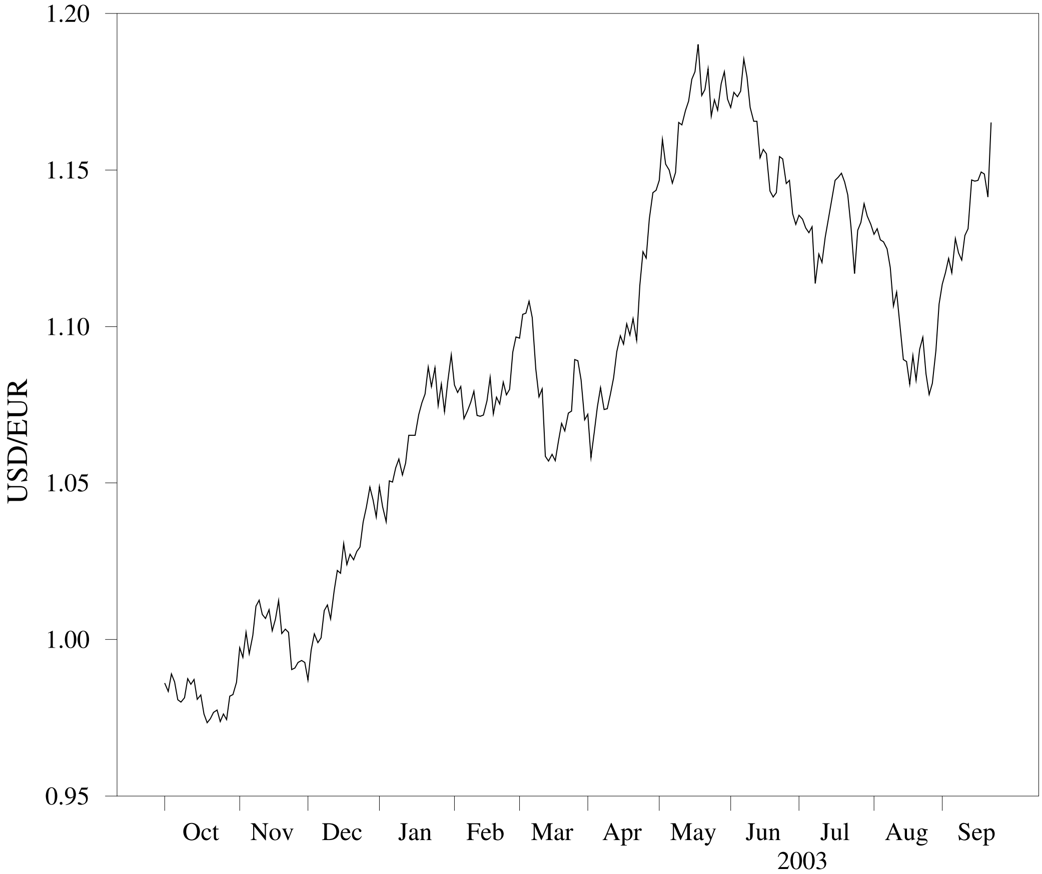

Figure 1: US dollar spot rate of the Euro