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5 Foreign Exchange Volume: Sound and Fury Signifying Nothing?

Richard K. Lyons

Volume in the spot foreign exchange market dwarfs that in any other financial market. But is all this trading informative? This paper provides some empirical evidence. At the broadest level, my results help clarify why trading volume in this market is extraordinarily high. At a narrower level, I provide some sharp results regarding the relation between the intensity of trading and the informativeness of trades.

Specifically, I provide results that discriminate between polar views of trading intensity, to which I refer as (1) the event-uncertainty view and (2) the hot potato view. The event-uncertainty view holds that trades are more informative when trading intensity is high; the hot potato view holds that trades are more informative when trading intensity is low. In general, theory admits both possibilities, depending primarily on the posited information structure.

To understand the event-uncertainty view—that trades are more informative when trading intensity is high—consider the work of Easley and O'Hara (1992). In contrast to earlier models where new information is known to exist, in Easley and O'Hara (1992) new information may not exist. That is, there is some probability, say p, of new information and probability $(1 - p)$ of no new information. In the event of new information, there is some probability, say q, that an informed trader has received good news and probability $(1 - q)$ of having received bad news. They demonstrate that, if there is no trade at time t, then a rational dealer raises the probability that she attaches to the no-

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information event and lowers the probability of news having occurred. Put differently, if trading intensity is low, an incoming trade of a given size induces a smaller update in beliefs since it is less likely to be signaling news. On the flip side, trades occurring when intensity is high should induce a larger update in beliefs.

To understand the term *the hot potato view*—that trades are more informative when trading intensity is low—consider the ideas of Admati and Pfleiderer (1988). Key to their model is the presence of discretionary liquidity traders: in order to minimize their losses to informed traders, rational liquidity traders clump together in their trading. (The reason that informed traders cannot fully offset this advantage to clumping is that information is short-lived.) Owing to this clumping of liquidity traders, trades occurring when intensity is high tend to be less informative.

The metaphor of the hot potato offers a link between this discretionary liquidity trading and foreign exchange trading. Foreign exchange dealers use the metaphor in referring to the repeated passage of idiosyncratic inventory imbalances from dealer to dealer following an innovation in customer order flow. These interdealer liquidity trades are clearly discretionary as to timing—hence the connection between discretionary liquidity trading and the hot potato view of order-flow information. To clarify the hot potato process, consider the following crude but not unrealistic example. (Keep in mind that roughly 85 percent of foreign exchange trading is interdealer, a much higher share than in other multiple-dealer markets.) Suppose that there are ten dealers, all of whom are risk averse, and each currently with a zero net position. A customer sale of $10 million worth of deutsche marks is accommodated by one of the dealers. Not wanting to carry the open position, the dealer calculates his share of this inventory imbalance—or one-tenth of $10 million—calls another dealer, and unloads $9 million worth of deutsche marks. The dealer receiving this trade then calculates his share of this inventory imbalance—or one tenth of $9 million—calls another dealer, and unloads $8.1 million worth of deutsche marks. The hot potato process continues. In the limit, the total interdealer volume generated from the $10 million customer trade is $9 million $/(1 - 0.9) =$ $90 million. Thus, the example produces an interdealer share of 90 percent, roughly matching the empirical share.

Here are two possible reactions to the example given above, neither of which vitiates its message. (*a*) Shouldn't the multiplier be infinite since risk-averse dealers would not choose to retain any of the imbalance? The answer is that, in equilibrium, price will adjust to induce dealers to hold some of the perceived excess supply. The 10 percent rule of the example is a crude approximation of a much richer short-run clearing mechanism.[1] (*b*) Interdealer trades can reduce idiosyncratic inventory imbalances—which reduces idiosyncratic risk rather

1. For an optimizing model in which hot potato trading arises between dealers, see Lyons (1995a). Flood (1992) examines simulation experiments that allow for hot potato trading.

than simply bouncing it—and this will mute the multiplier. This is true, particularly if the trades are brokered. It is therefore more reasonable to think about the example in terms of *net* customer orders rather than gross.

The role of time in the empirical microstructure literature has only recently emerged. Two important contributions are Hasbrouck (1991) and Hausman, Lo, and MacKinlay (1992). Hasbrouck decomposes the variance of stock price changes into trade-correlated and trade-uncorrelated components and finds that trades are more informative at the beginning of the trading day. Also working with stocks, Hausman et al. test for exogeneity of the length of time between transactions, which they reject at conventional significance levels. However, they argue that their estimates do not change when endogeneity is addressed using instrumental variables. On the basis of this, they forge ahead with the assumption of exogenous intertransaction times.

Empirical microstructure work in foreign exchange has been constrained until recently by a lack of transaction-level data. The paper most closely related to the analysis here is Lyons (1995b), which uses a transactions data set that is a subset of the data used here (namely, it uses dealt quotes only). That paper presents evidence supporting both of the two branches of microstructure theory: the asymmetric-information branch and the inventory-control branch. Although many papers have provided evidence supporting the asymmetric-information branch, little or no direct evidence had previously been found in support of the inventory-control branch (see, e.g., Madhavan and Smidt 1991; Manaster and Mann 1993; and the overview in O'Hara 1995). The fact that they are both present provides further impetus for the application of microstructural models to the foreign exchange market. The application here extends previous work by addressing the informational subtleties of order flow.

The chapter is organized as follows: section 5.1 presents a model of transaction prices that includes a relation between trading intensity and the information content of trades; section 5.2 describes the data; section 5.3 presents the results; and section 5.4 concludes.

5.1 A Model in Which Time Matters

The following model extends the model of Madhavan and Smidt (1991) by incorporating a role for intertransaction time. As they do, I will exploit the model's ability to disentangle the information effects of trades from the inventory-control effects. The result is a richer characterization of the effect of trades on price.

There are two assets in a pure exchange economy: one riskless (the numeraire) and one with a stochastic liquidation value (representing foreign exchange). The foreign exchange market is organized as a decentralized dealership market with n dealers. Here, we focus on the pricing behavior of a representative dealer, denoted dealer i. A period is defined by a transaction effected against dealer i's quote, with periods running from $t = 1, 2, \ldots, T$.

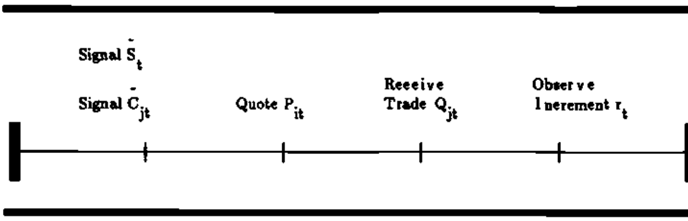

Fig. 5.1 Sequencing in each period

Note: $\tilde{S}_t$ is a public signal of the full information value V_t; $\tilde{C}_{jt}$ is dealer j's private signal of V_t, where j denotes the dealer requesting the quote from dealer i; P_{it} is dealer i's bilateral quote to dealer j, a schedule matching each transaction quantity with a price; Q_{jt} is the signed quantity traded, positive for dealer j's purchases, negative for sales; and r_t is the period t increment to V_t.

Let dealer j denote the dealer requesting dealer i's quote in any period. Figure 5.1 summarizes the timing in each period.

