Order Flow and Exchange Rate Dynamics

Martin D. D. Evans

Georgetown University and National Bureau of Economic Research

Richard K. Lyons

University of California, Berkeley and National Bureau of Economic Research

This paper presents an exchange rate model of a new kind. Instead of relying exclusively on macroeconomic determinants, the model includes a determinant from the field of microstructure finance—order flow. Order flow is a determinant because it conveys information. This is a radically different approach to exchange rates. It is also strikingly successful. Our model of daily deutsche mark/dollar log changes produces an R^2 statistic above 60 percent. For the deutsche mark/dollar spot market as a whole, we find that $1 billion of net dollar purchases increases the deutsche mark price of a dollar by 0.5 percent.

I. Introduction

Macroeconomic models of exchange rates perform poorly at frequencies higher than one year. Indeed, the explanatory power of these models is essentially zero (Meese and Rogoff 1983; Meese 1990). In the words of Frankel and Rose (1995, p. 1704), this negative result has had a “pessimistic effect on the field of empirical exchange rate modeling

We thank the following for valuable comments: three anonymous referees, Menzie Chinn, Peter DeMarzo, Frank Diebold, Petra Geraats, Robert Lucas (the editor), Richard Meese, Michael Melvin, Peter Reiss, Andrew Rose, Mark Taranto, Ingrid Werner, Alwyn Young, and seminar participants at Chicago, Wharton, Columbia, Massachusetts Institute of Technology, Iowa, Houston, Stanford, Berkeley, Princeton, the 1999 NBER Summer Institute, and the December 1999 NBER program meeting in microstructure. We thank the National Science Foundation for financial assistance.

[*Journal of Political Economy,* 2002, vol. 110, no. 1]

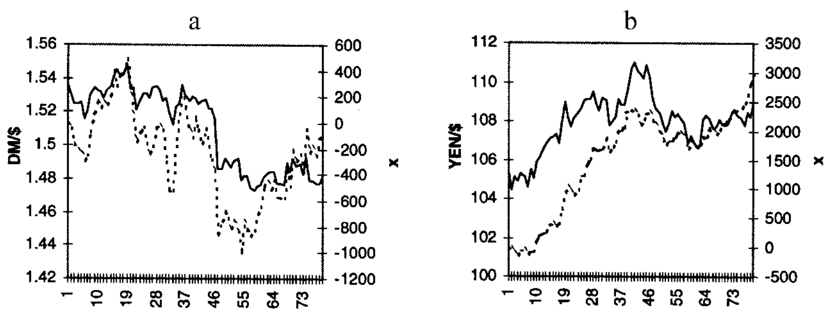

FIG. 1.—Four months of exchange rates (solid) and cumulative order flow (dashed), May 1–August 31, 1996: *a,* deutsche mark/dollar; *b,* yen/dollar.

in particular and international finance in general." The pessimistic effect has been with us 20 years.[1]

This paper moves in a new direction. We augment traditional macro analysis with some price determination microeconomics. This leads us to a class of models—from microstructure finance—that highlight new variables that macro models omit. The most important such variable is order flow. Order flow is defined as the net of buyer-initiated and seller-initiated orders; it is a measure of net buying pressure. Order flow is a proximate determinant of price in these models because it conveys information that currency markets need to aggregate.[2] This information includes anything pertaining to the realization of uncertain demands (differential interpretation of news, shocks to hedging demands, shocks to liquidity demands, etc.). When one maps information to price, order flow is essential to the transmission mechanism.

Figure 1 provides a first glimpse of order flow's role in this transmission mechanism. The solid lines are the spot rates of the deutsche mark and yen against the dollar over our four-month sample (May 1 to August 31, 1996). The dashed lines are worldwide order flow for the respective currencies. This order flow measure, denoted by x, is the sum

[1] Surveys of the literature include Frankel and Rose (1995), Isard (1995), and Taylor (1995). Alternatives to traditional models, such as the "new open-economy macro" approach (e.g., Obstfeld and Rogoff 1995), have yet to produce empirical exchange rate equations that alter the Meese-Rogoff conclusions.

