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Why Are Asset Markets Modeled Successfully, But Not Their Dealers?

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Market-level microstructure models of asset pricing succeed where dealer-level models do not. This study addresses this empirical difficulty in the context of foreign exchange dealers. New evidence is presented rejecting the latter models' specifications of how information asymmetry and inventory accumulation affect dealer pricing. This rejection is consistent with those of other dealer-level empirical studies. A new modeling avenue may be to reconsider optimal price setting while relaxing assumptions that specify incoming orders as the only component through which dealer inventories evolve. This approach is consistent with inventory evolution data and with market-level models' assumptions about currency markets. [JEL F3, F4, G1]

High-frequency data combined with recent microstructure models have delivered empirical success. For example, exchange rate models that reflect information gathering and risk sharing in their currency-trading processes outperform a random walk.[1] In these models (often referred to as micro exchange rate models), the exchange rate depends not just on tracked statistics of economic aggregates, such as inflation or investment, but also on other variables that reflect the market's

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[1]Out of sample, in the sense of Meese and Rogoff (1983). See Evans and Lyons (2002).

view of economic conditions. One can partition micro exchange rate models into market-level (ML) models and dealer-level (DL) models. ML micro exchange rate models study how a market-wide consensus of asset values is achieved. ML models focus on how the entire market builds such a consensus and settles on an exchange rate. These models can explain more than 50 percent of exchange rate movements.[2] DL micro exchange rate models abstract from the market as a whole and focus instead on price setting and risk management by individual currency market participants, or dealers. This study explores a rift between ML models and DL models. First, it shows new empirical rejections of some DL model predictions. Next, it shows that a basic DL assumption is inconsistent with ML models and with the data. This may be why some DL model predictions are routinely rejected both in this and in previous studies of equity and other asset markets.

Before explaining the difficulties with DL models put forth here, it is useful to map exactly where they lie in the literature of exchange rates. Figure 1 partitions the research on exchange rates into six broad categories. Traditional models of exchange rates, which face well-known empirical difficulties, are represented by Box (1) in Figure 1. In these models, a handful of parity conditions are assumed to link macroeconomic activity across countries. One such condition is purchasing power parity (PPP). PPP relates the difference in inflation rates across countries to their exchange rate depreciation. Although empirical predictions of macroeconomic models are generally inconsistent with exchange rate data, parity conditions are consistent. For example, Flood and Taylor (1996) show that long-run data support PPP and other parity conditions, as denoted in Box (2) in Figure 1.[3] The upshot of their study is given in equation (1). Exchange rate depreciation between two periods of time (t denotes time; Δe denotes exchange rate depreciation) depends on publicly observable fundamental macroeconomic variables (denoted by F) and an "unexplained" component (denoted by U):

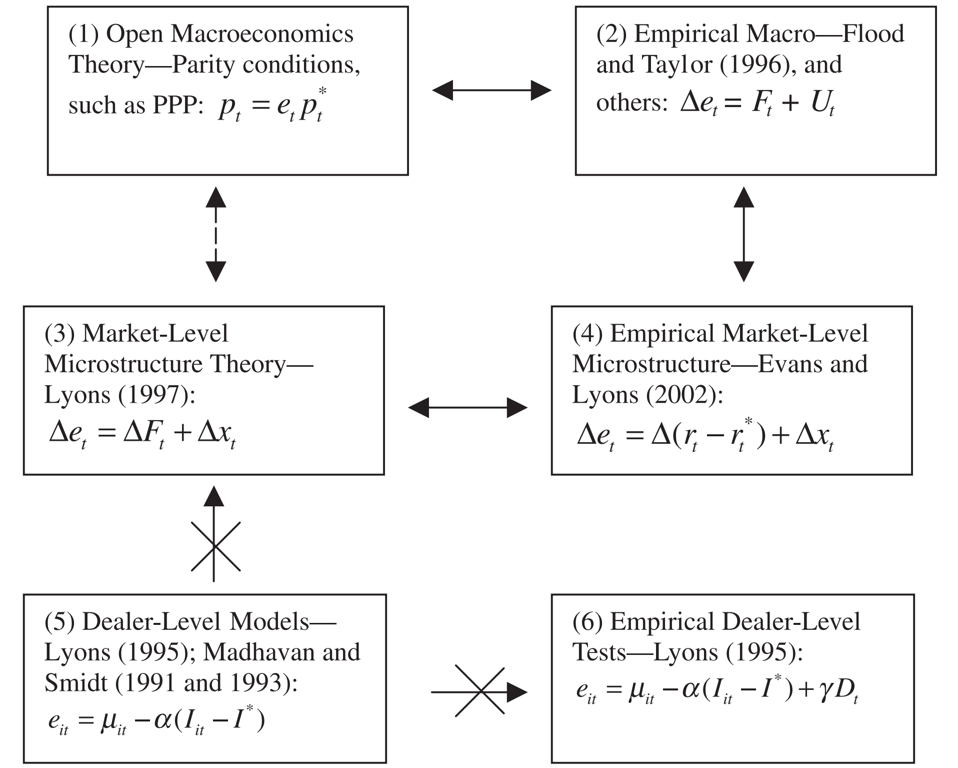
$$\Delta e_t = F_t + U_t. \tag{1}$$

Instead of assuming that parity conditions govern exchange rate evolution, micro exchange rate models consider factors that drive currency market participants' price setting. Empirical ML micro exchange rate models, such as Evans and Lyons (2002), are represented in Box (4) of Figure 1. In these models, market participants receive economic information through order flow that they cannot learn from public macroeconomic statistics. Order flow results from partitioning total traded volume into either buyer-initiated transactions or seller-initiated transactions and taking their difference. Order flow plays an important role in estimating the exchange rate because it captures changes in expectations and risk preferences that are absent from publicly tracked economic aggregates. The resulting exchange rate depreciation equation (2) is almost identical to equation (1). The interest rate differential change (denoted $\Delta(r_t - r_t^*)$) represents the fundamental variable, and the

[2]Evans (2002).

[3]Also confirmed by Sarno and Taylor (2002).

Figure 1. Partitions in the Exchange Rate Literature



Notes: e = exchange rate (i indicates that it is set by dealer i, t indicates at date/trade t).
p = price level (* indicates foreign).
I = inventory of foreign exchange (* indicates desired or optimal inventory level).
μ = the dealer's best guess of the full-information value of the currency.
x = order flow.
r = interest rate (* indicates foreign).
F = publicly observable measures of economic fundamentals, for example, interest rates, price levels.
U = exchange rate variation "unexplained" by publicly observable measures of economic fundamentals.
D = indicator that is 1 if $x > 0$, and is –1 if $x < 0$.
$\gamma, \alpha > 0$.

