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Seasonality in foreign exchange volatility

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The paper reports further empirical evidence on seasonality in foreign exchange volatility using high-frequency data. Using a basis of the signal plus noise framework, the approach decomposes tick-by-tick Reuters FXFX quotes into a random walk and a stationary component, termed the efficient price and the pricing error, respectively. The efficient price is not directly observable and is an approximation of the 'true' value. The pricing error captures the deviation between the observed indicative quote and the efficient price. Under the proposed model, daily and intraday volatilities of the efficient price are estimated. A pronounced pattern of volatility is uncovered and appears related to the daily activity cycle of major organized stock exchanges. It is argued that seasonality in volatility is a symptom of foreign exchange markets. Results confirm Andersen and Bollerslev's findings that significant seasonal effects are one important determinant of overall volatility at high frequencies.

I. INTRODUCTION

The behaviour of daily and intraday exchange rates have attracted considerable interest in recent years. Although the spot exchange market is a twenty-four hour market without a central trading location, previous studies of market activity across various time resolutions have revealed remarkably distinct volatility patterns, including the volatility persistence (autoregressive conditional heteroscedasticity (ARCH)), daily and intraday seasonal patterns.[1]

A great deal of effort has been devoted to explaining the empirical findings. Studies were often motivated by the hypothesis that price changes should reflect the arrival and processing of all relevant new information. Researchers in this vein have been carried out by examining the relationship between volatility of returns and economic news announcements. For example, Ederington and Lee (1993) studied five-minute intervals of return volatility in Deutschmark futures and found that volatility increased at the time of macroeconomic announcements. The impact occurred in the first minute after the announcement and died out after 45 minutes. Tanner (1997) examined the mark/dollar exchange rate and found that the exchange rate was affected only by unanticipated information about the trade deficit and the consumer price index but not by other news announcements including money supply, industrial production, the producer price index and unemployment. In an analysis by DeGennaro and Shrieves (1997), volatility in yen/dollar returns was found to be affected by both news releases and the market activity. The latter was proxied by quote arrivals.

One may question on how much of the total volatility can be explained by the news announcements. A more recent study by Andersen and Bollerslev (1998) on the mark/dollar exchange rate suggested that seasonal effects are the most important determinant of overall volatility at high frequencies. Although return volatility appears linked to the economic announcements and the cluster of news releases is helpful in explaining some of empirical findings in volatility, such as the day-of-week effect, the explanatory power of the major news announcements is low. This suggests that it might be important to test for seasonality in foreign exchange volatility.

In this paper we provide further evidence on seasonality in foreign exchange volatility by providing a comprehensive characterization of the seasonal patterns in return volatility in three exchange rates: mark/dollar, yen/dollar and yen/mark. The data underlying this study are one-year

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[1] See, for example, Müller *et al.* (1990), Baillie and Bollerslev (1991, 1997), Goodhart and Figliuoli (1991, 1992), Bollerslev and Domowitz (1993), Darcorogna *et al.* (1993), Bollerslev and Melvin (1994), Guillaume *et al.* (1997), and Andersen and Bollerslev (1998), among others.

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tick-by-tick Reuters FXFX quotes recorded from 1 October 1992 to 30 September 1993.[2]

Since there is already a growing consensus in recent studies that Reuters FXFX quotes are only indicative and there are substantial biases inherent in high-frequency quotation data for examining price and return movement,[3] it is necessary to apply some sort of filtering to keep the 'noise' low. Because of the significant negative first-order autocorrelation and the well-known heteroscedasticity in quotes, Baillie and Bollerslev (1991) employed autoregressive integrated moving average (ARIMA) models with ARCH disturbances to fit the logarithms of quotation data. This approach was also used by other studies including Bollerslev and Domowitz (1993) and Bollerslev and Melvin (1994). We use the signal plus noise (SN) approach developed by Fang (1998) as an alternative to Baillie and Bollerslev's approach. The SN approach decomposes the quotation data into a random walk and a stationary component. The random walk, called the efficient price, is not directly observable and is an approximation of the 'true' value whenever the market is approximately efficient. The difference between the observed quote and the efficient price, called the pricing error, captures negative first-order autocorrelations at high frequencies. Note that Baillie and Bollerslev's model is the reduced form of the random walk plus noise with ARCH disturbances. The SN model tracks the temporal dependencies in the conditional mean and variance of the observed high-frequency quotes, but assumes explicitly that the autocorrelations are attributed solely to the pricing error.

Under the SN model daily and intraday volatilities are estimated for three FXFX quotes. We found pronounced seasonal patterns which are very similar across three series during the one-year period considered. For example, we found high volatilities around the open and close of trading in organized stock exchanges, a lunch-hour dip in volatility during Asian lunch hours, and virtually discontinued activity on weekends. Our findings provide further evidence on seasonality in foreign exchange volatility and demonstrate the importance of seasonal components in overall volatility at high frequencies.

The remaining part of this study is organized as follows. Section II describes the data set and introduces the SN model. The volatility estimation methodology is outlined in Section III, and Section IV elaborates upon the results. We summarize briefly and conclude in Section V.