[2] For evidence that foreign exchange order flow conveys information, see Lyons (1995), Covrig and Melvin (1998), Ito, Lyons, and Melvin (1998), Yao (1998), Payne (1999), Cheung and Wong (2000), Naranjo and Nimalendran (2000), and Evans (2002).

over time of signed interdealer trades.[3] Order flow and nominal exchange rates are strongly positively correlated, indicating that price increases with buying pressure. Though seemingly natural, a causal relation of this kind has conceptual implications: actual trades are neither necessary nor sufficient for price movements in traditional macro models.

We develop and estimate a model that specifies how interdealer order flow drives price determination via information aggregation. Our estimates verify the significance of this correlation. The model accounts for more than 60 percent of daily changes in the log deutsche mark/dollar exchange rate and more than 40 percent of daily changes in the log yen/dollar rate. This analysis fills the missing middle between past microstructure work using tick-by-tick data and macro work using monthly data. It helps to clarify how lower-frequency exchange rate dynamics emerge from the market's operation in real time.

This paper has four remaining sections. Section II develops a model with both micro and macro determinants. Section III describes our data. Section IV presents our results. Section V presents conclusions.

II. Portfolio Shifts Model

The model sketched in this section serves several purposes. First, it is designed to accommodate data at the daily frequency (unlike existing transaction frequency models). Second, the model provides a clear null under which causation runs from order flow to price, with interdealer flow serving as the means by which nonpublic information is learned. Third, the model shows why order flow's impact on price should persist using a familiar portfolio balance channel; this clarification is important for those who believe that trades can have only fleeting "indigestion" effects on price.

There are two basic types of information that order flow can convey. The first is information about the stream of future cash flows (i.e., numerators in a security valuation model). In foreign exchange, this stream takes the form of future interest differentials. The second is information about market-clearing discount rates (i.e., valuation denominators). The trading model we develop is based on the second type. It adopts a simultaneous-trade approach (see, e.g., the transaction frequency model of Lyons [1997]). Where applicable, we compress our

[3] For example, if a dealer initiates a trade against another dealer's deutsche mark/dollar quote and the trade is a dollar purchase (sale), then order flow is $+1$ (-1). These unit order flow values are cumulated across dealers over each 24-hour trading day (weekend trading—which is minimal—is included in Monday). In spot foreign exchange, roughly 75 percent of total volume occurs between dealers (25 percent occurs between dealers and nondealer customers).

presentation of the model below by using results established for other simultaneous-trade models.

The economic intuition behind our model is quite simple. Uncertain public demands for foreign exchange are realized at the start of each day. These demand realizations produce orders that are not publicly observed, so any information they convey needs to be aggregated in the trading process. Also, these demand realizations are, for simplicity, uncorrelated with future interest differentials, so any price impact operates through discount rates. (Demands of this type include liquidity demands, hedging demands, and, more subtly, speculative demands from varying risk tolerance.) These demands affect price because the rest of the market—being less than perfectly elastic—requires a price concession to absorb them.[4]

Consider a pure exchange economy with T trading periods (days) and two assets, one riskless (with gross return equal to one) and one risky. The $T+1$ payoff on the risky asset—foreign exchange—is denoted R, where R is composed of a series of increments:

$$R = \sum_{t=1}^{T+1} \Delta r_t. \tag{1}$$

The Δr_t increments are independently and identically distributed normal$(0, \sigma_r^2)$ and are observed publicly each day before trading. These realized increments represent innovations over time in public macroeconomic information (e.g., changes in interest rates). The foreign exchange market is organized as a dealership market with N dealers, indexed by i, and a continuum of nondealer customers (the public), indexed by $z \in [0, 1]$. The mass of customers on $[0, 1]$ is large (in a convergence sense) relative to the N dealers. Dealers and customers all have identical negative exponential utility defined over $T+1$ wealth.