Figure 1 shows the disconnect between dealer-level (DL) and market-level (ML) microstructure, which is explored here. The exchange rate literature is partitioned into broad categories (each indicated by a numbered box), with arrows indicating theoretical/empirical support among areas. This paper shows that DL microstructure models predict a pricing equation (in Box (5)) that is rejected by DL empirical studies (and hence the broken link to Box (6)). Furthermore, DL microstructure models are inconsistent with ML microstructure models—represented by Box (3). However, ML microstructure models are empirically supported by microdata (Box (4)), and they are closely related to open macroeconomic empirical studies. These (in Box (2)) support parity conditions from open macroeconomic models using long-run data and the same estimating equation as predicted by ML microstructure models. Finally, the theoretical link from open macroeconomics to ML microstructure (Box (3) and Box (1)) is under development (for example, Evans and Lyons, 2004).

"unexplained" variable of Flood and Taylor (1996) is the order flow variable (denoted Δx_t) in Evans and Lyons (2002):

$$\Delta e_t = \Delta\left(r_t - r_t^*\right) + \Delta x_t. \tag{2}$$

The theory that yields the empirical specification in equation (2) is based on ML models of simultaneous trading in currency markets (see, for example, Lyons, 1997—Box (3) in Figure 1). In these models, first exchange rates are simultaneously set by currency dealers. These dealers must all set prices (simultaneously) at which they are willing to buy or sell any amount of currency. Next, market participants observe everyone else's exchange rates and submit their orders to the others in the market. These conditions guarantee that all dealers set the same exchange rate, because any differences would lead to large arbitrage opportunities and unravel the equilibrium. In equilibrium, all dealers set the same exchange rate and there are no opportunities for arbitrage. For all dealers to know which exchange rate to set, it must be based on publicly available information. Hence, in these models, dealers' exchange rates are common and based on publicly known order flow and macroeconomic variables.

Actual market participants, however, are constantly changing prices in over-the-counter currency markets.[4] That is, since currency trading occurs over the counter, at any point an individual dealer's exchange rate may diverge from others' in the market.[5] To study price setting in this market, DL models consider an individual dealers' exchange rate setting—Box (5) in Figure 1. Dealers in these models set prices as they receive incoming orders from other market participants. The initiators of the incoming orders may know more about future asset values than the dealers receiving the orders. In this situation, the incoming orders reflect information about future asset values and consequently drive currency prices. This is the asymmetric information effect. Also, in these models dealers have a finite inventory of the asset on which to draw for liquidity provision. As incoming orders drive the dealer's asset inventory away from her optimal level, she changes prices to induce compensating orders. This is the inventory effect. The classic DL pricing conjecture is given by Madhavan and Smidt (1991)—in Box (5) in Figure 1.

Empirical tests of DL models generally support asymmetric information effects;[6] they do not, however, find inventory effects.[7] One study, Lyons (1995),

[4]See Evans (2002) for evidence of concurrent, unequal prices in foreign exchange markets.

[5]Then one may ask why the assumptions of ML models guarantee that all dealers set the same price. The return in economic insight to modeling competitive dealers setting different prices concurrently is likely to be small relative to the cost of overcoming the intractability of competitive market equilibrium, particularly in terms of the necessary assumptions. See O'Hara (1995, Chapter 2) on precisely this intractability.

[6]For example, Hasbrouck (1988, 1991a, and 1991b) and Madhavan and Smidt (1991 and 1993) in equity markets; Lyons (1995), Yao (1998), and Bjønnes and Rime (2005) for foreign exchange markets, among others.

[7]Madhavan and Smidt (1991) do not find inventory effects. Madhavan and Smidt (1993) allow a changing optimal inventory level and find evidence of inventory management with a half-life of more than seven days, suggesting quite different effects from theoretical predictions. Furthermore, they reject the hypothesis of intraday inventory management, whereas Madhavan, Richardson, and Roomans (1997) argue that if there

finds direct evidence of asymmetric information and inventory management predicted by DL inventory theory—Box (6) in Figure 1.

This study reconsiders the use of traditional dealer-level pricing specifications, and, specifically, this study reexamines the Lyons (1995) result. Evidence of parameter instability and model misspecification in Lyons (1995) is presented. When estimated over the full data set, that study's DL pricing equation contains breaks. In subsamples where no breaks are present, the results do not fully support DL model predictions. Specifically, asymmetric information and inventory effects are not present simultaneously in subsamples; hence, although they do not reject the presence of asymmetric information or inventory effects in the data, the models' specifications of these effects are rejected. This is discussed further below and is indicated by the broken link between Box (5) and Box (6) in Figure 1. Then, Section II discusses an underlying assumption in DL models' pricing specification that may be behind their persistent empirical difficulties. Basically, the assumption that inventory accumulation is driven only by incoming order flow is questionable. This assumption is shown to be in contradiction to both the inventory data and ML micro exchange rate theory. This is indicated by the broken link between Box (3) and Box (5). Relaxing this assumption is a promising avenue for further DL modeling. Section III concludes.

I. Reconsidering the Lyons (1995) Result

This section reconsiders the Lyons (1995) DL exchange rate model (for details, see that study). Equation (3) gives the Lyons (1995) DL specification for how the dealer's price changes at each incoming trade (denoted by subscript t). Intuitively, the change in the exchange rate is a function of the incoming order size, direction of trade (that is, purchase or sale), and current and past inventory levels.

$$\Delta P_t = \beta_0 + \beta_1 Q_{jt} + \beta_2 I_t + \beta_3 I_{t-1} + \beta_4 D_t + \beta_5 D_{t-1} + ma(1), \qquad (3)$$

with predicted signs: $\{\beta_1, \beta_3, \beta_4 > 0\}$, $\{\beta_2, \beta_5 < 0\}$.

P_t: The price of the dealer at which an incoming sale or purchase occurred.
Q_{jt}: The incoming quantity demanded by the opposite party, that is, order flow.
I_t: This is the dealer's inventory at the time of (but not including) the incoming quantity Q_{jt}.
D_t: The indicator that picks up the direction of trade, positive for purchases, negative for sales.

is inventory management, it occurs toward the end of the day. Hasbrouck and Sofianos (1993) find very slow inventory adjustment as well, although they confirm that specialists are able to adjust inventory quickly during large exogenous shocks if they choose to. Hence, inventory levels are voluntary, not due to volume constraints, and must reflect long-term positions. Manaster and Mann (1996) find strong evidence that specialists do not control inventory as models would predict; rather, the exact opposite occurs. Furthermore, Madhavan and Sofianos (1998) also find that dealers do not change quotes to induce trades as theoretically predicted, but rather participate selectively in markets to unwind undesired positions. The general empirical failure of inventory model predictions described above for equity markets is borne out in foreign exchange market studies by Yao (1998) and Bjonnes and Rime (2000). Neither study can find the inventory management results predicted by the Madhavan and Smidt (1991) model.

