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By

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TRADING OLUMES AND TRANSACTION COSTS IN THE FOREIGN EXCHANGE MARKET

EVIDENCE FROM DAILY DOLLAR-YEN SPOT DATA

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Abstract: A Generalized Method of Moments estimation of the determinants of dollar/yen bid-ask spreads is undertaken. In particular, a long time-series of daily spot foreign exchange trading volumes is used for the first time. In line with standard spread models and volume theories, it can be shown that unpredictable foreign exchange turnover (a measure of the rate of information arrival) increases spreads, while predictable turnover decreases them. Both effects are strongly significant when employing spot turnover instead of proxies like forward turnover as in previous studies (Bessembinder, 1994). The results are also found to be robust when unpredictable Reuters quoting frequency is used as an instrument for unpredictable trading volumes to cope with their endogeneity. Spread estimations with plain (non-decomposed) volumes are rejected as misspecified. Finally, there is evidence for the conditional heteroscedasticity of unpredictable spot foreign exchange volumes.

KEYWORDS: foreign exchange markets, bid-ask spreads, trading volumes, time-series analysis, generalized method of moments estimation

JEL CLASSIFICATION: F31, G15, C32

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I. Introduction

Early time-series estimations on the short-term relation between transaction volume and transaction costs, as measured by bid-ask spreads, in the foreign exchange (forex) market resulted in the finding that spreads increase with volume at constant volatility (Glassman, 1987). Although information cost models of dealer spreads, such as that of Copeland and Galai (1983) together with an assumption on the information content of volume, can provide a theoretical basis for this result, recent empirical research by Bessembinder (1994) shows that the impact of predictable and unpredictable trading volume on spreads seems to be opposite in sign. This latter view is supported by standard spread models and the mixture of distributions hypothesis (Clark, 1973), which implies a positive correlation between unpredictable volatility and unpredictable volume, driven jointly by an (unobservable) information flow variable. Since predictable volume is likely to be unrelated to information related risk it will help decrease fixed costs of market making, increase dealers' revenues from liquidity traders, and therefore lower spreads. If predictable volatility is included as another explanatory variable, but not unpredictable volatility, then unpredictable volume alone will measure the rate of new information arrival and will therefore have a significant positive effect on spreads.

An apparent feature of Glassman's (1987) and Bessembinder's (1994) analyses is that the volume effects do not appear to be statistically strong. One explanation could be that they use forex future volumes from the Chicago International Monetary Market (IMM) as a proxy variable for global spot volumes in the currencies considered.[1] The lack of spot volume data at reasonably high frequencies is a principal handicap for many forex time-series analyses. Although there is some positive correlation between spot and futures volumes, their overall behaviour may be quite different. For example forex market spot turnover growth slowed down considerably in the late 1980s, while forward turnovers continued to grow forcefully (BIS, 1993). Dumas (1994) points out that the choice of future volumes from an organized market to measure total volumes of a market working mostly over the counter may also induce an omitted-variable problem in the estimations. Another explanation for the statistical weakness of the volume effects in these studies, and also another source of possible biases in parameter estimates, may be that the endogeneity of unpredictable turnover, measuring the rate of information arrival, is disregarded.

[1]Futures turnover in the forex market accounts for only about 1 percent of total global turnover (BIS, 1993).

In the present paper we use a new 8-year long (December 1986 through January 1995) daily volume series for the dollar/yen spot market in order to estimate the relation between volumes and spreads. As yet, to our knowledge, no comparable forex turnover data are currently available for any other spot market. Additionally, we are able to employ average spot Reuters quotes over the trading day to compute daily spreads and price changes between opening and closing of the Tokyo market, instead of single "representative" London quotes per day, as offered by most commercial databases.

The econometric technique chosen is Generalized Method of Moments (GMM) estimation of a log-linear spread equation. Thus we can introduce unpredictable Reuters quoting (tick) frequency as an instrumental variable for unpredictable volumes. Nonetheless, our results confirm those found by Bessembinder (1994). Predictable dollar/yen spot volume is negatively linked to spot spreads, while unpredictable volume is positively linked to spreads. However, using our daily spot volume measure and synchronous exchange rate quotes these parameter estimates are much more significant, usually way below the 5-percent level. When introducing additional instruments, tests of the overidentifying restrictions reject the specification with decomposed volumes and unpredictable ticks as an instrumental variable, while those with non-decomposed or non-instrumented volumes do not pass the test. From the clarity of these results one might infer that one would be likely to find similar results for other currencies if comparable volume data were available.

The remainder of the paper is organized as follows. In section II the theoretical basis of the present estimations is summarized. The following section considers variable measurement issues and describes the econometric approach chosen. The estimations themselves are presented in section IV. The final section concludes.