The timing of the model is summarized in figure 2. Within each day there are three rounds of trading. In the first round, dealers trade with the public. In the second round, dealers trade among themselves (to share the resulting inventory risk). In the third round, dealers trade again with the public (to share inventory risk more broadly).

Each day begins with public observation of the day's payoff increment Δr_t. On the basis of this increment and other available information, each dealer simultaneously and independently quotes a scalar price to his

[4] For evidence that aggregate demand across stocks is less than perfectly elastic, see Scholes (1972), Shleifer (1986), Bagwell (1992), and Kaul, Mehrotra, and Morck (2000). The spot deutsche mark/dollar market needs to absorb much larger portfolio shifts than the market for a representative stock (the daily volume per stock on the New York Stock Exchange in 1998 averaged less than \$10 million, whereas the daily volume in the spot deutsche mark/dollar market averaged about \$300 billion).

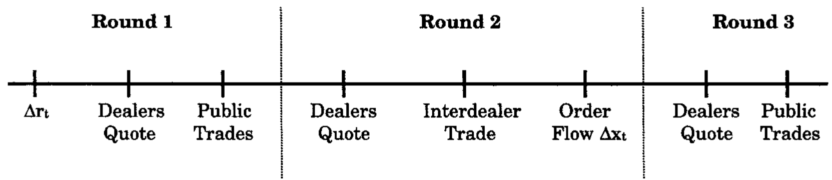

FIG. 2.—Daily timing

customers at which he agrees to buy and sell any amount.[5] We denote this round 1 price of dealer i on day t as P_{it}^1. Each dealer then receives a customer order realization C_{it}^1 that is executed at his quoted price P_{it}^1. Let $C_{it}^1 < 0$ denote net customer selling (dealer i buying). The individual C_{it}^1's are distributed normal$(0, \sigma_C^2)$; they are uncorrelated across dealers, are uncorrelated with the payoff increment Δr_t, and are not publicly observed. We refer to these orders as "portfolio shifts" of the nondealer public.

In round 2, each dealer simultaneously and independently quotes a scalar price to other dealers at which he agrees to buy and sell any amount. These interdealer quotes are observable and available to all dealers. Each dealer then simultaneously and independently trades on other dealers' quotes. (Orders at a given price are split evenly across dealers quoting that price.) Let T_{it} denote the (net) interdealer trade initiated by dealer i in round 2 (negative for dealer i net selling). At the close of round 2, all agents observe the interdealer order flow from that period:

$$\Delta x_t = \sum_{i=1}^{N} T_{it}. \tag{2}$$

In round 3 of each day, dealers share overnight risk with the nondealer public. In contrast to round 1, the public's motive for trading in round 3 is nonstochastic. Initially, each dealer simultaneously and independently quotes a scalar price P_{it}^3 at which he agrees to buy and sell any amount. These quotes are observable and available to the public. We assume that total public demand for the risky asset in round 3, denoted C_t^3, is less than infinitely elastic. With our earlier assumptions, this allows

[5] Introducing a bid-offer spread (or price schedule) in round 1 to endogenize the number of dealers is a straightforward—but distracting—extension.

us to write total public demand in round 3 as a linear function of the expected return:

$$C_t^3 = \gamma(E[P_{t+1}^3 \mid \Omega_3 \mid] - P_t^3), \tag{3}$$

where the positive coefficient γ captures the public's aggregate risk-bearing capacity, and Ω_3 is the available public information (includes all payoff increments Δr_t and interdealer flows Δx_t through day t).

The equilibrium relation between interdealer order flow and price adjustment follows directly from results established for the simultaneous-trade model of Lyons (1997). First, propositions 1 and 2 of that paper show that within a given round, all dealers quote a common price (this is necessary for no arbitrage). It follows that this price is conditioned on common information only. Though each day's payoff increment Δr_t is common information at the beginning of round 1, order flow Δx_t is not observed until the end of round 2. The price for round 3 trading, P_t^3, reflects the information in both Δr_t and Δx_t.