Table 1. Reproduction of Lyons (1995) Original Estimates

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	–1.29	0.00	–0.96	0.34
Q_{jt}	1.47	0.00	3.17	0.00
I_t	–0.92	0.00	–3.38	0.00
I_{t-1}	0.72	0.00	2.76	0.01
D_t	10.30	0.00	4.77	0.00
D_{t-1}	–9.16	0.00	–6.28	0.00
$MA(1)$	–0.09	0.03	–2.71	0.01
R-squared	0.22	F-statistic		39.28
Adjusted R-squared	0.22	Prob(F-statistic)		0.00

Notes: Table 1 reproduces the baseline DL model estimates of exchange rate changes given in equation (3). (See Lyons, 1995, Table 4, p. 340). All coefficients are multiplied by 10^5 except the moving average.

Equation (3) predicts increasing prices with purchase orders and larger lagged inventory, and decreasing prices with sale orders, and larger current inventory.[8] The Lyons (1995) estimates of this equation are presented in Table 1.[9] The estimates are consistent with model predictions and significant at better than 1 percent. The robustness of these estimates is the subject of this section.

Figure 2 shows evidence of parameter instability in equation (3). In each graph, the abscissa indexes the incoming trades. The top two panels graph the probability that the trade is a breakpoint, with P-values indicated in the ordinate (both the F-test and the Likelihood Ratio test are reported). As the graphs show, the null hypothesis of no break is rejected toward the middle of the sample, as well as toward the end (the left graph uses the Chow breakpoint tests, the right uses Wald tests). This is indicated by the declining P-values throughout the middle of the sample and again at the end. The bottom panels show how the coefficients on equation (3) change as the regression is estimated on a rolling window of 150 transactions (beginning with the transaction indicated on the abscissa). The bottom left panel graphs the coefficient on incoming order flow (β_1) and its t-statistic. The bottom right panel does the same for the contemporaneous inventory coefficient (β_2). While one would expect some variation in the significance of the estimates owing to a smaller sample, the variation should not be systematic and should reduce the estimates' significance uniformly. One can observe that order flow is significant in the

[8]The moving average coefficient on the error term in equation (3) is predicted negative.

[9]The data are a one-week (843 observations) data set of a New York currency dealer of the dollar/DM market from August 3–7, 1992. See Lyons (1995) for an extensive exposition of this data set. The Lyons (1995) model includes a public information signal and specification of equation (3) with an extra regressor—brokered trading, B_t. That study estimates equation (3) both with and without the public signal because of poor measurement of the public signal in relation to the measurement of the other variables. Essentially, the brokered trading variable has measurement error and is zero in 84 percent of the dealer's transactions. This section focuses on estimates without brokered trading; however, a single break is found with it included in the Sup-F test.

beginning of the sample, whereas inventory is significant toward the end of the sample. Hence, the DL model predictions of both asymmetric information (significant order flow coefficient β_1) and inventory effects (significant inventory coefficient β_2) appear to not hold in subsamples. To get a feel for what is occurring at these points, Figure 3 shows the price set by the dealer. Solid vertical lines show the end of days of the week, and dashed vertical lines show two breaks considered in this section. The declining *P*-values in Figure 2 come at the end of the third day and close to the end of the sample.

To investigate the possibility of parameter instability in equation (1), Table 2 reports the results for the presence or location of (possibly multiple) structural breaks.[10] A break is found at transaction 449.[11] The right column of Table 2 reports the starting and ending observations of each of the five trading days from which the data were recorded. As Figure 3 shows, the break occurs near the end of Wednesday (overnight observations are removed). This break coincides with the end of a trading day; however, with three other day changes, there is no evidence to suggest that these alone induce structural breaks. Figure 2 suggests that there is another break toward the end of the sample; however, Sup-F tests cannot detect breaks within 5 percent of sample endpoints. On the last day of the sample, a \$300 million Fed intervention occurred after the close of the European markets.[12] This event may cause further parameter instability in the DL model estimates.[13] Hence, Table 3 reports conventional break tests conducted on the trade at which the intervention begins. The breaks and price are jointly shown in Figure 3. Given these joint results, one may conclude that the DL model is subject to two breaks when estimated on the Lyons (1995) data.

Table 4 reports estimations of the DL model on the subsamples that result from segregating the data at the breaks. Estimates from the subsample prior to the first break (observations 2 to 448) are in the top two lines; this subsample of data represents more than 53 percent of the available observations. The estimates reveal that the coefficients for inventory are insignificant at conventional levels, whereas signed

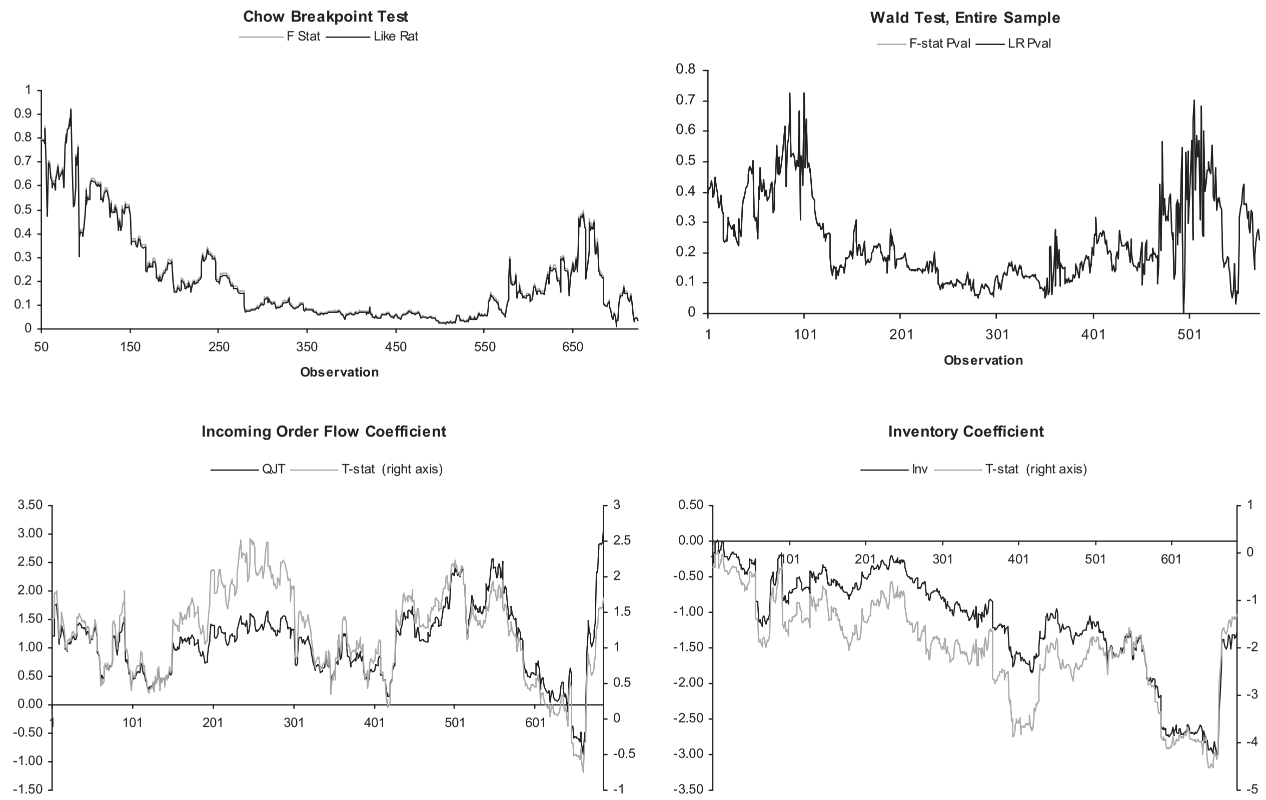
[10]Sup-F tests are based on Andrews (1993) and Bai and Perron (1998).