5.1.1 The Information Environment

The full information price of foreign exchange at time T is denoted by $\tilde{V}$, which is composed of a series of increments—for example, interest differentials—so that $\tilde{V} = \sum_{t=0}^{T} \tilde{r}_t$, where r_0 is a known constant. The increments are i.i.d. mean zero. Each increment r_t is realized immediately after trading in period t. Realizations of the increments can be thought to represent the flow of public information over time. The value of foreign exchange at t is thus defined as $V_t = \sum_{i=0}^{t} r_i$. At the time of quoting and trading in period t, that is, before $\tilde{r}_t$ is realized, $\tilde{V}_t$ is a random variable. In a market without private information or transaction costs, the quoted price of foreign exchange at time t, denoted P_t, would be equal to V_{t-1}, which is the expected value of the asset price conditional on public information available at t.

The following two signals define each period's information environment prior to dealer i's quote to dealer j:

$$\tilde{S}_t = V_t + \tilde{\eta}_t, \tag{1}$$

$$\tilde{C}_{jt} = V_t + \tilde{\omega}_{jt}, \tag{2}$$

where the noise terms η_t and ω_{jt} are normally distributed about zero, are independent of one another and across periods, and have variances σ^2_η and σ^2_ω, respectively. At the outset of each period t, all dealers receive a public signal S_t of the full-information value V_t. Also at the outset of each period t, dealer j—the dealer requesting a quote—receives a private signal C_{jt} of V_t. In the foreign exchange market, one potential source of private signals at the dealer level is order flow from nondealer customers; because each dealer has sole knowledge of his own-customer order flow, to the extent that this flow conveys information it is private information, which can be exploited in interdealer trading (see, e.g., Goodhart 1988, 456; and Lyons 1995a).

Dealer i conditions on S_t and then quotes his schedule as a function of possible Q_{jt}. The schedule's sensitivity to Q_{jt} ensures that any realization of Q_{jt} will be regret free for the quoting dealer, in the sense of Glosten and Milgrom (1985). That is, the quote takes account of the adverse selection arising from dealer j's additional information $\tilde{C}_{jt}$. Of course, the realization of Q_{jt} still provides dealer i a signal of $\tilde{C}_{jt}$. As is standard, the signed quantity that dealer j chooses to trade is linearly related to the deviation between dealer j's expectation and the transaction price, plus a quantity representing liquidity demand X_{jt} that is uncorrelated with V_t:

$$Q_{jt} = \theta(\mu_{jt} - P_{it}) + X_{jt}. \tag{3}$$

where μ_{jt} is the expectation of V_t conditional on information available to dealer j at t, and the value of X_{jt} is known only to dealer j. (The demand function that supports eq. [3] requires either exponential utility defined over a single period or mean-variance optimization over multiple periods.)

I introduce a role for time in the model via equation (3) and the liquidity demand X_{jt}. The hot potato hypothesis of order-flow information associates liquidity demand X_{jt} with inventory-adjustment trading. In foreign exchange—according to the hypothesis—innovations in nondealer order flow spark repeated interdealer trading of idiosyncratic inventory imbalances. This rapid passing of the hot potato generates a relatively large role for liquidity trades in periods of short intertransaction times. The event-uncertainty hypothesis, in contrast, associates short intertransaction times with a relatively large role for informative trading: in the presence of event uncertainty, intense trading is a signal that an information event has occurred. To summarize, for given precisions of the signals C_{jt} and S_t, we can characterize these views as follows:

Hot potato hypothesis:

$$\sigma^2_{Xj} \begin{cases} \text{high when intertransaction times are short;} \\ \text{low when intertransaction times are long.} \end{cases}$$

Event-uncertainty hypothesis:

$$\sigma^2_{Xj} \begin{cases} \text{low when intertransaction times are short;} \\ \text{high when intertransaction times are long.} \end{cases}$$

This change in the relative intensity of liquidity trading will alter the signal extraction problem faced by the quoting dealer, to which we now turn.

5.1.2 The Formation of Expectations

Dealer i's quotes depend on his conditional expectation of V_t at the time of quoting, which I denote μ_{it}. This expectation, in turn, is a function of the variables described above: S_t and Q_{jt}; the third variable described above, $\tilde{C}_{jt}$, is communicated (noisily) to dealer i via Q_{jt}.

I now address the determination of this expectation μ_{it}. Dealer i's prior belief regarding V_t is summarized by the public signal S_t. Dealer i then considers the "what if" of various possible Q_{jt}'s. In particular, from any Q_{jt} dealer i can form the statistic Z_{jt} (see the appendix):

$$(4) \qquad Z_{jt} \equiv \frac{Q_{jt}/\theta + P_{it} - \lambda S_t}{1 - \lambda} = V_t + \tilde{\omega}_{jt} + [1/\theta(1 - \lambda)]\tilde{X}_{jt},$$

where $\lambda \equiv \sigma^2_\omega/(\sigma^2_\eta + \sigma^2_\omega)$. This statistic is normally distributed, with mean V_t and variance equal to the variance of the last two terms, both of which are orthogonal to V_t. Via X_{jt}, the variance of the second of these two terms is a function of intertransaction times, per above. Let σ^2_{Zs} denote the variance of the statistic Z_{jt} when intertransaction times are short, and let σ^2_{Zl} denote the variance of Z_{jt} when intertransaction times are long.

Since Z_{jt} is statistically independent of S_t, dealer i's posterior μ_{it}, expressed as a function of any Q_{jt}, takes the form of a weighted average of S_t and Z_{jt}:

$$(5) \qquad \mu_{it} = \kappa_k S_t + (1 - \kappa_k)Z_{jt}, \quad k = s, l,$$

where $\kappa_s \equiv \sigma^2_{Zs}/(\sigma^2_{Zs} + \sigma^2_\eta)$, and $\kappa_l \equiv \sigma^2_{Zl}/(\sigma^2_{Zl} + \sigma^2_\eta)$. This expectation plays a central role in determining dealer i's quote. Note that $\kappa_s > \kappa_l$ if $\sigma^2_{Zs} > \sigma^2_{Zl}$, that is, if liquidity trading is relatively important when intertransaction times are short.

5.1.3 The Determination of Bid/Offer Quotes

Consider the following prototypical inventory-control model. Here, the transaction price is linearly related to the dealer's current inventory—a specification that is optimal in a number of inventory control models:

$$(6) \qquad P_{it} = \mu_{it} - \alpha(I_{it} - I^*_t) + \gamma D_t,$$

where μ_{it} is the expectation of V_t conditional on information available to dealer i at t, I_{it} is dealer i's current inventory position, and I^*_t is i's desired position. The inventory-control effect, governed by α, will in general be a function of relative interest rates, firm capital, and carrying costs. The variable D_t is a direction-indicator variable with a value of 1 when a buyer-initiated trade occurs and a value of -1 when a seller-initiated trade occurs. Thus, the term γD_t picks up (half) the baseline spread: if dealer j is a buyer, then the realized transaction price P_{it} will be on the offer side and therefore a little higher, ceteris paribus. (To be precise, γD_t picks up half the spread for trade quantities approaching zero, i.e., for which there is no adverse selection effect on μ_{it}.) This term can be interpreted as compensation resulting from execution costs, price discreteness, or rents.