The information in the payoff increment Δr_t is straightforward. The information in the order flow Δx_t relates to portfolio balance effects. To understand why, note first that in equilibrium each dealer's interdealer trade, T_{it}, will be proportional to the customer order C_{it}^1 he receives (see Lyons 1996, proposition 4). This implies that when dealers observe Δx_t at the end of round 2 (eq. [2]), they can infer the aggregate portfolio shift on the part of the public in round 1, $\sum_{i=1}^{N} C_{it}^1$ (henceforth denoted C_t^1). Dealers also know that, for a risk-averse public to reabsorb this portfolio shift in round 3, price must adjust. In particular, price adjusts in round 3 so that $C_t^1 + C_t^3 = 0$, where C_t^3 is given by equation (3). The resulting price change from the end of period $t-1$ to the end of period t can be written as

$$\Delta P_t = \Delta r_t + \lambda \Delta x_t, \tag{4}$$

where λ is a positive constant that depends on γ and the variances σ_r^2 and σ_C^2 (see the working paper version of this article [Evans and Lyons 1999] for details).[6]

We make two changes to equation (4) for estimation purposes. First, we specialize the public information increment Δr_t to equal the change in the nominal interest differential, $\Delta(i_t - i_t^*)$, plus a white-noise error term, where i_t is the nominal dollar interest rate and i_t^* is the nominal nondollar interest rate (deutsche mark or yen). Although Δr_t could also

[6] For intuition on eq. (4), consider P_T, the final day's price. This is a one-period problem with Δr_{T+1} yet to be realized. The price P_T reflects all past payoff increments Δr_t, as well as all changes in risky asset "effective supply"—the sum of public portfolio shifts ($\sum_{t=1}^{T} C_t^1$), the size of which is conveyed by past interdealer flow Δx_t. These effective-supply effects on price are no less fundamental than the Δr_t effects; this is how the market facilitates redistribution among risk-averse agents.

be correlated with other macro fundamentals, we use the interest differential because it is the main engine of exchange rate variation in macro models and is readily available daily. Second, we replace the dependent variable with the change in the log spot rate, Δp_t. This substitution makes our empirical specification comparable to standard macro models. Estimates using ΔP_t produce results nearly identical to those we report (R^2's, coefficient significance, lack of autocorrelation, etc.).

III. Data

Our data set includes all the deutsche mark/dollar and yen/dollar transactions that occurred from May 1 to August 31, 1996, on an interdealer trading system called Reuters Dealing 2000-1.[7] All trades on this system take the form of electronic bilateral conversations. A conversation is initiated when a dealer calls another dealer using the system to request a quote. If the calling dealer buys (sells) dollars, then order flow from that trade is $+1$ (-1).[8] A dealer who has been called is expected to provide a fast two-way quote with a tight spread. Quotes are take-it-or-leave-it, and if not dealt or declined quickly (i.e., within seconds), the quoting dealer retracts the quote, ending the conversation. To settle disputes, Reuters keeps a record of all bilateral conversations. This record is the source of our data. (For more detail on the Dealing 2000-1 system, see Lyons [1995] and Evans [1997].)

The three variables in our portfolio shifts model are measured as follows. The change in the spot rate (deutsche mark/dollar or yen/dollar), Δp_t, is the log change in the purchase transaction price between 4:00 P.M. (Greenwich mean time [GMT]) on day t and 4:00 P.M. on day $t-1$. When a purchase transaction does not occur precisely at 4:00 P.M., we use the subsequent purchase transaction (with roughly one million trades per day, the subsequent transaction is generally within a few seconds of 4:00 P.M.). When day t is a Monday, the day $t-1$ price is the previous Friday's price. The daily order flow, Δx_t, is the difference between the number of buyer-initiated trades and the number of seller-

[7] In 1996, interdealer transactions account for about 75 percent of total volume in major spot markets (see Bank for International Settlements 1996). This 75 percent from interdealer trading breaks into two transaction types, direct and brokered. Direct trading accounts for about 60 percent of interdealer volume, and brokered trading accounts for about 40 percent. Reuters Dealing 2000-1 is used for the direct portion. According to Reuters, over 90 percent of the world's direct interdealer transactions take place on this system (only dealers have access).