[11]The Sup-F tests allow for heterogeneity and autocorrelation in residuals using the Andrews (1991) method. Separate tests of the Lyons (1995) residuals fail to reject the null hypothesis of no breaks at conventional significance levels, although an overnight break for the first day is found at the 10 percent significance level.

[12]The Federal Reserve confirms a \$300 million intervention on that day but does not reveal its intervention timing or strategy. The financial press widely report (ex post) the approximate intervention start. The most precise timing is documented by the *Wall Street Journal,* August 10, 1992: "The Federal Reserve Bank of New York moved to support the U.S. currency . . . as the dollar traded at 1.4720" (Linton, 1992). That price corresponds to 12:32 p.m. in the Lyons (1995) data set, and that time is consistent with other financial news reports.

[13]Models that show how interventions affect trading include Bhattacharya and Weller (1997), Vitale (1999), Evans and Lyons (2001), Dominguez (2003), and others. For example, the Evans and Lyons (2001) model finds evidence of portfolio balance effects from interventions. A late-day and end-of-week intervention, one that occurs after other major markets (London and Tokyo) have closed for the weekend, would presumably bring to bear these effects. That is, the dealer would have very little time and fewer market participants (since the entire market would be affected) with which to share the intervention's portfolio imbalance over the weekend and, hence, would charge a higher premium for liquidity provision than at other times.

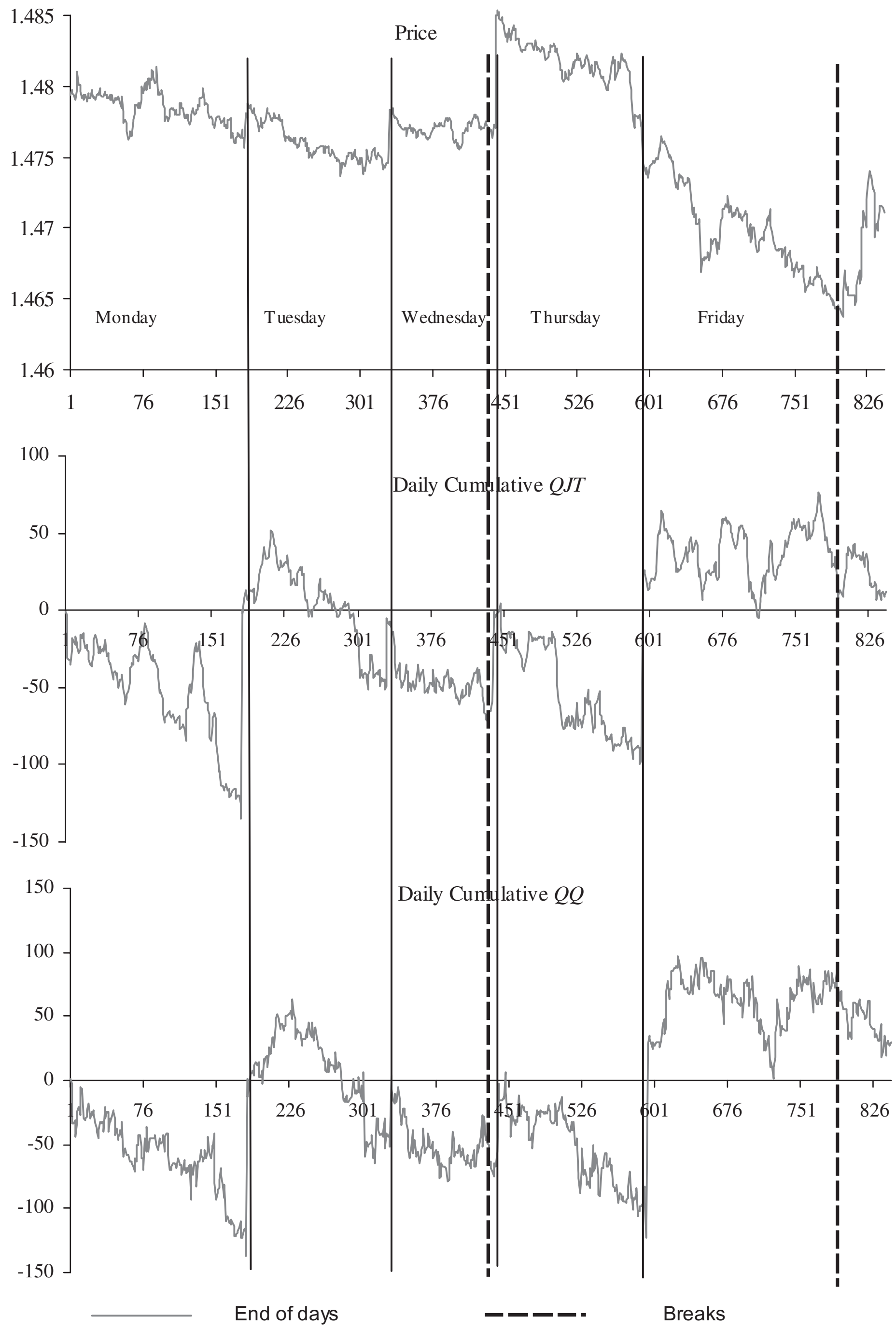
Figure 2. Rolling Estimates of Break Tests and DL Pricing Equation



Source: Lyons (1995) data: New York–based dollar/DM dealer, August 3–7, 1992.

Notes: The abscissa indexes observation number of the sample (on all graphs). The top left panel graphs the probability that the observation is a breakpoint, with the P-value indicated in the ordinate (both the F-test and the Likelihood Ratio test are reported). The top right graphs the same using a Wald test. The bottom left panel graphs the coefficient on incoming order flow using a rolling window of 150 observations (beginning with the observation indicated on the abscissa) and also reports the t-statistic. The bottom right panel does the same for the contemporaneous inventory coefficient.

Figure 3. Price, Daily Cumulative Components of Inventory, and Breaks



Source: Lyons (1995) data: New York–based dollar/DM dealer, August 3–7, 1992.

Notes: Figure 3 graphs the price set by the dealer in the top panel. The middle panel graphs cumulative daily incoming order flow, and the bottom panel graphs the cumulative sum of the unmodeled inventory evolution variable, *QQ*. The solid vertical lines represent the end of days; the dashed lines represent breaks.