II. Spread Theory

Finance theory has identified three basic sources of bid-ask spreads: 1) order processing costs, 2) inventory holding costs, and 3) information costs of market making. Each one is influenced by trading volume in a particular manner. Order processing cost models assume the existence of some fixed costs of market making or of providing "immediacy" for the exchange of ownership titles (Demsetz, 1968). These costs may come, for example, from the need to acquire trading know how and a name in the market, as well as from subscriptions to electronic information and trading systems (such as Reuters or Telerate in the forex market). They give rise to economies of scale of market making. At a given spread, when a dealer expects that trading volume will increase in the next trading period, *ceteris paribus* his expected profit goes up as well. However, inter-dealer competition will force him to narrow his spread to avoid losing business to competitors undercutting him. Hence *predictable volume* should reduce spreads through an order processing cost effect (Stoll, 1978; Black, 1991; Hartmann, 1994).

In contrast, the effect of trading volume on inventory holding costs is ambiguous, depending, for example, on transaction sizes. Inventory cost models, like Stoll (1978), Ho and Stoll (1981) and others, view dealers not only as providers of liquidity services but also as optimizers of their own securities portfolio. In this framework they try to choose the return-risk efficient portfolio, which maximizes their (or their shareholders') utility. However, since providing "immediacy" (standing ready to trade in a security at any time desired by customers) implies being pushed away from this portfolio, they announce bid and ask prices which assure that their positions are not too far from the optimal portfolio and provide revenues compensating for the remaining utility losses. On average, larger transactions will push the dealer "farer" away from his desired portfolio, such that *ceteris paribus* the larger the transaction sizes in the order flow expected, the larger the spreads.

However, if trading volume is expected to come in many small, statistically independent orders, then by the law of large numbers increased (predictable) volume could also decrease spreads through an opposite inventory cost effect. Since additionally larger volume is not necessarily driven by larger transaction sizes (dealers may decompose one large transaction into several smaller ones of "standard" size for example or transaction frequency may increase) and Reuters quoted spreads are only binding up to a certain maximum transaction size, it is unlikely that inventory cost effects can be identified through volumes and spreads.

Information cost models suggest a relation between bid-ask spreads and information arrival or the presence of agents with better information than dealers in the market (Copeland and Galai, 1983; Glosten and Milgrom, 1985; Kyle, 1985). If new information has arrived, such that dealers risk getting into transactions with "insiders", then they will widen spreads in order to deter some of the informed traders or to earn higher mark-ups from liquidity-motivated traders, whose demand elasticity is rather low. (When asked for a quote, dealers do not know whether the counterparty is an information or a liquidity trader.) Therefore, the more important the information arrival during a trading period, the higher the dealers' information costs, the larger their spreads. However, a major obstacle to the empirical implementation of these models is that the rate of information arrival or the share of information trading in overall trading is unobservable. The use of *unpredictable* forex volume as a solution to this observability problem is proposed further below.

There are two more arguments which may reinforce the point made by the order processing cost literature, advancing a negative impact of predictable volume on bid-ask spreads. The first, advanced by Easley and O'Hara (1992), again comes from the information cost literature. Since market makers gain from transactions with liquidity traders, spreads decrease with an increase in the expected (or "normal") order flow from them. The second is a search cost argument. When the interbank market grows, and liquidity is not reduced by overproportional increases in transactions sizes, then it becomes easier for the dealing banks to square undesired or take on desired positions. One might think though that the pure search cost reduction in a market as liquid as the one for dollar/yen is relatively small. Since both effects create scale economies in market making, we shall refer to them below as order processing effects as well.

All the three types of spread models above also highlight the role of *expected* return volatility. Since our primary interest is in trading volume here, we do not dwell on this. Instead we note that most of these models predict that spreads widen with the volatility predicted for the coming trading period. Putting all the pieces together we can then write the following model of forex dealer spreads.

$$s = f(\sigma^p, x^p, I), \qquad \mathbf{1}$$

where s is the dealer spread, σ is the predictable volatility of the exchange rate, x^p the predictable component of trading volume, and I the flow of new information. Theory predicts that $\partial f/\partial\sigma > 0$ and $\partial f/\partial I > 0$. Strictly speaking the sign of $\partial f/\partial x^p$ is not determined, since when volume increases come in large blocks then the economies of scale in market making could be compensated by a surge in inventory costs. As argued above this is very unlikely to happen and the sign is most likely to be negative.

Most of the models quoted above have been developed to analyze the behavior of stock market specialists. Although there are differences between the microstructure of stock and foreign exchange markets, attempts to explicitly model these differences have been scarce (Flood, 1991). In a recent study Lyons (1995a) highlights the additional tools of inventory control available for forex dealers as compared to stock market specialists.

Model (1) is not specified in a way that it can be estimated and tested directly. As noted before, the rate of new information arrival *I* is not observable. As pointed out by Bessembinder (1994) models of the mixture of distributions hypothesis (MDH) make a link between information flow, volume and volatility, which helps finding a testable specification. However, it has to be noted that these models are rather of statistical character and have not yet been integrated with the more behavioral information cost models. Since the interest of the present paper is mainly empirical we do not embark on a rigorous unification of both types of models.