[8] Our data set does not identify the size of individual transactions. (See Jones, Kaul, and Lipson [1994] for evidence that trade size contains no information beyond that in the number of transactions.) Our data set does include total dollar volume over our sample, however, which allows us to calculate an average trade size; we use this below to interpret the estimated coefficients.

TABLE 1
MODEL ESTIMATES

				Diagnostics		
Specification	$\Delta(i_t - i_t^*)$ (1)	Δx_t (2)	$i_{t-1} - i_{t-1}^*$ (3)	R^2 (4)	Serial (5)	Heteroskedasticity (6)
			Deutsche Mark/Dollar			
I	.51	2.14		.64	.77	.07
	(.26)	(.29)			.40	.02
II		2.15		.63	.73	.05
		(.29)			.45	.03
III	.62			.01	.78	.92
	(.77)				.77	.99
IV		2.15	.022	.64	.49	.17
		(.29)	(.013)		.43	.01
V			.022	.00	.04	.83
			(.022)		.24	.98
			Yen/Dollar			
I	2.47	2.86		.46	.06	.92
	(.92)	(.36)			.44	.74
II		2.61		.40	.19	.60
		(.36)			.33	.83
III	.57			.00	.85	.13
	(1.20)				.81	.67
IV		2.78	.016	.42	.00	.66
		(.38)	(.011)		.03	.72
V			−.009	.00	.12	.18
			(.014)		.46	.79

NOTE.—The table reports ordinary least squares estimates of the portfolio shifts model (specification I), $\Delta p_t = \beta_1 \Delta(i_t - i_t^*) + \beta_2 \Delta x_t + \eta_t$, and four alternatives (specifications II–V). The dependent variable Δp_t is the change in the log spot exchange rate from 4:00 P.M. (GMT) on day $t-1$ to 4:00 P.M. (GMT) on day t (deutsche mark/dollar or yen/dollar). The regressor $\Delta(i_t - i_t^*)$ is the change in the one-day interest differential from day $t-1$ to day t (an asterisk denotes deutsche mark or yen, annual basis). The regressor Δx_t is the interdealer order flow between 4:00 P.M. (GMT) on day $t-1$ and 4:00 P.M. (GMT) on day t (negative for net dollar sales, in thousands). Specifications IV and V replace $\Delta(i_t - i_t^*)$ with the interest differential at 4:00 P.M. on day $t-1$. Standard errors are shown in parentheses (corrected for heteroskedasticity in the case of the deutsche mark). The sample spans four months (May 1 to August 31, 1996). Col. 5 presents the p-value of Breusch-Godfrey Lagrange multiplier tests for residual serial correlation, first-order in the top row and fifth-order (one week) in the bottom row. Col. 6 presents the p-values of Engle (1982) Lagrange multiplier tests for autoregressive conditional heteroskedasticity in the residuals, first-order in the top row and fifth-order in the bottom row.

initiated trades (in thousands), also measured from 4:00 P.M. (GMT) on day $t-1$ to 4:00 P.M. on day t (a negative sign denotes net dollar sales). The change in interest differential, $\Delta(i_t - i_t^*)$, is calculated from the daily overnight interest rates for the dollar, the deutsche mark, and the yen (annual basis); the source is Datastream (typically measured at approximately 4:00 P.M. GMT).

IV. Empirical Results

Table 1 presents estimates of the portfolio shifts model (specification I) using daily data for the deutsche mark/dollar and yen/dollar. The coefficient on order flow Δx_t is correctly signed and significant, with t-

statistics above five for both currency pairs. The positive sign indicates that net dollar purchases—a positive Δx_t—lead to a higher deutsche mark price of dollars. The traditional macro fundamental—the interest differential—is correctly signed and significant. (The positive sign arises in the sticky-price monetary model, e.g., because an increase in the dollar interest rate i_t requires immediate dollar appreciation—increase in deutsche mark/dollar—to make room for dollar depreciation induced by uncovered interest parity.) The equation for the deutsche mark shows some evidence of heteroskedasticity, so we correct the standard errors in that case using a heteroskedasticity-consistent covariance matrix (White 1980).