Consistent with the regret-free property of quotes, I substitute dealer i's expectation conditional on possible Q_{jt}'s—equation (5)—into equation (6), yielding:

(7) $$P_{it} = \kappa_k S_t + (1 - \kappa_k)Z_{jt} - \alpha(I_{it} - I_i^*) + \gamma D_t, \quad k = s, l,$$

which is equivalent to (see the appendix)

(8) $$P_{it} = S_t + \left(\frac{1 - \phi_k}{\phi_k \theta}\right)Q_{jt} - \left(\frac{\alpha}{\phi_k}\right)(I_{it} - I_i^*) + \left(\frac{\gamma}{\phi_k}\right)D_t,$$

where $\phi_k \equiv (\kappa_k - \lambda)/(1 - \lambda)$ and $0 < \phi_k < 1$ since $0 < \kappa_k < 1$, $0 < \lambda < 1$, and $\kappa_k > \lambda$.

5.1.4 An Estimable Equation

Equation (8) is not directly estimable because S_t is not observable to the econometrician. My assumptions about the signals available and the evolution of V_t allow me to express the period t prior S_t as equal to the period $t - 1$ posterior from equation (6) lagged one period, plus an expectational error term ε_{it}:

(9) $$S_t = \mu_{it-1} + \varepsilon_{it} = P_{it-1} + \alpha(I_{it-1} - I_i^*) - \gamma D_{t-1} + \varepsilon_{it}.$$

Substituting this expression for S_t into equation (8) yields

$$P_{it} = \left[P_{it-1} + \alpha(I_{it-1} - I_i^*) - \gamma D_{t-1} + \varepsilon_{it}\right] + \left[\frac{1 - \phi_k}{\phi_k \theta}\right] Q_{jt} - \left[\frac{\alpha}{\phi_k}\right](I_{it} - I_i^*) + \left[\frac{\gamma}{\phi_k}\right] D_t,$$

which implies:

(10) $$\Delta P_{it} = \left[\frac{\alpha}{\phi_k} - \alpha\right] I_i^* + \left[\frac{1 - \phi_k}{\phi_k \theta}\right] Q_{jt} - \left[\frac{\alpha}{\phi_k}\right] I_{it} + \alpha I_{it-1} + \left[\frac{\gamma}{\phi_k}\right] D_t - \gamma D_{t-1} + \varepsilon_{it}.$$

This corresponds to a reduced-form estimating equation of

(11) $$\Delta P_{it} = \beta_0 + \beta_1 Q_{jt} + \beta_2 I_{it} + \beta_3 I_{it-1} + \beta_4 D_t + \beta_5 D_{t-1} + \varepsilon_{it}.$$

Thus, the change in the transaction price from $t - 1$ to t is linearly related to (i) the signed incoming order at t, (ii) the inventory level at t, (iii) the inventory level at $t - 1$, (iv) whether P_{it} is at the bid or the offer, and (v) whether P_{it-1} is at the bid or the offer. Note that the last two regressors—the indicator variables D_t and D_{t-1}—are accounting for bid-offer bounce. The model predicts that $\{\beta_1, \beta_3, \beta_4\} > 0$, $\{\beta_2, \beta_5\} < 0$, $|\beta_2| > \beta_3$, and $\beta_4 > |\beta_5|$, irrespective of the intertransaction time. (The latter inequalities derive from the fact that $0 < \phi_k < 1$.) These more general predictions are borne out in the data and are presented in Lyons (1995b). Here, the focus is on the information in order flow measured by β_1, which in turn is a function of the structural parameter κ from equation (5). That is, I want to test whether the coefficient β_1 is sensitive to intertransaction time and, if so, in which direction. The hot potato hypothesis predicts a lower β_1 when intertransaction times are short; the event-uncertainty hypothesis predicts a higher β_1 when intertransaction times are short. These predictions derive from the relative importance of liquidity trading (σ^2_{Xj}) in the signal extraction problem.

My final comment on the model concerns the assumption of a time-invariant desired inventory. First, note that with a slight reinterpretation the model can accommodate variability in desired inventories, that is, an I^*_i that varies through time. Consider the model $I^*_{it} = \bar{I}_i + \delta(\mu_{it} - S_t)$, which is consistent with the linear demands arising from negative exponential utility, where the public information S_t represents the market price away from dealer i. Further, Q_{jt} is the only information available to dealer i that is not reflected in S_t. Under the assumptions of my model, $(\mu_{it} - S_t)$ is proportional to Q_{jt}. Accordingly, I write $(\mu_{it} - S_t) = \pi Q_{jt}$. Hence, I can express the desired inventory as $I^*_{it} = \bar{I}_i + \delta\pi Q_{jt}$. In estimation, $\bar{I}_i$ is absorbed in the constant. The estimate of β_1 now represents

$$\left(\frac{1 - \phi_k}{\phi_k\theta}\right) Q_{jt} + \left(\frac{\alpha}{\phi_k} - \alpha\right)\delta\pi,$$

whose significance still evinces an information effect, although I have to be more careful in interpreting its magnitude.

5.2 Data

My data set has significant advantages over foreign exchange data used in the past, in particular, Reuters FXFX indications data (see, e.g., Goodhart 1989; and Bollerslev and Domowitz 1993). The main shortcomings of the Reuters indications are three: first, these are only indications, not firm quotes at which dealers can transact; second, there is no measure of order flow or transaction prices; and, third, the spreads in the indications data set are two to three times the size of firm quotes in the interdealer market.

My data set consists of two linked components, covering the five trading days of the week 3–7 August 1992, from the informal start of trading at 8:30 EST to roughly 1:30 EST. The first component includes the time-stamped quotes, prices, and quantities for all the direct interdealer transactions of a single deutsche mark/dollar dealer at a major New York bank. The second component comprises the same dealer's position cards, which includes all indirect (brokered) trades.

5.2.1 Dealer Data: Direct Quotes and Trades

The first component of the data set includes the dealer's quotes, prices, and quantities for all direct transactions. The availability of this component is due to a recent change in technology in this market: the Reuters Dealing 2000-1 system. This system—very different from the system that produces the Reuters indications—allows dealers to communicate quotes and trades *bilaterally* via computer rather than verbally over the telephone.[2] Among other things, this allows dealers to request up to four quotes simultaneously, whereas phone requests are necessarily sequential. Another advantage is that the computerized documentation reduces the paperwork required of the dealers. Although use of this technology differs by dealer and is currently diffusing more widely, this dealer uses Dealing 2000-1 for nearly all his direct interbank trades: less than 0.4 percent of all transactions were conducted over the phone over my sample week (as indicated on the position cards).

Each record of the data covering the dealer's direct trading includes the first five of the following seven variables; the last two are included only if a trade takes place:

1. The time the communication is initiated (to the minute, with no lag).
2. Which of the two dealers is requesting the quote.
3. The quote quantity.
4. The bid quote.
5. The offer quote.
6. The quantity traded (which provides Q_{jt}).
7. The transaction price (which provides P_{it}).

This component of the data set includes 952 transactions amounting to $4.1 billion.

Figure 5.2 provides an example of a dealer communication as recorded by the Dealing 2000-1 printout (for more details, see Reuters [1990]). The first word indicates that the call came "From" another dealer. Then comes the institution code and name of the counterparty, followed by the time (Greenwich Mean, computer assigned), the date (day first), and the number assigned to the communication. On line 3, "SP DMK 10" identifies this as a request for a spot deutsche mark/dollar quote for up to $10 million. Line 4 provides the quoted bid and offer price: typically, dealers quote only the last two digits of each price, the rest being superfluous in such a fast-moving market. These two quotes correspond to a bid of 1.58*88* deutsche marks/dollars and an offer of 1.58*91* deutsche marks/dollars. In confirming the transaction, the communication record provides the first three digits. Here, the calling dealer buys $10 million at the deutsche mark offer price of 1.5891. The record confirms the exact price and quantity. In the current data set, transactions never take place within the spread; the transaction price always equals either the bid or the offer.