Table 2. Sup-F Tests for Location and Number of Structural Breaks

Structural Breaks

Significance = 1%			End of Day	
Fixed	Break(s)	Point(s)	Monday	181
(p=0)	1	449	Tuesday	330
			Wednesday	440
			Thursday	592
			Friday	843

Notes: Table 2 shows the results of Sup-F tests for multiple structural breaks on equation (3). The test finds a break at observation 449 at the 1 percent significance level. The right column shows changes in days in the sample; breaks are not found at changes from one day to the next (overnight observations are excluded), however, the break date is close to the change from Wednesday to Thursday. All estimations and break tests are based on the Lyons (1995) DL specification that excludes B_t—brokered trading. Lyons (1995) data: New York–based dollar/DM dealer, August 3–7, 1992.

order flow (that is, the asymmetric information effect) and the order flow indicators are significant and estimated at magnitudes similar to the baseline estimates.

The estimates from the subsample 449 to 794 are reported in the third and fourth lines. The order flow coefficient is now insignificant, and the inventory components are significant at all conventional levels. These estimates suggest that asymmetric information is not present in dealer pricing on the last two days of the sample, which is just prior to the Fed intervention.

The third subsample, consisting of approximately 5 percent of the total available observations, likely reflects the effects of the Fed intervention. The only significant effect (at the 10 percent level) is the asymmetric information effect, and it seems to be an order of magnitude larger than the other subsample estimates. In general, the model fits this section of the sample poorly.

The bottom two lines shows estimates that result from joining the third subsample to the second, essentially ignoring the Fed intervention break. The Sup-F test cannot find this break (because of its proximity to the sample endpoint), but the Chow test rejects the null of no break at this point. Estimating these two subsamples jointly shows order flow and the order flow indicator coefficients significant at the 10 percent level but not at 1 percent. The inventory effects are significant, and the signs of the coefficients are as predicted (which was not the case for the Fed intervention subsample alone). However, the proportion of variation explained by the

Table 3. Break Test for Fed Intervention

Chow Breakpoint Test: Observation 795

F-statistic	5.8	Probability	0.00
Log likelihood ratio	40.5	Probability	0.00

Note: Table 3 shows the results of traditional break tests on the suspected entry point of the Fed in the market.

Table 4. Estimates of DL Pricing Model in Subsamples with No Breaks

	C	Q_{jt}	I_t	I_{t-1}	D_t	D_{t-1}	$MA(1)$	Subsample	Adj. R^2
Coefficient	–1.75	1.28	–0.354	0.12	12.60	–8.82	–0.20	2 to 448	0.32
Prob.	0.15	0.01	0.20	0.65	0.00	0.00	0.00		
Coefficient	–3.17	0.90	–2.04	1.86	11.00	–11.2	–0.10	449 to 794	0.30
Prob.	0.14	0.19	0.00	0.00	0.00	0.00	0.06		
Coefficient	15.40	14.40	3.22	–2.58	–28.1	–1.65	0.10	795 to 839	–0.05
Prob.	0.38	0.06	0.39	0.43	0.30	0.92	0.54		
Coefficient	–0.78	1.73	–1.63	1.45	7.12	–10.1	–0.04	449 to 839	0.17
Prob.	0.77	0.04	0.00	0.00	0.07	0.00	0.40		

Source: Lyons (1995) data: New York–based dollar/DM dealer, August 3–7, 1992.

Notes: Table 4 shows estimates of the three subsamples, with breaks at observations 449 and 795. The first break is given by the Sup-F test. The second break, observation 795, is given by the traditional F-test. The top panel reports the first subsample, observations 1 to 448. The second panel reports estimates from observations 449 to 794. The third panel reports estimates from observations 795 to 838. The fourth panel reports the second and third subsamples estimated together. All coefficients are multiplied by 10^5 except the moving average.

regression falls from 32 percent (without the intervention subsample) to 17 percent (with the intervention subsample). Hence, while the estimation that averages across the two subsamples (that is, ignoring the Fed intervention) recuperates to some extent DL model predictions, adding observations reduces its explanatory power.[14]

II. A Puzzle of Microstructure Market Maker Models

DL models study the transaction prices that currency dealers set as orders arrive throughout the trading day. They draw from equity market studies, which consider the price-setting behavior of a "monopoly" specialist, a single market maker with no other source of liquidity. Consistent with specialists' inventory management theory,[15] DL models assume that dealers set prices to control an inventory that evolves according to equation (4):[16]

$$I_{it+1} = I_{it} - Q_{jt}, \tag{4}$$

[14]Furthermore, identifying the first break at the first or last observation at which the Chow test p-value falls below 5 percent in Figure 2 (observations 392 and 541) does not change the result that the first regime does not have inventory effects, and the second has no asymmetric information effects.

[15]For example, Stoll (1978), Amihud and Mendelson (1980), Ho and Stoll (1981), O'Hara and Oldfield (1986), among others. It is useful to note, however, that equity market specialists on the New York Stock Exchange compete aggressively against a limit order book that they themselves manage and, if necessary, can induce orders from the trading floor through moral suasion.

[16]Equivalently, some models (for example, Madhavan and Smidt, 1991; or Lyons, 1995) conjecture a pricing equation consistent with inventory of equations (4) and (5). Prices are assumed to be set according to $P_{it} = \mu_{it} - \alpha(I_{it} - I^*) + \gamma D_t$, where I^* is the dealer i's desired inventory level, and D_t is one if the transaction is on the offer (that is, the aggressor purchases), and negative one if the transaction occurs on the bid (that is, the aggressor sells). It picks up the bid-ask bounce for quantities close to zero. Hence, prices are set according to the best estimate of the full information value and then adjusted to induce inventory-compensating trades.

with I_{it} dealer i's inventory at the beginning of period t, and Q_{jt}, the incoming order flow from other dealers (represented by subscript j), given by:

$$Q_{jt} = \theta\left(\mu_{jt} - P_{it}\right) + X_{jt}. \tag{5}$$

In equation (5), μ_{it} is dealer i's best estimate of the full information value, $\tilde{v}_t$, at the time of quoting. Thus, order flow is a scaled deviation of dealer i's price from dealer j's expectation of $\tilde{v}_t$, plus an orthogonal liquidity shock, X_{jt}.

In the world of equations (4) and (5), price setting is used to control inventory imbalances (and reduce inventory risk) owing to incoming orders. Intuitively, the dealer's pricing strategy reduces the randomness of the order arrival process by balancing incoming purchases with incoming sales. Such assumptions imply that inventory control is achieved by diverting asset prices away from the full-information value, thus discounting the asset to attract inventory-compensating trades. The DL model specifications for inventory effects that these assumptions yield are consistently rejected by the data.