One MDH model, which elaborates on Clark (1973) and Epps and Epps (1976), is presented in Tauchen and Pitts (1983). In this model the joint distribution of (observable) daily price changes and transaction volumes of an asset is derived from a model of (unobservable) intra-day equilibrium price changes and intra-day volumes. New information during the day causes traders to update their reservation prices and demand or supply the respective asset until the average of their individual reservation prices clears the market again. If they disagree about the interpretation of the new information then the respective equilibrium price change comes with high transaction volume, while relative unanimity results in a price change with little volume. More formally, Tauchen and Pitts find the following expression for daily trading volumes.

$$v = \sum_{i=1}^{I} v_i = my_v I + \sigma_v \sqrt{I} n, \qquad \mathbf{2}$$

where *I* is a random variable measuring the number of intra-day equilibria (or in other words the daily information arrival rate),

$$v_i \sim \mathrm{N}\left(my_v, \sigma_v^2\right) \qquad \mathbf{3}$$

is the trading volume related to the *i*-th intra-day information arrival and *n* a standard normal random variable. The mean μ_v and the standard deviation σ_v of intra-day volumes are both increasing functions in trader disagreement, as measured by the standard deviation of individual traders' reservation price update due to a new information arrival (see Tauchen and Pitts, 1983, formula 7).

Following Bessembinder (1994) we assume that the major part of this information-driven volume comes as a surprise to dealers. Then we can write *unpredictable volume* (x^u) as a function g of the information arrival rate.[2]

$$x^u = g(I, \bullet) \tag{4}$$

(1) and (4) give the new spread equation (5) which contains only observable variables.

$$s = f\left(\sigma^p, x^p, g^{-1}\left(x^u\right)\right) \tag{5}$$

As a final remark, it is noted that the Tauchen-Pitts model implies an equation similar to (2) relating information arrival to *unexpected volatility* (σ^u). Hence x^u and σ^u are jointly driven by I and therefore strongly correlated. An econometric specification of the spread model should therefore include x^u alone and not σ^u (or vice versa). Even then x^u is clearly endogenous and thus has to be instrumented in the econometric implementation of (5). A fact which was ignored by the previous studies.

III. Data and Econometric Approach

1

a) Trading volume and information arrival

One distinguishing feature of the present study is the use of daily *spot* forex volumes. These data are published by the financial newspaper *Nihon Keizai Shimbun* (Tokyo), for the

[2]The use of *plain* volume as a measure of the information arrival rate might be disputed on the basis of a "hot-potato view" (Lyons, 1995b) of forex trading intensity, claiming that trades occurring when transaction intensity is low are more informative than those occurring when trading is very active. At the end of section 4 we relate our approach and results to those of Lyons.

dollar/yen market exclusively.[3] In Tokyo all forex *brokers* have to report their volume of transactions in dollar/yen concluded between opening and 3.30pm (local time) to the Bank of Japan. The resulting sum can be expected to cover a considerable part of global dollar/yen spot forex turnover. In 1992 about 37 percent of total Japanese inter-dealer trading was realized through brokers and about 38 percent of global dollar/yen forex volume had at least one Japanese bank on one side of the transaction (BIS, 1993). Another advantage of broker volume is that it is free of the double-counting problems encountered in dealer surveys.

One might object that the share of brokered deals in total trading can change over time. For example, due to extensions of 24-hours dealing and the use of automatic trading systems it declined by 14 percentage points in Japan between 1989 and 1992 (Bank of Japan, 1993). It might also be maintained that dealers tend to turn to brokers for larger transactions, since for these anonymity is often more important than for smaller deals. If this is true, then the spot volume proxy used might overrepresent larger ("block") transactions and information-based trading. Lyons (1995a), who followed one dealer and one broker in the US market for five days in August 1992, reports that the *median* spot transaction size of the former (with other dealers and non-brokered) was smaller than that of the broker, although the median size of the transactions *initiated* by that dealer were not. The Federal Reserve Bank of New York (1992) reports that - for deals concluded by banks, non-bank financial institutions and brokers located in the US during April 1992 - the difference in *average* transaction sizes between broker and bank deals came entirely from forward, swap and option transactions, while for spot dealings the average size of broker transactions was about the same as that of transactions by banks and non-bank financial institutions. Although these two points illustrate that our volume data are not a perfect measure of global dollar/yen turnover, imprecisions with other spot volume proxies, such as futures volumes, will be much more severe.