2. Dealing 2000-1 is also very different than Dealing 2000-2. The former is wholly bilateral, while the latter is akin to an electronic broker, where multiple dealers participate. See Goodhart, Ito, and Payne, chap. 4 in this volume.

```
From CODE    FULL NAME HERE   * 1250GMT 030892 */1080
Our Terminal : CODE   Our user   : DMK
   SP DMK 10
# 8891
   BUY

#  10 MIO AGREED
#  VAL 6AUG92
#  MY DMK TO FULL NAME HERE
#  TO CONFIRM AT 1.5891 I SELL 10 MIO USD
#
     TO CONFIRM AT 1.5891 I SELL 10 MIO USD
     VAL 6AUG92
     MY USD TO FULL NAME HERE  AC 0-00-00000
     THKS N BIFN
#
#  #END LOCAL#
#
 ## WRAP UP BY DMK DMK 1250GMT 3AUG92

 #END#

( 265 CHARS)
```

Fig. 5.2 Example of a Reuters Dealing 2000-1 communication

Note: "From" establishes this as an incoming call; the caller's four-digit code and institution name follow; "GMT" denotes Greenwich Mean Time; the date follows, with the day listed first; "SP DMK 10" identifies this as request for a spot, deutsche mark/dollar quote for up to \$10 million; "8891" denotes a bid of 88 and an offer of 91 (only the last two digits are quoted); the confirmation provides the complete transaction price and verifies the transaction quantity; "THKS N BIFN" is shorthand for "thanks and bye for now."

5.2.2 Dealer Data: Position Cards

The second component of the data set is composed of the dealer's position cards over the same five days covered by the direct-transaction data, 3–7 August 1992. In order to track their positions, spot dealers record all transactions on handwritten position cards as they go along. An average day consists of approximately twenty cards, each with about fifteen transaction entries.

There are two key benefits to this component of the data set. First, it provides a very clean measure of the dealer's inventory I_t at any time since it includes both direct trades and any brokered trades. Second, it provides a means of error checking the first component of the data set.

Each card includes the following information for every trade:

1. The signed quantity traded (which determines I_t).
2. The transaction price.
3. The counterparty, including whether brokered.

Note that the bid/offer quotes at the time of the transaction are not included, so this component of the data set alone is not sufficient for estimating the model. Note also that each entry is not time-stamped; at the outset of every card, and often within the card too, the dealer records the time to the minute. Hence, the exact timing of some of the brokered transactions is not pinned down since these trades do not get confirmed via a Dealing 2000-1 record. Nevertheless, this is not a drawback for my purposes: the observations for the empirical model are the direct transactions initiated at the dealer's quoted prices; since the timing of these is pinned down by the Dealing 2000-1 records, and since these transactions appear sequentially in both components, the intervening changes in inventory due to brokered trades can be determined exactly.

5.2.3 Descriptive Statistics

Table 5.1 presents the data in the form of daily averages to convey a sense of the typical day's activity. This is masking some daily variation in the sample: the heaviest day (Friday, 7 August) is a little less than twice as active as the lightest day (Wednesday, 5 August). Note that this dealer averages well over $1

Table 5.1 Overview Statistics, 3–7 August 1992

	Direct	Brokered
1. Average number of transactions daily:	190	77
a) Incoming	170	
b) Outgoing	20	
2. Average value of transactions daily:[a]	.8	.4
a) Incoming	.65	
b) Outgoing	.15	
3. Median transaction size:[b]	3	4
a) Incoming	3	
b) Outgoing	5	
4. Average number of quotes daily:	924	
a) Made	502	
b) Received	422	
5. Median quoted spread: dealt:[c]	.0003	
a) Made	.0003	
b) Received	.0003	
6. Median quoted spread: not dealt:[c]	.0003	
a) Made	.0003	
b) Received	.0005	

Note: Data for the dealer's direct (interdealer) quotes and transactions are from the Reuters Dealing 2000-1 communications. *Incoming* refers to transactions initiated by another dealer; *outgoing* refers to transactions initiated by my dealer. *Made* refers to quotes made by my dealer; *received* refers to quotes received by my dealer. The trades in these two columns reflect more than 95 percent of this dealer's trading; the trades that make up the remainder are executed either (i) over the phone, (ii) with a nondealer customer, or (iii) in the futures market (IMM). Data for the dealer's brokered transactions are from the dealer's position sheets; it is not possible to identify the aggressor from these data. The dealer's trading day begins at 8:30 A.M. EST and ends around 1:30 P.M. on average.

[a]$Billion.

[b]$Million.

[c]DM.

billion of interdealer trading daily (brokered trades are necessarily interdealer). With respect to quoting, because this dealer is among the larger in this market, he has $10 million "relationships" with many other dealers; that is, quote requests from other high-volume dealers that do not specify a quantity are understood to be good for up to $10 million. Note the tightness of the median spread. For comparison, the median spread in the Reuters indications data set is two to three times as large. A bid/offer spread of three pips is less than 0.02 percent of the spot price.

A natural concern is whether this dealer is representative of the larger dealers in the spot market. While I cannot answer this definitively, I offer a few relevant facts. First, he has been trading in this market for many years and is well known among the other major dealers. Second, in terms of trading volume, he is without a doubt one of the key players, trading well over $1 billion per day and maintaining $10 million quote relationships with a number of other dealers. Although this would probably not put him in the top five in terms of volume, he is not far back, possibly in the fifth to fifteenth range somewhere. In the end, my view is that he is representative, at least with respect to the issues addressed here. There is no doubt, however, that different trading styles exist.

5.2.4 Relevant Institutional Background

Here, I highlight two institutional factors relevant to my analysis: (i) trading limits imposed on dealers and (ii) trading on the International Money Market (IMM) futures market. As for trading limits, there is an important distinction between intraday limits and overnight limits. At my dealer's bank, which is typical of major banks, there are no explicit intraday limits on senior dealers, although dealers are expected to communicate particularly large trades to their immediate supervisor (about $50 million and above for many banks in the current deutsche mark/dollar market). In contrast, most banks impose overnight limits on their dealers. Currently, a common overnight limit on a single dealer's open position is about $75 million, considerably larger than the largest open position in my sample. Most dealers, however, close their day with a zero net position; carrying an open position means monitoring it through the evening, an unattractive prospect after a full day of trading. My dealer ended his day with a zero net position each of the five days in the sample. Finally, although broader risk-management programs are in place at the bank for which my dealer trades, it is rare in foreign exchange that a dealer's position is hedged because it aggregates unfavorably with others; when this does occur, it is typically without the participation of the individual dealer.

As for trading on the IMM futures market while dealing spot, this differs by dealer. I stress, however, that, unlike equity markets, the spot foreign exchange market is many times larger than the futures market: in 1992 the average daily volume in New York in spot deutsche mark/dollar was roughly $50 billion (New York Federal Reserve Bank [1992], adjusted for double counting); in the same year, the average daily volume on all IMM deutsche mark/dollar contracts was less than \$5 billion. As for my dealer, his position cards show that he traded less than \$1 million daily in futures over the sample period, which is negligible relative to his daily spot volume. Like other spot dealers, he does listen to an intercom that communicates futures prices. However, this intercom is less important to a spot dealer than the intercoms connected to interdealer brokers in the spot market.