The explanatory power of these regressions is due to order flow Δx_t: regressing Δp_t only on $\Delta(i_t - i_t^*)$ produces an R^2 statistic at 1 percent or lower for both currency pairs and coefficients on $\Delta(i_t - i_t^*)$ that are insignificant at the 5 percent level. (The same story emerges when the *level* of the interest differential is included rather than the change—specifications IV and V.) Adding order flow is what increases the fit so dramatically: R^2 statistics of 64 percent and 46 percent for the deutsche mark and yen equations (specification I), respectively.[9]

The size of the order flow coefficient is consistent with past estimates from single-dealer data. The coefficient of 2.1 in the deutsche mark equation implies that a day with 1,000 more dollar purchases than sales increases the deutsche mark price of a dollar by 2.1 percent. Given an average trade size in our sample of $3.9 million, $1 billion of net dollar purchases increases the deutsche mark price by 0.54 percent (= 2.1/3.9), or, at a spot rate of 1.5 deutsche mark/dollar, 0.8 pfennig. For comparison, at the single-dealer level, Lyons (1995) finds that information asymmetry induces the dealer he tracks to increase price by 0.01 of a pfennig (0.0001 deutsche mark) for every incoming buy order of $10 million. That is 1 pfennig per $1 billion, quite close to the 0.8 pfennig found here. (Though linearly extrapolating the single-dealer estimate is not an accurate description of individual dealers, it may be a good description of the market's aggregate elasticity.)

V. Conclusion

This paper presents a model of exchange rate determination of a new kind. Instead of relying exclusively on macroeconomic determinants, we draw on a determinant from the field of microstructure: order flow. Order flow is a determinant because it conveys information. This is a

[9] We refer readers to Evans and Lyons (1999) for results on robustness regarding (1) adding constants, insignificant in all equations, (2) direction of causality, (3) nonlinearities, (4) dependence on day of week and activity level, and (5) forecasting.

radical departure from traditional macro approaches, which—with their common-knowledge environments—admit no role for information aggregation. Our findings suggest instead that this market is indeed aggregating information.

Our portfolio shifts model provides explicit characterization of this information aggregation process. The model is also quite successful in that it accounts for more than 60 percent of daily changes in the deutsche mark/dollar rate and more than 40 percent of daily changes in the yen/dollar rate. Our estimates of the sensitivity of the spot rate to order flow are sensible as well and square with past estimates at the individual-dealer level.

Our objective in this paper is to clarify order flow's role in transmitting information to price. Pushing this line further, one may ask, What precisely is the information driving order flow? As noted, from a valuation perspective, there are two distinct views. The first view is that order flow reflects new information about valuation numerators (i.e., future interest differentials). The second view is that order flow reflects new information about valuation denominators (i.e., anything that affects discount rates). Our portfolio shifts model is an example of the latter: by assumption, order flow is unrelated to valuation numerators—the future Δr_t. Order flow of this type can result from, for example, shocks to liquidity demands, shocks to hedging demands, or time-varying risk tolerance. An example consistent with the valuation numerators view is that order flow proxies for changes in individuals' interest differential *expectations*. Future work can distinguish the two views, for example, by decomposing order flow to determine whether specific trader types produce higher-impact (i.e., more informative) orders, as opposed to the undifferentiated price impact of public orders in the portfolio shifts model.

References

Bagwell, Laurie S. "Dutch Auction Repurchases: An Analysis of Shareholder Heterogeneity." *J. Finance* 47 (March 1992): 71–105.

Bank for International Settlements. *Central Bank Survey of Foreign Exchange Market Activity in April 1995.* Basle: Bank Internat. Settlements, Monetary and Econ. Dept., 1996.