Perron test rejected the presence of non-stationarity, all ARMA-specifications tried had one root of the estimated AR polynomial outside the unit circle. The solution to this enigma was found in a unit root in the MA part. The MA(1)-parameter turned always out to be close to -1. Applying Phillips' (1987) theory of vector-autoregressions with generalized error structure, Phillips and Perron (1988) show that standard unit root tests incur asymptotic size distortions, when the MA(1) is negative, and that the bias is the larger the closer the MA-parameter is to -1. Since the AR-root and the near-root in the MA tend to offset each other, the original series (and its autocorrelation function) behave(s) rather like a stationary process.[4] This leads to overrejection.

A second argument against relying on standard unit-root tests in our case is provided by Kim and Schmidt (1993). They show that in small samples these tests can be biased in favor of rejecting the null, when ARIMA-residuals are conditionally heteroscedastic, and that these biases reduce only slowly with growing sample sizes. As reported in Table 1 (last line), a Lagrange-multiplier test of conditional heteroscedasticity in the ARIMA-residuals rejects homoscedasticity against an ARCH(1).[5]

Table 1: ARIMA(9,1,1) model estimation for log volumes

$(1-\phi_1L-\phi_2L^2-\phi_3L^3-\phi_4L^4-\phi_5L^5-\phi_6L^6-\phi_7L^7-\phi_8L^8-\phi_9L^9)\_x_t=(1-\theta_1L)\__t$, $\_\sim(0,\sigma I)$

Par.	ϕ_1	ϕ_2	ϕ_3	ϕ_4	ϕ_5	ϕ_6	ϕ_7	ϕ_8	ϕ_9	θ_1
Est.	0.33	0.11	0.09	0.08	0.02	-0.02	0.01	-0.01	0.07	0.98
t-stat.	14.1	4.4	3.8	3.3	0.9	-0.6	0.3	-0.4	2.9	188
Test/ Stat.	adj. R^2: 0.31		Ljung-Box test:[a)] Q(20)=14.9 [0.14]			ARCH test:[b)] $\chi^2(1)=13.21$		Theil's inequality coefficient:[c)] 0.04		

Notes: Conditional sum of squares estimation with 100 back-forecasted residuals, T=1976 observations. _=1-L is the difference operator.
a) Statistic for 20 lags, p-value in square brackets.
b) Lagrange-multiplier test of ARCH(1) against ARCH(0) in ARIMA-residuals.

[4]To illustrate this, consider the example of an ARIMA(1,1,1) $(1-\phi_1L)(1-L)y_t=(1-\theta_1L)\__t$, where L is the backward-shift operator and $\phi_1<1$. For $\theta_1=1$ this becomes $(1-\phi_1L)(1-L)y_t=(1-L)\__t$ and (1-L) cancels out. In this example the ARIMA(1,1,1) reduces to an AR(1). Campbell and Perron (1991) report more data-generating processes under which standard unit-root tests suffer from size distortions or power problems.

[5]For a theoretical model explaining the conditional heteroscedasticity of financial market trading volumes, see Foster and Viswanathan (1995).

c) Statistic between 0 (perfect fit) and 1 (Theil, 1961).

On the basis of standard Box-Jenkins diagnostic checks, the Akaike information criterion (Harvey, 1981) and (in-the-sample) forecasting performance (root-mean-square error and Theil's inequality coefficient), it was found that an ARIMA(9,1,1) specification performed best (Table 1).[6] The fitted log volumes were then taken to measure the predictable component ($x=E_{t-1}x_t$) and the residuals to measure the unpredictable component ($x=x_t-E_{t-1}x_t$). Bessembinder's (1994) specification for futures volumes - an ARIMA(10,1,0) - did not pass the diagnostic checks and produced worse forecasts for our spot volume data than the process in Table 1 (with an MA(1) component). Jorion (1994) specified a transfer function model of a deterministic trend with ARMA(1,1) residuals, again for futures volumes. However, our dollar/yen spot volumes do not have a deterministic trend.

b) Volatility

The exchange rate data are sampled from the Reuters FXFX page.[7] Our third explanatory variable is predictable dollar/yen volatility. In contrast to trading volumes, the presence of autoregressive conditional heteroscedasticity (ARCH) in daily forex returns is a well known and often reported fact (Bollerslev, 1992). This means that a good deal of daily volatility is also predictable. Baillie and Bollerslev (1989) make a convincing case in favor of a GARCH(1,1) to be a reasonably precise and parsimonious specification for forex returns. Therefore we use GARCH(1,1)-forecasted volatilities from daily log returns to measure σ^p.[8] Table 2 reports the estimation and a likelihood-ratio test rejecting conditional homoscedasticity and ARCH(1) against the GARCH(1,1).

Table 2: GARCH(1,1) model estimation for log returns

$$\sigma_t=\sigma_0+\_{}_{t}\ , \quad \_{}_{t}\,|\,\_{}_{t-1}\sim N(0,h_t)\ , \quad h_t=\alpha_0+\alpha_1\_{}_{-1}+\gamma_1 h_{t-1}$$

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[6]All estimations in this paper are realized with TSP 4.2B.