5.3 Estimation Results

I begin with results from direct estimation of the model in equation (11), which are presented in table 5.2. Although these estimates do not include any role for intertransaction time, they provide a benchmark for the later results regarding the hot potato and event-uncertainty hypotheses. Note that these estimates are essentially a replication of a result presented in Lyons (1995b). Accordingly, I refer readers to that earlier work for more detailed interpretation.

Given these benchmark results, henceforth I present only those coefficients that bear on the information content of order flow—namely, variations of β_1 from equation (11). All nonreported coefficients remain significant at at least the 5 percent level, with the predicted signs and relative magnitudes. Presenting the results this way allows me to focus on the informational subtleties outlined in section 5.1.

5.3.1 The Core Model of Trading Intensity

Table 5.3 presents my estimates of the information content of order flow, distinguishing between short and long intertransaction times. This is achieved via the introduction of dummy variables s_t and l_t (see the equation heading the table). The dummy s_t equals 1 if intertransaction time is short, 0 otherwise; the dummy l_t equals 0 if intertransaction time is short, 1 otherwise. Short inter-

Table 5.2 **Benchmark Results**

(11) $\Delta P_{it} = \beta_0 + \beta_1 Q_{jt} + \beta_2 I_{it} + \beta_3 I_{it-1} + \beta_4 D_t + \beta_5 D_{t-1} + \varepsilon_{it}$

	β_0	β_1	β_2	β_3	β_4	β_5	R^2
Estimated	−1.37	1.34	−.92	.72	10.85	−9.14	.22
	(−1.07)	(2.80)	(−3.03)	(2.46)	(5.69)	(−6.04)	
Predicted		>0	<0	>0	>0	<0	

Note: t-statistics are given in parentheses. ΔP_{it} is the change in the transaction price (DM/\$) from $t-1$ to t. Q_{jt} is the dollar quantity transacted directly at dealer i's quoted prices, positive for buyer-initiated trades (i.e., effected at the offer) and negative for seller-initiated trades (at the bid). I_t is i's position at the end of period t. D_t is an indicator variable with the value 1 if the trade is buyer initiated and the value −1 if seller initiated. The units of Q_{jt}, I_{it}, and I_{it-1} are such that a coefficient of unity implies a price effect of DM 0.0001 for every \$10 million. The units of the indicator variable D_{t-1} are such that a coefficient of 10 implies DM 0.0002/\$ between bid and offer at quantity zero. Estimated using OLS, with heteroskedasticity- and autocorrelation-consistent (first-order) standard errors. Sample: 3–7 August 1992, 842 observations.

Table 5.3 **Is Order Flow Less Informative When Intertransaction Time Is Short?**

$$\Delta P_{it} = \beta_0 + \beta_1 s_t Q_{jt} + \beta_1' l_t Q_{jt} + \beta_2 I_{it} + \beta_3 I_{it-1} + \beta_4 D_t + \beta_5 D_{t-1} + \varepsilon_{it}$$

	β_1 (short)	β_1' (long)	Fraction Short	$\beta_1 = \beta_1'$, *P*-value
Intertransaction time short if:				
Less than 1 minute	−.01	2.20	262/842	.000
	(−.01)	(3.84)		
Less than 2 minutes	.76	2.60	506/842	.009
	(1.63)	(3.40)		

Note: t-statistics are given in parentheses. The coefficient β_1 measures the information effect of trades for which the time from the previous transaction is short ($s_t = 1$ and $l_t = 0$ in the equation in the heading), where *short* is defined in the first column. The coefficient β_1' measures the information effect of those trades for which the time from the previous transaction is long ($s_t = 0$, $l_t = 1$), where *long* is defined as not short. The "Fraction Short" column presents the fraction of observations satisfying the corresponding definition of *short intertransaction times*. In each case, the remaining observations fall into the long category. The *P*-value column presents the significance level at which the null $\beta_1 = \beta_1'$ can just be rejected. ΔP_{it} is the change in the transaction price (DM/$) from $t - 1$ to t. Q_{jt} is the dollar quantity transacted directly at dealer i's quoted prices, positive for buyer-initiated trades (i.e., effected at the offer) and negative for seller-initiated trades (at the bid). The units of Q_{jt} are such that $\beta_1 = 1$ implies a price effect of DM 0.0001 for every $10 million. I_t is i's position at the end of period t. D_t is an indicator variable with the value 1 if the trade is buyer initiated and the value −1 if seller initiated. Estimated using OLS, with heteroskedasticity- and autocorrelation-consistent (first-order) standard errors. Sample: 3–7 August 1992, 842 observations.

transaction times are defined two ways: less than one minute from the previous transaction and less than two minutes. The time-stamps on the data are very precise since they are assigned by the computer; however, they do not provide precision beyond the minute. Hence, less than one minute includes trades with the same time-stamp; less than two minutes includes trades with time-stamps differing by one minute or less. These categories bracket the mean intertransaction time of 1.8 minutes. The second category corresponds to a break at the median intertransaction time.

The results provide strong support for the hot potato hypothesis over the event-uncertainty hypothesis. The coefficient β_1—which measures the information effect of incoming trades with short intertransaction times—is insignificant at conventional levels. In contrast, the coefficient β_1'—which measures the information effect of incoming trades with long intertransaction times—is significant. Moreover, a test of the restriction that $\beta_1 = \beta_1'$ is rejected at the 1 percent level in both cases. In summary, trades occurring when transaction intensity is high are significantly less informative than trades occurring when transaction intensity is low. This is the main result of the paper.

5.3.2 The Pattern of the Market

There is an additional testable implication of the hot potato hypothesis: it follows directly from the story of bouncing inventories outlined above that these discretionary liquidity trades will tend to be in the same direction (i.e., have the same sign). The obverse is that clumped trading is more likely to be hot potato (liquidity) trading if trades follow in the same direction. The implication for prices is that, even if martingales, they are not necessarily Markov.

The test presented in table 5.4 addresses the question, Is clumped order flow less informative when transactions follow the same direction? Again, I introduce dummy variables, in this case s_t, o_t, and l_t (see the equation heading the table). The dummy s_t equals 1 if (i) intertransaction time is short and (ii) the previous incoming trade has the *same* direction, 0 otherwise; the dummy o_t equals 1 if (i) intertransaction time is short and (ii) the previous incoming trade has the *opposite* direction, 0 otherwise; the dummy l_t equals 0 if intertransaction time is short, 1 otherwise. A short intertransaction time is defined as less than the median of two minutes.

Once again, the results support the hot potato hypothesis. The coefficient β_1—short intertransaction times and same direction—is insignificant. In contrast, the coefficient β_1'—short intertransaction times and opposite direction—is significant. A test of the restriction that $\beta_1 = \beta_1'$ is rejected at the 1 percent level. To summarize, clumped trades occurring in the same direction are significantly less informative than clumped trades occurring in the opposite direction.