To find a new direction for market maker modeling, one may consider a small part of the Lyons (1995) data set, which is shown on Table 5. The first column indexes the observations according to the order of arrival; the second column shows the price set by the dealer; the next columns show incoming order flow, the inventory at the beginning of the trade, and a variable called QQ_{it} that is backed out of equation (6):

$$I_{it+1} = I_{it} - Q_{jt} + QQ_{it}. \tag{6}$$

QQ_{it} in equation (6) reflects inconsistencies between the data and the inventory evolution assumed in equation (4). Consider, for example, the third incoming trade, which was a sale to the dealer of \$28.5 million. At the time of the trade, the dealer was long \$1 million. If equation (4) held, then the \$28.5 million purchase would imply a \$29.5-million-long inventory at entry four. Instead, the dealer is short \$1.5 million at the next incoming trade, which implies that the inventory somehow declined by \$30.5 million between the third and the fourth trade. This decline is

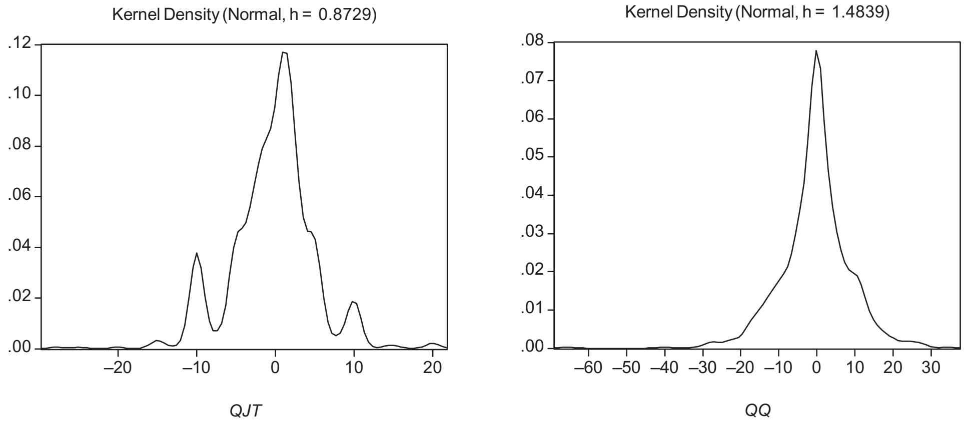
Table 5. First Five Entries of Lyons (1995) Data Set

Entry	P_{it}	Q_{jt}	I_t	QQ
1	1.4794	–1	1	1
2	1.4797	–2	3	–4
3	1.4795	–28	1	–30.5
4	1.4794	–0.5	–1.5	0.25
5	1.479	–0.75	–0.75	0

Source: Lyons (1995) data: New York–based dollar/DM dealer, August 3–7, 1992.

Notes: Table 5 shows the first five entries of the price (second column), incoming order flow (third column), and inventory (fourth column) variables from the data set. The last column is backed out from the equation: $I_{it+1} = I_{it} - Q_{jt} + QQ_{it}$. The generated variable QQ captures the part of inventory evolution that is not due to incoming order flow.

Figure 4. Kernel Density Plots for QQ_{it} and Q_{jt}



Source: Lyons (1995) data: New York–based dollar/DM dealer, August 3–7, 1992.

Notes: Figure 4 shows Gaussian kernel densities for the empirical distributions of the unmodeled inventory evolution variable, *QQ,* and incoming order flow, Q_{jt} . The two peaks in the distribution of Q_{jt} most likely reflect clustering at the standard order sizes of $10 million.

reflected in QQ_{i3}. It captures the gap in the inventory evolution that incoming order flow did not generate.

Figure 3 graphs the daily cumulative incoming order flow and the daily cumulative gap, *QQ*. This variable appears to be synchronized with incoming order flow. This suggests that whatever is driving *QQ* may balance the asynchronous arrival of incoming purchases and incoming sales. *QQ* may, for example, reflect other methods of inventory control available to the dealer.[17] In this case, optimal pricing problems based on equation (4) may be misspecified. Furthermore, DL modeling of *QQ* may also consider information about asset values contained similar to those specified in equation (5) that reflect alternate sources of information available to the dealer.[18]

According to both inventory management theory and market data, inventory is strongly managed by dealers (I_{it} is mean-reverting), implying that $E[I_{it+1} - I_{it}]$ is stationary. According to equation (4), Q_{jt} is then also stationary (which would be consistent with price setting that induces a balance between incoming purchases and sales), thereby making QQ_{it} noise. However, another possibility is that $[-Q_{jt} + QQ_{it}]$ is stationary. This would imply that QQ_{it} and Q_{jt} are economically related, and that QQ_{it} may be a good candidate for microstructure modeling. Figure 4 plots kernel densities of the empirical distribution of these two series (the two peaks in the dis-

[17]In currency markets, these methods include initiating interdealer bilateral trades, interdealer brokered trades, or International Monetary Market Futures trades.

[18]Ho and Stoll (1983) model inventory management with two dealers and two assets, thereby including aspects of competitive trading. Romeu (2003) models DL pricing with a dealer that takes into account multiple methods of inventory control and multiple sources of information. See footnote 5 for an important caveat regarding these types of models.

Table 6. Descriptive Statistics for QQ_{it} and Q_{jt}

	Mean	Median	Max	Min	Std. Dev.	Skew.	Kurt.	Correl.
QQ	–0.39	0.00	34.45	–66	8.99	–0.55	7.44	0.64
QJT	–0.39	0.45	20.00	–28	5.24	–0.29	5.44	
Test for Equality of Means								
Included observations: 843								
Method		df	Value	Probability				
t-test		1684	0.00	1.00				
Anova F-statistic		(1,1684)	0.00	1.00				

Source: Lyons (1995) data: New York–based dollar/DM dealer, August 3–7, 1992.

Notes: Table 6 shows descriptive statistics for the unmodeled inventory evolution variable, *QQ*, and incoming order flow, Q_{jt}. Tests for equality of means fail to reject equality, and the correlation between the series is presented.

tribution of Q_{jt} most likely reflect clustering at the standard order sizes of $10 million), which appear to be similar. Table 6 gives descriptive statistics, which show that the means of the distributions are almost equal in magnitude, the pair-wise correlation is 0.64, and tests fail to reject the null hypothesis that the variables' means are equal. The similarity in distributions suggests that QQ_{it} may be a good candidate for microstructure modeling. Table 7 shows lag selection criteria for a vector

Table 7. VAR Lag Order Selection Criteria

Endogenous variables: *QJT QQ*
Exogenous variables: *C*
Included observations: 835

Lag	LogL	LR	FPE	AIC	SC	HQ
0	–5353.6	NA	1276.6	12.8	12.8	12.8
1	–5151.7	402.3	794.8	12.4	12.4	12.4
2	–5131.1	40.9*	763.8*	12.3*	12.4*	12.3*
3	–5128.3	5.6	765.9	12.3	12.4	12.3
4	–5123.6	9.2	764.7	12.3	12.4	12.4
5	–5122.0	3.3	769.0	12.3	12.4	12.4
6	–5120.0	3.8	772.8	12.3	12.5	12.4
7	–5118.4	3.0	777.4	12.3	12.5	12.4
8	–5115.2	6.3	778.8	12.3	12.5	12.4

Source: Lyons (1995) data: New York–based dollar/DM dealer, August 3–7, 1992.
* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Notes: Table 7 shows multiple lag selection tests for a vector auto regression (VAR) of the unmodeled inventory evolution variable, *QQ*, and incoming order flow, Q_{jt}. Two lags are selected by multiple criteria.