[7]I am most grateful to Olsen & Associates (Zurich) for providing these data.

[8]In accordance with the volume measure "daily" is defined to mean from Tokyo opening until 3.30pm. Volatilities are computed from "middle prices", defined as the arithmetic mean of log bids and log asks.
A different approach, chosen by Wei (1994) and Jorion (1994), is the extraction of expected volatilities from forex option prices.

Parameter	σ_0	α_0	α_1	γ_1
Estimation	0.78	461.51	0.11	0.45
Asy. t-stat.	1.03	9.14	5.88	9.31
Likel.-ratio tests of GARCH(1,1) against ARCH(0) and ARCH(1)			$\chi^2(2)=94.69$ [0.00] $\chi^2(1)=31.11$ [0.00]	

Notes: Quasi-maximum-likelihood estimation, T=1976 observations, log returns multiplied by 10 000.

c) Spreads

Daily spreads are measured as tick-wise averages over the daily trading period (Reuters FXFX quotations). Since absolute dollar/yen spreads (ask minus bid) clearly move proportionally to the dollar/yen exchange rate, preference was given to relative spreads (log ask minus log bid), more precisely the log relative spreads.[9]

Reuters FXFX spreads have some well known drawbacks. First, they are indicative quotes and not transaction prices. Second, they are about two to three times larger than directly transactable quotes in the Reuters 2000-1 dealing system (Lyons, 1995a), although usually bracketing the transacted prices. However, notice first that they are the explained variable in our estimations and that measurement errors in the explained variable do not *bias* the estimated parameters. Second, their shortcomings are much more severe for intra-day than for inter-day estimations (Goodhart et al., 1994). Only at very high frequencies does it really matter whether transaction prices lie sometimes outside the FXFX spreads, because the latter are fed into the system relatively slowly. This is not to deny that FXFX prices suffer from lost information, but up to date researchers did not have access to transaction prices for sufficiently long time periods.[10]

[9]Since the yen mostly depreciated against the dollar between 1987 and 1995, absolute spreads have a deterministic downward trend. Unit root tests show that they are stationary around this trend. See Glassman (1987) for a discussion of the choice between absolute and relative spreads.

[1] For more discussion of Reuters FXFX data, see Hartmann (1995) and Lyons (1995a).

2. Econometric Strategy

a) GMM estimation

We employ Hansen's (1982) GMM estimator in order to estimate the following log-linear specification of model (5).

$$s_t = \beta_0 + \beta_1 \sigma_t^p + \beta_2 x_t^p + \beta_3 x_t^u + \varepsilon_t, \quad \varepsilon\_(0,\Sigma), \quad t = 1,\dots,T \qquad \mathbf{6}$$

For a given (T×l) instrument matrix Z this estimator finds the parameter vector for which the (squared) moment functions $J() = (T^{-1}Z'\_)'W^{-1}(T^{-1}Z'\_)$ are closest to zero. It is consistent and asymptotically normal under quite weak distributional assumptions. With the weighting matrix W equal to the covariance matrix of the moment functions ($Z'\_$) it is also asymptotically efficient. GMM is most adequate for financial data, because, inter alia, it does not require knowledge of the likelihood function's form and residual covariance matrices robust against conditional heteroscedasticity and autocorrelation of any order are directly available (Andrews, 1991).

Under the hypothesis that Z and _ are orthogonal the asymptotic distribution of the (adjusted) objective function $TJ(\cdot)$ (a quadratic form) is χ^2(l-k), with degrees of freedom equal to the difference between the number of instruments (or orthogonality conditions) l and the number of explanatory variables k. In the case of overidentification (l>k) this delivers a test of general model misspecification, the test of the overidentifying restrictions (TOR; Hansen, 1982). For more specific hypothesis testing we use the GMM-analogue of the likelihood-ratio test outlined in Newey and West (1987b). The test statistic (D) is the difference of the objective functions of the restricted and the unrestricted model at convergence, $D=T[J(\beta_R)-J(\beta_U)]$, which follows itself a χ^2(r), with degrees of freedom equal to the number r of restrictions imposed.[11] Newey and West show that this test, which is called moment-function difference test here, is equivalent to Wald and Lagrange-mulitplier tests, if the moment functions as well as the constraints are linear in the parameters, which will be the case below.

[11]For normalization the same instruments have to be used in both estimations and the covariance matrix of the moment conditions has to be kept constant.

b) Instruments

Since GMM requires stationarity, we differenced the fitted ARIMA(9,1,1) volume series for the estimation of (6). Additionally, two dummy variables are introduced to account for weekends (dw_t) and holidays (dh_t). The choice of instruments (Z) involves a number of problems, which were avoided by Bessembinder (1994), who chose the explanatory variables as instruments and hence could not test for the overidentifying restrictions. First of all, the relation between unpredictable volume and information arrival sketched in section II is not deterministic, such that estimations without an instrument for x are biased. In this paper we propose to solve this problem by using daily dollar/yen quoting (tick) frequency on the Reuters FXFX page, here denoted q_t, as a measure of daily trading volume.[1] Looking for an instrument for *unpredictable* volume we fit an ARIMA(11,1,1) on ticks applying the same techniques as above and use the ARIMA residual as the instrumental variable. To identify the model the remaining explanatory variables (including the constant and the dummies) are also chosen as instruments.