Table 5.4 **Is Clumped Order Flow Less Informative When Transactions Follow the Same Direction?**

$$\Delta P_{it} = \beta_0 + \beta_1 s_t Q_{jt} + \beta_1' o_t Q_{jt} + \beta_1'' l_t Q_{jt} + \beta_2 I_{it} + \beta_3 I_{it-1} + \beta_4 D_t + \beta_5 D_{t-1} + \varepsilon_{it}$$

β_1 (short and same)	β_1' (short and opposite)	β_1'' (long)	Fraction Short and Same	Fraction Short and Opposite	$\beta_1 = \beta_1'$. P-value
−.06	1.90	2.64	276/842	230/842	.009
(−.11)	(3.01)	(3.46)			

Note: t-statistics are given in parentheses. The coefficient β_1 measures the information effect of trades that (i) have short intertransaction times, defined as less than the median of two minutes, and (ii) have the same direction as the previous trade ($s_t = 1$, $o_t = 0$, and $l_t = 0$ in the equation in the heading). The coefficient β_1' measures the information effect of trades that (i) have short intertransaction times, defined as less than the median of two minutes, and (ii) have the opposite direction of the previous trade ($s_t = 0$, $o_t = 1$, $l_t = 0$). The coefficient β_1'' measures the information effect of trades that have long intertransaction times, defined as greater than or equal to the median of two minutes ($s_t = 0$, $o_t = 0$, $l_t = 1$). The "Fraction Short and Same" column presents the fraction of observations satisfying the corresponding definition of *short and same* (similarly for the "Fraction Short and Opposite" column). The remaining 336/842 observations fall into the long category. The P-value column presents the significance level at which the null $\beta_1 = \beta_1'$ can just be rejected. ΔP_{it} is the change in the transaction price (DM/$) from $t - 1$ to t. Q_{jt} is the dollar quantity transacted directly at dealer i's quoted prices, positive for buyer-initiated trades (i.e., effected at the offer) and negative for seller-initiated trades (at the bid). The units of Q_{jt} are such that $\beta_1 = 1$ implies a price effect of DM 0.0001 for every $10 million. I_t is i's position at the end of period t. D_t is an indicator variable with the value 1 if the trade is buyer initiated and the value −1 if seller initiated. Estimated using OLS, with heteroskedasticity- and autocorrelation-consistent (first-order) standard errors. Sample: 3–7 August 1992, 842 observations.

5.3.3 Another Measure of Market Pace: Quote Intensity

The results of table 5.4 highlight another important observation: although the hot potato and event-uncertainty hypotheses make opposite predictions regarding the relation between information and trading intensity, they are not necessarily competing hypotheses. That is, both effects could be operative: hot potato trading simply dominates when trading is most intense in this market.

To examine whether there is independent support for event uncertainty, I exploit an "instrument" that is arguably more closely related to event uncertainty than inventory control. To understand this instrument, recognize that in Easley and O'Hara (1992) transaction intensity per se is the only dimension of trading intensity available for signaling the underlying state. The problem for our purposes is that transaction intensity is also the linchpin of the hot potato model. My data set, on the other hand, includes a second dimension of trading intensity: quoting intensity. The roughly 4:1 ratio of not-dealt quotes to dealt quotes in table 5.1 above indicates that transactions alone may not be telling the full story. More important for discriminating event uncertainty from hot potato is the fact that quote requests per se typically signal heightened uncertainty and information gathering, whereas hot potato transactions minimize on quote requests in order to unload inventory rapidly. In short, quoting intensity provides another vehicle for Easley and O'Hara.

Table 5.5 presents estimates of the information content of order flow, distinguishing between high and low quoting intensity as a measure of market pace. Once again I introduce dummy variables, in this case h_t and l_t (see the equation heading the table). The dummy h_t equals 1 if the total number of intervening quotes per minute is high, 0 otherwise; the dummy l_t equals 0 if the total number of intervening quotes per minute is high, 1 otherwise. The different definitions of a high number of intervening quotes appear in the far-left-hand column. These quotes are from the Dealing 2000-1 portion of the data set, described in section 5.2.1.

These results provide support for the event-uncertainty hypothesis. The coefficient β_1 reflecting high quoting intensity is significant, whereas the coefficient β_1' reflecting low quoting intensity is insignificant. A test of the restriction that $\beta_1 = \beta_1'$ is rejected at the 5 percent level in all three cases. To summarize, trades occurring when quoting intensity is high are significantly more informative than trades occurring when quoting intensity is low.

5.4 Conclusions

Our results suggest that, in foreign exchange, trading begets trading. The trading begotten is relatively uninformative, arising from repeated passage of inventory imbalances among dealers. Clearly, this could not arise under a specialist microstructure. A broad implication is that a microstructural understand-

Table 5.5 Is Order-Flow More Informative When Quoting Intensity Is High?
$$\Delta P_{it} = \beta_0 + \beta_1 h_t Q_{jt} + \beta_1' l_t Q_{jt} + \beta_2 I_{it-1} + \beta_4 D_t + \beta_5 D_{t-1} + \varepsilon_{it}$$

	β_1 (high)	β_1' (low)	Fraction High	$\beta_1 = \beta_1'$, P-value
Quoting intensity high if:				
≥ 3 intervening quotes per minute	2.16	.87	301/842	.046
	(3.42)	(1.70)		
≥ 4 intervening quotes per minute	2.41	.84	215/842	.026
	(3.56)	(1.66)		
≥ 5 intervening quotes per minute	2.72	.89	144/842	.025
	(3.47)	(1.79)		

Note: t-statistics are given in parentheses. The coefficient β_1 measures the information effect of those trades occurring when quoting intensity is high ($h_t = 1$, $l_t = 0$), where *high intensity* is defined in the first column by the total number of quotes—both made and received—since the previous incoming transaction. The coefficient β_1' measures the information effect of those trades occurring when quoting intensity is low ($h_t = 0$, $l_t = 1$), where *low intensity* is defined as not high. The "Fraction High" column presents the fraction of observations satisfying the corresponding definition of high-intensity quoting. The P-value column presents the significance level at which the null $\beta_1 = \beta_1'$ can just be rejected. ΔP_{it} is the change in the transaction price (DM/\$) from $t - 1$ to t. Q_{jt} is the dollar quantity transacted directly at dealer i's quoted prices, positive for buyer-initiated trades (i.e., effected at the offer) and negative for seller-initiated trades (at the bid). The units of Q_{jt} are such that $\beta_1 = 1$ implies a price effect of DM 0.0001 for every \$10 million. I_t is i's position at the end of period t. D_t is an indicator variable with the value 1 if the trade is buyer initiated and the value -1 if seller initiated. Estimated using OLS, with heteroskedasticity- and autocorrelation-consistent (first-order) standard errors. Sample: 3–7 August 1992, 842 observations.

ing of this market requires much richer multiple-dealer theory than now exists (see, e.g., Ho and Stoll 1983).

My principal empirical findings are the following:

1. Trades occurring when transaction intensity is high are significantly less informative than trades occurring when transaction intensity is low.
2. Clumped trades occurring in the same direction are significantly less informative than clumped trades occurring in the opposite direction.
3. Trades occurring when quoting intensity is high are significantly more informative than trades occurring when quoting intensity is low.

I interpret the first two results as supportive of hot potato trading among dealers in foreign exchange. I interpret the third result as supportive of the Easley and O'Hara event-uncertainty hypothesis, although the vehicle differs from the transaction focus of their paper. Taken together, the results highlight the potential complementarity between these seemingly polar views.

There is an important hardship in focusing on a dealership market like foreign exchange that warrants recognition. Empirical work on the specialist structure has the luxury of describing the behavior of a lone dealer. It is much more difficult to argue that by documenting the behavior of a single dealer in the foreign exchange market I have similarly captured the foreign exchange market. The data required to generate a more complete picture are out of the question given current availability. Nevertheless, the dealer whom I have tracked is without a doubt one of the key players in this market, trading well over \$1 billion per day and maintaining \$10 million quote relationships with a number of other dealers. Is he representative of dealers in the core of the wholesale spot market? I would argue yes, at least with respect to the issues addressed here. But there is no doubt that different dealers have different trading styles.