Cheung, Yin-Wong, and Wong, Clement Yuk-Pang. "A Survey of Market Practitioners' Views on Exchange Rate Dynamics." *J. Internat. Econ.* 51 (August 2000): 401–19.

Covrig, Vincentiu, and Melvin, Michael T. "Asymmetric Information and Price Discovery in the FX Market: Does Tokyo Know More about the Yen?" Manuscript. Tempe: Arizona State Univ., Dept. Econ., 1998.

Engle, Robert F. "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation." *Econometrica* 50 (July 1982): 987–1007.

Evans, Martin D. D. "The Microstructure of Foreign Exchange Dynamics." Manuscript. Washington: Georgetown Univ., Dept. Econ., 1997.
———. "FX Trading and Exchange Rate Dynamics." *J. Finance* (2002), in press.
Evans, Martin D. D., and Lyons, Richard K. "Order Flow and Exchange-Rate Dynamics." Manuscript. Berkeley: Univ. California, Haas School Bus., 1999. http://www.haas.berkeley.edu/~lyons.
Frankel, Jeffrey A., and Rose, Andrew K. "Empirical Research on Nominal Exchange Rates." In *Handbook of International Economics,* vol. 3, edited by Gene M. Grossman and Kenneth S. Rogoff. Amsterdam: Elsevier, 1995.
Isard, Peter. *Exchange Rate Economics.* Cambridge: Cambridge Univ. Press, 1995.
Ito, Takatoshi; Lyons, Richard K.; and Melvin, Michael T. "Is There Private Information in the FX Market? The Tokyo Experiment." *J. Finance* 53 (June 1998): 1111–30.
Jones, Charles M.; Kaul, Gautam; and Lipson, Marc L. "Transactions, Volume, and Volatility." *Rev. Financial Studies* 7 (Winter 1994): 631–51.
Kaul, Aditya; Mehrotra, Vikas; and Morck, Randall. "Demand Curves for Stock Do Slope Down: New Evidence from an Index Weights Adjustment." *J. Finance* 55 (April 2000): 893–912.
Lyons, Richard K. "Tests of Microstructural Hypotheses in the Foreign Exchange Market." *J. Financial Econ.* 39 (October 1995): 321–51.
———. "Optimal Transparency in a Dealer Market with an Application to Foreign Exchange." *J. Financial Intermediation* 5 (July 1996): 225–54.
———. "A Simultaneous Trade Model of the Foreign Exchange Hot Potato." *J. Internat. Econ.* 42 (May 1997): 275–98.
Meese, Richard A. "Currency Fluctuations in the Post–Bretton Woods Era." *J. Econ. Perspectives* 4 (Winter 1990): 117–34.
Meese, Richard A., and Rogoff, Kenneth S. "Empirical Exchange Rate Models of the Seventies: Do They Fit out of Sample?" *J. Internat. Econ.* 14 (February 1983): 3–24.
Naranjo, Andy, and Nimalendran, M. "Government Intervention and Adverse Selection Costs in Foreign Exchange Markets." *Rev. Financial Studies* 13 (Summer 2000): 453–77.
Obstfeld, Maurice, and Rogoff, Kenneth S. "Exchange Rate Dynamics Redux." *J.P.E.* 103 (June 1995): 624–60.
Payne, Richard. "Informed Trade in Spot Foreign Exchange Markets: An Empirical Investigation." Manuscript. London: London School Econ., 1999.
Scholes, Myron S. "The Market for Securities: Substitution versus Price Pressure and the Effects of Information on Share Prices." *J. Bus.* 45 (April 1972): 179–211.
Shleifer, Andrei. "Do Demand Curves for Stocks Slope Down?" *J. Finance* 41 (July 1986): 579–90.
Taylor, Mark P. "The Economics of Exchange Rates." *J. Econ. Literature* 33 (March 1995): 13–47.
White, Halbert. "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity." *Econometrica* 48 (May 1980): 817–38.
Yao, Jian. "Market Making in the Interbank Foreign Exchange Market." Working Paper no. S-98-3. New York: New York Univ., Salomon Center, 1998.