Table 8. Vector Auto Regression Estimates

	QJT(–1)	*QJT*(–2)	*QQ*(–1)	*QQ*(–2)	*C*
QJT	0.47 [11.84]	0.24 [5.88]	–0.47 [–22.69]	–0.15 [–5.67]	–0.35 [–2.48]
QQ	0.68 [8.72]	0.27 [3.38]	–0.58 [–14.34]	–0.13 [–2.60]	–0.30 [–1.07]
t-statistics in [ ]					
R-squared	0.39	Akaike AIC	5.67		
Adj. R-squared	0.39	Schwarz SC	5.69		
F-statistic	134.65	Mean dependent	–0.38		
Log likelihood	–2377.6	S.D. dependent	5.25		

Source: Lyons (1995) data: New York–based dollar/DM dealer, August 3–7, 1992.

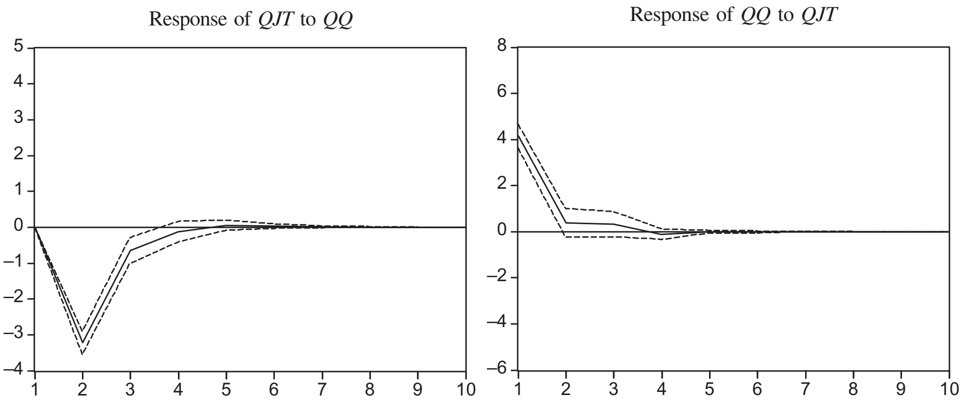
Notes: Table 8 shows the results of a two-lag vector auto regression on the unmodeled inventory evolution variable, QQ_{it}, and incoming order flow, Q_{jt} (*t*-statistics in parentheses).

auto regression (VAR) of the variables. All tests select two lags, which are then estimated in Table 8. The coefficients are significant at conventional levels and show an inverse relationship between the lags and contemporaneous values of QQ_{it} and Q_{jt}. Hence, the evolution in time of incoming order flow may be compensated by the evolution of QQ_{it}. Figure 5 shows the impulse responses of each variable to a shock in the other. A shock in Q_{jt} invokes an immediate response in QQ_{it}, which further suggests that elements of microstructure models may be useful in explaining the evolution of QQ_{it} and consequently of inventories and prices.

Finally, DL models that assume equation (4) and ML models such as Lyons (1997) have conflicting inventory evolution assumptions. In ML models, dealers'

Figure 5. Impulse Responses for QQ_{it} and Q_{jt}

(Response to Cholesky one S.D. innovations ± 2 S.E.)



Source: Lyons (1995) data: New York–based dollar/DM dealer, August 3–7, 1992.

Notes: Figure 5 shows the responses of the unmodeled inventory evolution variable, *QQ*, and incoming order flow, Q_{jt}, to a one-standard-deviation shock in the other respective variable.

inventories change not just by incoming orders, but also by outgoing and customer orders. That is, ML dealers (for example, Lyons, 1997—Box (3) in Figure 1) receive incoming orders but also initiate orders with other dealers and trade with customers. Hence, these models allow a role for customers and outgoing orders in price determination. DL models where a dealer's position is governed by equation (4) only receive incoming orders. They do not incorporate these other trading venues into the dealer's price-setting optimization.[19]

III. Conclusion

This paper considers the empirical viability of (partial equilibrium) dealer-level microstructure models. It presents new empirical results that reject the specifications of such models. The DL model of currency dealer price setting is found to contain structural breaks when estimated on a one-week sample of currency trading. In the two relevant subsample estimations, asymmetric information effects are rejected in one, and inventory effects are reflected in the other. That is, they do not occur simultaneously, as the model would predict. This rejection of the DL model is consistent with other empirical studies (see footnote 7).

Future work may investigate whether the consistent rejection of dealer-level models stems from assumptions limiting the sources of inventory changes. In the rejected dealer models, inventory is assumed to evolve only through incoming purchases or sales. This implies that price setting is crucial for controlling inventory. This study suggests, however, that inventory evolution may also depend on other factors beyond incoming orders. In particular, evidence is presented of an unexplained component of inventory evolution that is correlated with incoming orders and is of similar magnitude. Evidence of causality running in both directions between this unexplained inventory component and incoming orders is presented. Taken together, these suggest that this component may be a good candidate for where dealer-level modeling should go next. Furthermore, including this unexplained component may allow the inclusion of assumptions that condition dealer prices on incoming, outgoing, and customer orders, as in ML models.

BIBLIOGRAPHY

Admati, A., and P. Pfleiderer, 1988, "A Theory of Intraday Patterns: Volume and Price Variability," *Review of Financial Studies,* Vol. 1 (Spring), pp. 3–40.

Amihud, Y., and H. Mendelson, 1980, "Dealership Market: Marketmaking with Inventory," *Journal of Financial Economics,* Vol. 8 (March), pp. 31–53.

Andrews, D. W. K., 1991, "Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimation," *Econometrica,* Vol. 59 (November), pp. 817–58.

———, 1993, "Testing for Parameter Instability and Structural Change with Unknown Change Point," *Econometrica,* Vol. 61 (July), pp. 821–56.

[19]Lyons (1995) controls empirically for outgoing orders and finds that these do not bias the effects reported in Table 1; however, the underlying pricing relation in that model is rejected here.

Bai, J., and P. Perron, 1998, "Estimating and Testing Linear Models with Multiple Structural Changes," *Econometrica,* Vol. 66 (January), pp. 47–78.

Bhattacharya, U., and P. Weller, 1997, "The Advantage to Hiding One's Hand: Speculation and Central Bank Intervention in the Foreign Exchange Market," *Journal of Monetary Economics,* Vol. 39 (July), pp. 251–77.

Bjønnes, G. H., and D. Rime, 2005, "Dealer Behavior and Trading Systems in the Foreign Exchange Market," *Journal of Financial Economics,* Vol. 75 (March), pp. 571–605.