Appendix

Derivation of the Statistic Z_{jt} in Equation (4)

Beginning with equation (3),

$$(3) \quad Q_{jt} = \theta(\mu_{jt} - P_{it}) + X_{jt}$$

$$\Rightarrow Q_{jt}/\theta + P_{it} = \mu_{jt} + X_{jt}/\theta$$

$$\Rightarrow Q_{jt}/\theta + P_{it} = \lambda S_t + (1-\lambda)C_{jt} + X_{jt}/\theta, \quad \text{where } \lambda \equiv \sigma_\omega^2/(\sigma_\eta^2 + \sigma_\omega^2),$$

$$\Rightarrow Q_{jt}/\theta + P_{it} - \lambda S_t = (1-\lambda)(V_t + \tilde{\omega}_{jt}) + \tilde{X}_{jt}/\theta, \quad \text{since } C_{jt} = V_t + \tilde{\omega}_{jt},$$

$$(4) \Rightarrow Z_{jt} \equiv \frac{Q_{jt}/\theta + P_{it} - \lambda S_t}{1-\lambda} = V_t + \tilde{\omega}_{jt} + [1/\theta(1-\lambda)]\tilde{X}_{jt}.$$

Derivation of the Price Representation in Equation (8)

Beginning with equation (6),

$$(6) \qquad P_{it} = \mu_{it} - \alpha(I_{it} - I_i^*) + \gamma D_t,$$

I can write (where $\kappa_k \equiv \sigma_{Zk}^2/[\sigma_{Zk}^2 + \sigma_\eta^2]$, $k = s, l$):

$$\begin{aligned}
\mu_{it} &= \kappa_k S_t + (1-\kappa_k)Z_{jt} \\
&= \kappa_k S_t + \left[\frac{1-\kappa_k}{1-\lambda}\right]\left[Q_{jt}/\theta + P_{it} - \lambda S_t\right] \\
&= \kappa_k S_t - \left[\frac{\lambda(1-\kappa_k)}{1-\lambda}\right]S_t + \left[\frac{1-\kappa_k}{1-\lambda}\right]\left[Q_{jt}/\theta + P_{it}\right] \\
&= \left[\kappa_k - \frac{\lambda(1-\kappa_k)}{1-\lambda}\right]S_t + \left[\frac{1-\kappa_k}{1-\lambda}\right]\left[Q_{jt}/\theta + P_{it}\right] \\
&\equiv \phi_k S_t + (1-\phi_k)\left[Q_{jt}/\theta + P_{it}\right], \quad k = s, l,
\end{aligned}$$

$$\text{since} \left[\kappa_k - \frac{\lambda(1-\kappa_k)}{1-\lambda}\right] + \left[\frac{1-\kappa_k}{1-\lambda}\right] = 1.$$

Note also that $0 < \phi_k < 1$ since $0 < \kappa_k < 1$, $0 < \lambda < 1$, and $\kappa_k > \lambda$ for both $k = s$ and $k = l$. Each of these properties follows from the definitions of κ_k and λ and the fact that $\sigma^2_{Zj} = \sigma^2_\omega + [\theta(1 - \lambda)]^{-2}\sigma^2_X$.

Substituting this expression for μ_{it} into equation (6) yields

$$(8) \qquad P_{it} = \phi_k S_t + (1 - \phi_k)\left(Q_{jt}/\theta + P_{it}\right) - \alpha(I_{it} - I_i^*) + \gamma D_t$$

$$\Rightarrow P_{it} = S_t + \left(\frac{1 - \phi_k}{\phi_k \theta}\right) Q_{jt} - \left(\frac{\alpha}{\phi_k}\right)(I_{it} - I_i^*) + \left(\frac{\gamma}{\phi_k}\right) D_t .$$

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Comment Mark D. Flood

A comment on Richard Lyons's paper must begin with mention of its data. Lyons has assembled a data set with a level of detail that is unusual in microstructural studies and unprecedented in studies of foreign exchange market microstructure. For the first time, we have an essentially complete and sufficiently long (one-week) time series of quoted spreads (both direct and brokered) and transaction prices for a foreign exchange marketmaker. It should be emphasized that even the untransacted prices in this data set are live quotes—and not the indicative prices (such as those collected by Charles Goodhart) that heretofore represented the best intradaily data set available to researchers. Moreover, the data set also includes the quantity of all transactions and the marketmaker's inventory position, with everything time-stamped to the minute. We thus have contemporaneous measurement of all main aspects of a marketmaker's behavior and the major inputs to his or her decision-making process.

At the risk of sounding ungrateful, let me point out the only two significant shortcomings of the data set. First, there is, as I understand it, no listing of intradaily news announcements to accompany the marketmaker's data. Such data would have been available, for example, from the Reuters financial newswire—indeed, they may still exist in a Reuters archive—and would have allowed analysis of the marketmaker's response to such events. Second, the data are limited to a single marketmaker. I must acknowledge that it is almost inconceivable that anyone could get access to such data for multiple marketmakers simultaneously. Nonetheless, this is a limitation for two reasons. First, as Lyons acknowledges, we cannot be sure that the marketmaker observed here is representative. It is reasonable to suppose that different marketmakers have different strengths, weaknesses, and constraints and that, therefore, they will have different trading strategies. Second, there are interesting characteristics of the microstructure, including especially the alleged hot potato phenomenon, that best reveal themselves in the interaction of marketmakers rather than the isolated behavior of an individual.

I turn now to the theory that Lyons uses to motivate and derive the central empirical hypotheses of the paper, the hot potato and event-uncertainty hypotheses. I suggest an avenue for improving the model as a representation of a foreign exchange marketmaker, as distinguished from a stock exchange specialist. Let me emphasize that what follows is intended as a suggestion for future research rather than an indictment of the present paper. Lyons is aware of the issues raised here and addresses most of them in the paper or in the companion piece, Lyons (1995), which is recommended to readers of the present paper. I found that many of my questions about the latter were answered by reference to the former.

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The theoretical model used here is taken essentially unaltered from Madhavan and Smidt (1991). They are modeling a stock exchange specialist facing a "trader," potentially with inside information. We can reason that the Madhavan and Smidt analysis cannot be a fully accurate model of the foreign exchange market. I shall use Lyons's equation (6), which defines the marketmaker's transaction prices, to focus my explanation of why this is so:

$$P_{it} = \mu_{it} + \alpha(I_{it} - I_t^*) + \gamma D_{it},$$

or, substituting,

$$P_{it} = (\sigma_\omega^2 S_t + \sigma_\eta^2 C_{it})/(\sigma_\omega^2 + \sigma_\eta^2) + \alpha(I_{it} - I_i^*) + \gamma D_{it}.$$

Equation (6) divides the marketmaker's transaction price into three additive factors: (1) there is a baseline estimate, μ_{it}, of the intrinsic value of the foreign currency, stated as a convex combination of two signals, one public (S_t) and one private (C_{it}); (2) there is a technical "inventory-shading" adjustment, $\alpha(I_{it} - I_i^*)$, to this baseline estimate; and (3) there is a second technical adjustment for the bid-ask spread, γD_{it}. In this model, all informational innovations are impounded in the first term.