In order to test against possible remaining misspecifications additional instruments are needed. Unfortunately the residuals of (6) exhibit quite long autocorrelation such that lagged values of the original instruments would be correlated with them and thus not useful to test for the overidentifying restrictions. Instead we have to overidentify the model with the squares of predictable volatility, predictable volume and unpredictable ticks. Hence the χ^2-statistic of Hansen's TOR has 3 degrees of freedom.

IV. Estimation Results

Table 3 reports the results of two estimations. Line one contains a preliminary GMM estimation with the explanatory variables (including unpredictable *volume*) and their squares as instruments (GMM1). Line two contains the estimation, where unpredictable *ticks* replace unpredictable volumes in the instruments (GMM2). Asymptotic t-statistics (in parentheses) are computed from Gallant's (1987) conditional heteroscedasticity- and autocorrelation-

[12]For a discussion of Reuters tick frequency as a measure of trading volume, see Hartmann (1995) and the papers quoted there.

consistent covariance matrix.[1] Since Andrews' (1991) optimal lag truncation parameter turned out to be quite sensitive to the specification of the moment-functions process we realized all estimations for autocorrelation-corrections varying between 10 and 30. As the main results did not change during this sensitivity analysis Table 3 only reports those for 20-lag autocorrelation correction. The TOR statistics are in the last column.

Table 3: Spread model estimations with decomposed volumes

$$s_t=\beta_0+\beta_1 h_t+\beta_2\_E_{t-1}x_t+\beta_3(x_t-E_{t-1}x_t)+\beta_4 dw_t+\beta_5 dh_t+\__t\ ,\quad \_\sim(0,\Sigma)\ ,\quad t=1,\ldots,T$$

Estimation	β_1	β_2	β_3	β_4	β_5	TOR[c)]
GMM1[a)]	0.38	-3.82	7.08	0.01	0.02	$\chi^2(3)=19.0$
	(3.23)	(-2.72)	(8.21)	(2.98)	(1.25)	[0.01]
GMM2[b)]	0.52	-2.76	4.14	0.01	0.02	$\chi^2(3)=4.4$
	(4.24)	(-2.01)	(3.15)	(3.19)	(1.43)	[0.22]

Moment-function difference test of $\beta_2=\beta_3$:[d)] $\chi^2(1)=9.1$ [0.00]   adj. R^2: 0.11

Notes: s_t is the daily average over relative Reuters spreads, h_t is the one-step-ahead GARCH(1,1)-predicted log return variance (table 1 with $\sigma_0=0$), $\_E_{t-1}x_t$ is the first difference of the ARIMA(9,1,1)-fit of daily log volumes (table 2), $x_t-E_{t-1}x_t$ is the ARIMA(9,1,1)-residual of daily log volumes (table 2), dw_t and dh_t are weekend and holiday dummies respectively. Asymptotic (conditional) heteroscedasticity- and autocorrelation-consistent t-statistics (20 lags; Gallant, 1987) in parentheses, p-values in square brackets, T=1976 observations.

a) Instruments: constant, h_t, $\_E_{t-1}x_t$, $x_t-E_{t-1}x_t$, dw_t, dh_t, $(h_t)^2$, $(\_E_{t-1}x_t)^2$, $(x_t-E_{t-1}x_t)^2$.

b) Instruments: constant, h_t, $\_E_{t-1}q_t$, $q_t-E_{t-1}q_t$, dw_t, dh_t, $(h_t)^2$, $(\_E_{t-1}q_t)^2$, $(q_t-E_{t-1}q_t)^2$, with q_t daily log quoting frequency from Reuters FXFX.

c) Test of the overidentifying restrictions (Hansen, 1982).

d) Test from Newey and West (1987b) using the difference of the restricted and unrestricted GMM objective functions with constant weighting at convergence.

The first observation from Table 3 is that the GMM1 specification is strongly rejected by TOR while GMM2 is not. This indicates that unpredictable volumes are, in fact, correlated with GMM1-residuals and that spread estimations without an appropriate instrumentation for them are therefore biased. However, comparing the parameter estimates of both specifications, it turns out that there are no qualitative differences justifying different interpretations. One implication is that Bessembinder's (1994) conclusions can be confirmed, although he did not instrument unpredictable volumes.

[1] Andrews (1991) argues that Gallant's covariance matrix estimator, using the Parzen kernel to assure positive semidefiniteness, is superior to that of Newey and West (1987a), employing the Bartlett kernel, if both heteroscedasticity and autocorrelation are present.