Cao, H. H., M. D. D. Evans, and R. K. Lyons, 2005, "Inventory Information," *Journal of Business* (forthcoming).

Dominguez, K. M. E., 2003, "When Do Central Bank Interventions Influence Intra-Daily and Longer-Term Exchange Rate Movements?" NBER Working Paper No. 9875 (Cambridge, Massachusetts: National Bureau of Economic Research).

Easley, D., and M. O'Hara, 1987, "Price, Trade Size, and Information in Securities Markets," *Journal of Financial Economics,* Vol. 19 (September), pp. 69–90.

———, 1992, "Time and the Process of Security Price Adjustment," *Journal of Finance,* Vol. 47 (June), pp. 577–605.

Evans, M. D. D., 2002, "FX Trading and Exchange Rate Dynamics," *Journal of Finance,* Vol. 57 (December), pp. 2405–47.

———, and R. K. Lyons, 2001, "Portfolio Balance, Price Impact, and Secret Intervention," NBER Working Paper No. 8356 (Cambridge, Massachusetts: National Bureau of Economic Research).

———, 2002, "Order Flow and Exchange Rate Dynamics," *Journal of Political Economy,* Vol. 110 (February), pp. 170–80.

———, 2004, "A New Micro Model of Exchange Rate Dynamics," NBER Working Paper No. 10379 (Cambridge, Massachusetts: National Bureau of Economic Research).

Flood, R., and M. Taylor, 1996, "Exchange Rate Economics: What's Wrong with the Conventional Macro Approach?" *The Microstructure of Foreign Exchange Markets,* ed. by J. Frankel, G. Galli, and A. Giovannini (Chicago: University of Chicago Press), pp. 261–94.

Frankel, J., and A. Rose, 1995, "Empirical Research on Nominal Exchange Rates," *Handbook of International Economics,* Vol. 3, ed. by G. Grossman and K. Rogoff (Amsterdam: Elsevier Science), pp. 1689–729.

Glosten, L., and P. Milgrom, 1985, "Bid, Ask, and Transaction Prices in a Specialist Market with Heterogeneously Informed Agents," *Journal of Financial Economics,* Vol. 14 (March), pp. 71–100.

Hasbrouck, J., 1988, "Trades, Quotes, Inventories, and Information," *Journal of Financial Economics,* Vol. 22 (December), pp. 229–52.

———, 1991a, "Measuring the Information Content of Stock Trades," *Journal of Finance,* Vol. 46 (March), pp. 179–207.

———, 1991b, "The Summary Informativeness of Stock Trades: An Econometric Analysis," *Review of Financial Studies,* Vol. 4, No. 3, pp. 571–95.

———, and G. Sofianos, 1993, "The Trades of Market Makers: An Empirical Examination of NYSE Specialists," *Journal of Finance* Vol. 48, pp. 1565–93.

Ho, T., and H. Stoll, 1981, "Optimal Dealer Pricing Under Transactions and Return Uncertainty," *Journal of Financial Economics,* Vol. 9 (March), pp. 47–73.

———, 1983, "The Dynamics of Dealer Markets Under Competition," *Journal of Finance,* Vol. 38 (September), pp. 1053–74.

Ito, T., R.K. Lyons, and M. Melvin, 1998, "Is There Private Information in the FX Market? The Tokyo Experiment," *Journal of Finance,* Vol. 53 (June), pp. 1111–30.

Kyle, A., 1985, "Continuous Auctions and Insider Trading," *Econometrica,* Vol. 53 (November), pp. 1315–35.

Linton, Clifton, 1992, "Dollar Likely to Fall Though Banks May Try to Slow Currency's Descent," *Wall Street Journal* (New York), August 10, p. C13.

Lyons, R., 1995, "Tests of Microstructural Hypotheses in the Foreign Exchange Market," *Journal of Financial Economics,* Vol. 39 (October), pp. 321–51.

———, 1996, "Optimal Transparency in a Dealer Market with an Application to Foreign Exchange," *Journal of Financial Intermediation,* Vol. 5 (July), pp. 225–54.

———, 1997, "A Simultaneous Trade Model of the Foreign Exchange Hot Potato," *Journal of International Economics,* Vol. 42 (May), pp. 275–98.

———, 1998, "Profits and Position Control: A Week of FX Dealing," *Journal of International Money and Finance,* Vol. 17 (February), pp. 97–115.

———, 2001, *The Microstructure Approach to Exchange Rates* (Cambridge, Massachusetts; and London: MIT Press).

Madhavan, A., and G. Sofianos, 1998, "An Empirical Analysis of NYSE Specialist Trading," *Journal of Financial Economics,* Vol. 48 (May), pp. 189–210.

Madhavan, A., M. Richardson, and M. Roomans, 1997, "Why Do Security Prices Change? A Transaction-level Analysis of NYSE Stocks," *Review of Financial Studies,* Vol. 10, pp. 1035–64.

Madhavan, A., and S. Smidt, 1991, "A Bayesian Model of Intraday Specialist Pricing," *Journal of Financial Economics,* Vol. 30 (November), pp. 99–134.

———, 1993, "An Analysis of Daily Changes in Specialist Inventories and Quotations," *Journal of Finance,* Vol. 48 (December), pp. 1595–648.

Manaster, S., and S. C. Mann, 1996, "Life in the Pits: Competitive Market Making and Inventory Control," *Review of Financial Studies,* Vol. 9 (Fall), pp. 953–75.

Meese, R., and K. Rogoff, 1983, "The Out-of-Sample Failure of Empirical Exchange Rate Models," *Exchange Rate and International Macro-economics,* ed. by J. Frenkel (Chicago: University of Chicago Press).

O'Hara, M., 1995, *Market Microstructure Theory* (Malden, Massachusetts: Blackwell Publishers Inc.).

———, and G. S. Oldfield, 1986, "The Microeconomics of Market Making," *Journal of Financial and Quantitative Analysis,* Vol. 21 (December), pp. 361–76.

Romeu, R.B., 2003, "An Intraday Pricing Model of Foreign Exchange Markets" IMF Working Paper 03/115 (Washington: International Monetary Fund).

Sarno, L., and M. Taylor, 2002, "Purchasing Power Parity and the Real Exchange Rate," *IMF Staff Papers,* Vol. 49 (April), pp. 65–105.

Stoll, Hans R., 1978, "The Supply of Dealer Services in Securities Markets," *Journal of Finance,* Vol. 33 (September), pp. 1133–51.

"U.S. Fed Intervenes as Dollar Nears Low Against D-Mark," *Financial Times* (London), August 8, 1992, p.1.

Vitale, P., 1999, "Sterilized Central Bank Intervention in the Foreign Exchange Market," *Journal of International Economics,* Vol. 49 (December), pp. 245–67.

Yao, J., 1998, "Market Making in the Interbank Foreign Exchange Market," Salomon Center Working Paper No. S-98-3 (unpublished; New York: New York University).