This arrangement reflects the intellectual lineage of the theory. In traditional microstructural models going back at least as far as Stigler (1964) and his "jobber's turn" or Demsetz (1968), the (monopolistic) marketmaker—by definition one who stands ready to quote prices and transact on demand—provides liquidity services. The marketmaker, typically conceived as a stock exchange specialist, quotes a market-clearing price (or, under uncertainty, her best estimate of the market-clearing price) and is compensated through the bid-ask spread for her service: waiting around with a securities inventory and trading with all comers. Because she quotes a market-clearing price, she accumulates no inventory (on average). In the later "adverse selection" models, the marketmaker must also be compensated for risk bearing since some traders will come to the marketmaker with profitable insider information, a situation that the marketmaker cannot avoid and therefore must insure against via a wider bid-ask spread.

The reason that this cannot accurately represent a foreign exchange marketmaker is that foreign exchange marketmakers cannot base their quoted prices on an estimate of the market-clearing price. Foreign exchange marketmakers are surrounded by competing marketmakers, all of whom have the resources to exploit arbitrage opportunities. This produces an imperative of arbitrage avoidance. Marketmakers who would quote off-market prices (i.e., a bid-ask spread that does not overlap with the spreads prevailing elsewhere in the market) are extremely likely to find themselves with a large inventory that could have been had at a better price. Thus, marketmakers must attempt to keep their quotes consistent with those of all other marketmakers.

For this reason, the determination of prices in equation (6) should be dominated by price information. It is instructive to consider the following counterargument: that the model does not specify the exact nature of the signals (S_t and C_{it}) and that these therefore need not include nonprice information at all; therefore, the model indeed allows for marketmakers' behavior that is dominated by price information. There are two significant flaws with such an argument.

First, even if μ_{it} is determined only by price information, the arbitrage avoidance rule will still be violated if the inventory discrepancy ($I_{it} - I_i^*$) is sufficiently large. The problem is therefore with the functional form of equation (6) rather than simply the interpretation given to S_t and C_{it}. Lyons is aware of this concern: Lyons (1995) estimates the coefficient α and calculates the size of an inventory discrepancy required for the inventory shading adjustment in equation (6) to overwhelm the bid-ask spread: roughly $40 million. In fact, the marketmaker whose behavior is measured here seldom has an inventory in excess of $40 million (see Lyons 1995, fig. 3). This fact reduces the status of my criticism here from an indictment to a quibble.

Second, and more fundamentally, behavior that considers *only* price information under an arbitrage avoidance rule leaves the exchange rate indeterminate: any price consensus will avoid arbitrage. While this would be consistent with the herd behavior (e.g., speculative bubbles) that some researchers believe characterizes certain exchange rate episodes, a very heavy burden of proof must be placed on anyone who would argue that marketmaker behavior ignores nonprice information.

Positing that marketmaker pricing is dominated by price information does not imply, of course, that marketmakers ignore or even discount nonprice information. The desired inventory position represents the other main element of the marketmaker's strategy. To the extent that the current market consensus price fails to reflect all the marketmaker's (nonprice) information, this discrepancy should be exploited through speculative position taking. Borrowing a bit of monetary policy jargon, there are two targets (arbitrage avoidance and speculative profits) and two policy instruments (price and inventory). I^* is thus a measure of the extent to which the marketmaker believes that the market price misestimates the value of the foreign currency. Unfortunately, in the Madhavan and Smidt model, I^* is a constant. Although Lyons offers a technique for making I^* depend on information (see his section 1.4), this approach requires that public information (S_t) be limited to price information. Moreover, this approach is not incorporated elsewhere in the paper.

Representing a separate role for nonprice information ultimately requires that one distinguish between price and nonprice signals in the notation of the model. If we achieve this with superscripts, then equation (6) can be rewritten as

$$P_{it} = \mu(S_t^p, C_{it}^p) + f[\mu_{it}, I_{it} - I_i^*(\mu_{it}, S_t^{np}, C_{it}^{np})] + \gamma D_{it}.$$

There are three differences in this proposed reformulation: (1) the baseline estimate, μ_{it}, is a function only of price signals, S_t^p and C_{it}^p; (2) inventory shading is allowed, but now as a nonlinear function of both μ_{it} and the inventory discrepancy, to incorporate the arbitrage avoidance rule; and (3) desired inventory is a function of the nonprice signals, S_t^{np} and C_{it}^{np}, as well as the baseline estimate, μ_{it}. This, of course, is a reformulation of a single equation in a larger model. While rederiving the model to address the concerns raised here is a nontrivial assignment, such a derivation would represent an important advance in our theoretical understanding of decentralized, multiple-dealer markets such as the foreign exchange market.

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Comment António Mello

This paper is a case study of the motives for trading foreign exchange currency. The author tests two hypotheses: either trading is generated by inventory reasons, and in that case it does not convey information when time between consecutive trades is short, or, alternatively, trading is generated by the arrival of new information and intense trading means that an information event has occurred. Using direct quotes and trades from a dealer, covering the five trading days of a particular week in the summer of 1992, the author concludes that both motives can explain trading.

The strength and originality of the study results from the data set used. It shows how important it is, in doing work on high-frequency data, to use the correct transaction series. Indeed, data can significantly affect the results as well as our understanding of the economic phenomena. In this respect, the analysis of the behavior of a particular dealer is very informative and certainly improves our knowledge. However, having established that directly reported real-time transactions data are best to test a particular hypothesis (against another), one needs not only to spend more time with the same dealer—that is, having not just one week, but several weeks, and especially different event weeks (turbulent vs. calm periods)—but also to collect data from a panel of

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different dealers, to control for differences in preferences, in size, in capital, and in information.

The two views of trading intensity analyzed, the event-uncertainty view and the hot potato view, deserve some comment. First, I find it difficult to justify the hot potato view: either a dealer is at the optimal inventory level, or he is not. If he is, then he must be indifferent, on a risk-adjusted basis, to trade and not to trade, and the quotes from trading with a liquidity trader must reflect the fact that he must be compensated, on average, for deviating from an optimal inventory level. This makes the trade movement in one direction neither necessary nor optimal. So it does not when the dealer's inventory is not at the optimal level. Perhaps what is really happening is that the dealer is frequently trading to rebalance his optimal inventory level. This would be consistent with a model that accounts for changes in the desired level of inventory. If the relative price of currencies changes, then optimal inventory composition should also change, as the opportunity cost of holding different currencies changes. This should happen regardless of the length of period analyzed, although in practice the revisions of the desired positions should occur only at discrete and endogenous intervals. This more general formulation is certainly difficult to test, but it is also a more realistic one. It requires nonlinear estimation methods, and the interpretation of the results is surely more complex.

Second, the tests are based on the sensitivity of price changes to the order flow, which can be interpreted as a test of market depth. In that case, as the time interval shortens, on average, one expects the price changes to be smaller, which is exactly the result the author obtains. Indeed, the feeling that I have is that the results seem to be highly dependent on the definition of *short time*, a metric that must be endogenous and dependent on the prevailing market conditions.

Third, to test a particular theory, it is not sufficient to show whether a particular coefficient is significant and has the right sign. It is also necessary to look at other coefficients and to show that the estimated model displays good adherence to the data.

Finally, in testing and interpreting the results, it is important to consider the fact that price improvement is discrete. Depending on the relevance of this matter, OLS may not be appropriate. Also, if prices change discretely, it may very well be the case that prices are revised only after ΣQ, and the interpretation of the results in the tables changes accordingly.

Although there are some points that deserve attention and must be tightened, overall I think that this paper is a contribution in the right direction, and therefore it must be welcomed.

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