Summarizing GMM2, the signs of the parameters are consistent with the theories sketched in section II. Predictable volume decreases spreads and unpredictable volume increases spreads. The former effect is significant at the 5-percent level, while the latter is significant at the 1-percent level. Comparing again GMM1 and GMM2, the misspecification of instruments results in an overestimation of absolute volume parameter values by about one third. Asymptotic t-statistics of the volume parameters are also biased upwards. The volatility effect is positive and strongly significant. Here the misspecification of GMM1 resulted in an underestimation of the parameter value and the t-statistic. Moreover, dollar/yen forex spreads increase before weekends and - almost unnoticably - before Japanese holidays, the former effect being significant at 1 percent, the latter only at about 15 percent. Intercepts are -7.4 in GMM1 as well as GMM2 (not reported in the table). We also estimated GMM2 with yearly intercept variables. Although some structural instability was visible (and the fit improved), the sizes of the intercepts varied very little and estimates of and inferences on slope parameters differed only negligibly from those reported in Table 3.[1] Precisely the same results as for GMM2 occurred, when overidentification was achieved with third moments of the instruments instead of second moments as in GMM2.

The negative impact of predictable volume on spreads suggests the presence of important order processing effects on forex spot spreads. (This corresponds to recent research on stock market spreads, also finding an important order processing cost component (de Jong et al., 1995).) (As could be expected, these order processing cost effects are not swamped by possible positive inventory cost effects of block trading.) Furthermore, the strong effects of predictable volatility (positive) and unpredictable volume (new information arrival, positive) indicate the presence of important other inventory and information cost components. The statistical weakness of the holiday effect compared to the weekend effect on spreads can be explained by the fact that, in many cases, other large forex trading centers, for example London or New York, remain open when there is a Japanese banking holiday (JP Morgan, 1994).

In order to juxtapose these findings with the former literature on spreads and plain (non-

[14]We also estimated GMM2 allowing *both* intercepts and slopes to change on a yearly basis. Again there was some structural instability, but the major results remained unchanged. As a last check the GMM2 specification was estimated for the four 2-yearly subperiods separately. In all four cases the signs of the parameters stayed the same as in Table 3, although at lower levels of significance.

decomposed) volumes we also estimated a restricted specification of (2), where $\beta_2=\beta_3$. Table 4 summarizes two (overidentified) GMM estimations for plain volumes. In GMM3 plain volumes are differenced and in GMM4 they are not. The second case is also reported because the *original* (non-decomposed) series of an ARIMA(p,1,1) with the MA-parameter close to -1 behaves rather like a (stationary) AR(p).[15] In both cases volumes are instrumented with (plain) Reuters ticks.

Table 4: Spread estimations with plain volumes

GMM3: $s_t=\beta_0+\beta_1h_t+\beta_2\_x_t+\beta_4dw_t+\beta_5dh_t+\_{_t}$, $\_\sim(0,\Sigma)$, $t=1,\ldots,T$

GMM4: $s_t=\beta_0+\beta_1h_t+\beta_2x_t+\beta_4dw_t+\beta_5dh_t+\_{_t}$, $\_\sim(0,\Sigma)$, $t=1,\ldots,T$

Estimation	β_1	β_2	β_4	β_5	TOR[c)]
GMM3[a)]	0.61	3.58	0.01	0.02	$\chi^2(2)=4.77$
	(4.68)	(3.59)	(3.82)	(1.18)	[0.09]
GMM4[b)]	0.84	-8.94	0.01	0.01	$\chi^2(2)=5.71$
	(6.71)	(-4.43)	(1.88)	(0.48)	[0.06]

Notes: Spreads, volatilities and dummies as in table 3. $\_x_t$ is the first difference of plain daily log volumes, and x_t is undifferenced plain volume. Asymptotic (conditional) heteroscedasticity- and autocorrelation-consistent t-statistics (20 lags; Gallant, 1987) in parentheses, p-values in square brackets, T=1976 observations.
a) Instruments: constant, h_t, $\_q_t$, dw_t, dh_t, $(h_t)^2$, $(\_q_t)^2$, with q_t daily log quoting frequency from Reuters FXFX..
b) Instruments: constant, h_t, q_t, dw_t, dh_t, $(h_t)^2$, $(q_t)^2$.
c) Test of the overidentifying restrictions (Hansen, 1982).

The parameter estimates for GMM3 are largely analogous to those found in Glassman (1987) and Wei (1994). Relative spreads seem to increase with plain trading volume. In other words, one is tempted to infer that the information cost component seems to dominate the other spread components related to volumes. However, in GMM4 the volume parameter is negative. In any case, Newey and West's (1987b) moment-functions difference test strongly rejects the null of equality of β_2 and β_3 (Table 3, last row). Furthermore, contrary to the findings for decomposed volumes (Table 3), in both cases with plain volumes TOR rejects at a significance level lower than 10 percent (Table 4, last column). These results give a warning that predictable daily transaction volume should not be mixed with information-related surprises in trading. Since the parameter estimates in Table 4 appear to be inconsistent, it

[15] See section III above.

cannot be excluded that - overall - relative spreads *decrease* with higher volume, even in the short run.

Our results also need to be delineated from recent tests of microstructural hypotheses in the foreign exchange market with intra-day high-frequency transactions data. Lyons (1995a) recorded the transactions of one dealer and one broker in the US market for 5 days in August 1992. He then uses an extended version of Madhavan and Smidt's (1991) Bayesian pricing model to test for the existence of inventory cost and information cost components in dollar/mark exchange rate changes. The model also allows one to draw some inferences on the relation between trading "volume" and bid-ask spreads, because it considers a dealer quoting a complete price schedule, which is differentiated according to *transaction sizes* as well as transaction directions, with a symmetric execution cost mark-up at each price for sale (positive) and purchase orders (negative). In this model the quoted spread, is larger for larger *transaction sizes*, since the dealer associates larger orders with an increased likelihood of an information disadvantage. Lyons' econometric results confirm the positive correlation.

This approach and the underlying data are very different from those in the present paper. First, Lyons' specification is in transaction time and not in real time with on average 267 dealer transactions per day (median inter-transaction time less than 2 minutes) and therefore ultra-short term. His sample is set up from two individual institutions, while our data are aggregated over all Japanese forex brokers. His "volume" measure is basically the *size of single transactions*, while ours gives more emphasis to *daily transaction frequency*. Also Lyons' *theory* aims at very short-term horizons. For example, possible economies of scale in market making through order processing effects are not considered at all.

In a companion paper Lyons (1995b) uses the same framework to test more specifically for the information content of transaction sizes when trading "intensity" is high or low. He contrasts an "event-uncertainty hypothesis", claiming that trades are more informative (and hence price changes larger) when intensity is high, with the opposing "hot-potato hypothesis". His estimations support one or the other hypothesis depending on the measure of trading intensity employed, underlining the possible complementarity of both views at very short time horizons. Notice that neither of these two views is in contradiction with the approach taken in this paper, claiming that the *unpredictable* part of *daily* trading *volumes* reflects the daily rate of information arrival and therefore most of the information asymmetry costs for forex dealers. In this respect it is also instructive to look at some stock-market evidence from

NASDAQ-NMS, which is an inter-dealer market as well. For this market Jones et al. (1994) find - for daily data - that transaction sizes have no information content beyond that already contained in transaction frequency, reinforcing the usefulness of the mixture of distributions hypothesis.

IV. Conclusions

In this paper it was argued that time-series estimations of the daily relation between spot foreign exchange spreads and plain trading volumes fail to consider the fact that, to a large extent, trading volume (like volatility) in this market is predictable. The informational content of trading volumes is likely to exist in the unpredictable component, and following Bessembinder (1994) it is argued here that the impact of this component is likely to be of the opposite sign to that of predictable volume.

A GMM estimation of forex spreads expectedly shows that unpredictable volumes drive spreads up while predictable volumes drives them down. With a unique daily dollar/yen volume data set, precisely synchronous exchange rate data and proper instrumenting of endogenous unpredictable volumes, the effects turn out to be strongly significant. These results provide evidence in favor of information cost effects on spreads and economies of scale in market making. One implication is that - at least in the short run - growing (shrinking) trading activity *may* increase (reduce) transaction costs. However, cross-section evidence over currency pairs suggests that this is unlikely to hold in the long run (Black, 1991; Hartmann, 1995). Moreover, in the present study, daily time-series estimations of spreads with plain volumes turn out to be misspecified. Therefore the results showing a positive correlation between these two variables should be interpreted with caution.

It comes immediately to mind that, in a market as active as that for foreign exchange, one might want to further reduce the time horizon for spread estimations and pass to intra-day analyses. The lack of turnover data at higher frequencies might be overcome through the use of Reuters quoting frequency as a proxy for trading activity (Bollerslev and Domowitz, 1993; Davé, 1993; Demos and Goodhart, 1992; Hartmann, 1995). Moreover, one might want to pass from global turnover to dealer order flows and from quoted spreads to traded spreads in order to better disentangle the different channels through which trading volume affects transaction costs in the very short run (Lyons, 1995a, 1995b). However, it is uncertain whether these data will become available for researchers with the necessary coverage in the near future. Finally, measurement of expected volatility might be improvable by replacing GARCH-forecasts with implied volatilities in forex-options prices (Jorion, 1995). This change seems to be unlikely to alter the results found in the present paper (Jorion, 1994). Another approach to better track expected volatilities could involve the use of stochastic volatility models (Andersen, 1994).

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