II. THE DATA AND THE MODEL

The data set used in this paper consists of tick-by-tick Reuters FXFX quotations of the mark/dollar, yen/dollar, and yen/mark. The data cover a one-year time period from 1 October 1992 to 30 September 1993. There are a total of 1 466 946, 567 759 and 158 485 quotes, respectively. The database contains Greenwich Mean Time (GMT), a time stamp to the second at which quotes are posted, bid and ask prices as well as information on quote origination. These Reuters FXFX quotes are from 592 banks who are a part of the spot market. These quotes are the only information available to *all* traders around world.[4] We use the bid–ask midpoints in calculating returns as the most of the previous empirical studies did.

Overall, returns have strong heavy tails with sample kurtosis 6.87, 32.17 and 23.26 for the three FXFX series. The data also reveals significant negative first-order autocorrelations in successive tick-by-tick returns: −0.451, −0.425 and −0.107 for the three series, respectively.

The model in this paper takes the logarithm of the quote at time t, $\tilde{P}_t$, as the sum of two components:

$$\tilde{P}_t = P_t + \varepsilon_t \qquad (1)$$

where P_t follows a random walk and ε_t is the deviation between the random walk and the observed quotes. These two components are called the efficient price and the pricing error, respectively. The notion of an efficient price is central to this paper. It is viewed as an approximation of the unobserved 'true' value.[5]

Suppose the process $\tilde{P}_t$ is sampled at $n+1$ discrete points in time $t_0, t_1, \ldots, t_n$, not necessarily equally spaced apart. For convenience, we assumed that $t_0 = 0$ and $t_n = T$. Additionally, let Y_i denote the observed return at time t_i. Then we have:

$$Y_i = X_i + (\varepsilon_i - \varepsilon_{i-1}) \qquad (2)$$

where $Y_i = \tilde{P}_i - \tilde{P}_{i-1}$ and $X_i = P_i - P_{p-1}$ are the observed and the efficient continuously compounded single-period returns, respectively. From Equation 2, we estimate the accumulated variance of X_t over a given time interval $[0, T]$ (for example, T could be a hour or a day), which is

$$\sigma_n^2 \equiv \sum_{i=1}^{n} \mathrm{Var}\,(X_i) \qquad (3)$$

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[2] The data set was provided by Olsen and Associates.

[3] See Evans (1998), Goodhart *et al.* and Martens and Kofman (1998).

[4] Other systems used for spot market trading in addition to the Reuters FXFX page include Knight and Telerate. According to Reuters, about 60% of transactions in the interbank market take place through the Reuters FXFX system (Evans, 1998).

[5] The assumption that the 'true' value follows approximately a random walk is based on the standard financial asset pricing argument. Whether this assumption is reasonable is an open empirical question.

under the limit of $n \to \infty$. If we further assume that X_t is a diffusion process, σ_n^2 defined in Equation 3 becomes $\int_0^T \sigma_t^2 \, dt$ when the number of observations n increases without bound, where σ_t is the diffusion coefficient.

Although X_t does not have autocorrelations Y_t does because of the appearance of the second term $(\varepsilon_i - \varepsilon_{i-1})$ in Equation 2. Note that if ε_t is uncorrelated, the first-order autocorrelation of Y_t is always negative, bounded below by $-\frac{1}{2}$ and approaches $-\frac{1}{2}$ as n increases without bound and with T fixed. If the process ε_t is not restricted to be white, Y_t has more flexible autocorrelations to match those observed in FXFX quotes at high frequencies.

III. ESTIMATION METHODOLOGY

To estimate volatility of the efficient price based on quotations, we apply the volatility estimator proposed by Fang (1998):

$$\hat{\sigma}_q^2 = \hat{\sigma}^2 + 2\sum_{i=1}^{q} p_i w_i(q) \hat{\gamma}_{i,Y} \tag{4}$$

where the first term on the right-hand side, $\hat{\sigma}^2$, is the quadratic variation.[6] The terms $\hat{\gamma}_{i,Y}$s are autocovariance estimators of Y_t and p_i is the number of observations in the estimation of $\hat{\gamma}_{i,Y}$. The weight functions $w_i(q)$ are defined as $(1 - j/(q+1))$ for $q < n$. Because of these weight functions (the Bartlett window) the estimator (4) is always nonnegative (Newey and West, 1987). Since the asymptotic sampling theory for estimator (4) is fully developed in Fang (1998), we present only a brief summary here.

If the pricing error $\epsilon_t \equiv 0$, the quadratic variation $\hat{\sigma}^2$ is the maximum likelihood estimator and yields consistent estimation of Equation 3 under very general condition. When $\varepsilon_t \neq 0$, $\hat{\sigma}^2$ does not suffice. In fact, it is not even (asymptotic) unbiased. The estimator (4) is simply the quadratic variation adjusted to account for the estimation bias resulting from the pricing error. It can be shown that the estimator (4) is asymptotically unbiased as the truncation lag $q \to \infty$ under the following assumptions:

(A1) X_is are uncorrelated with finite but not necessarily equal variances;
(A2) the limit of σ_n^2 exists as $n \to \infty$ and does not degenerate;
(A3) ε is weakly stationary with a zero mean and the covariance function $\Gamma(i,j) = \gamma(i-j)$, which is uncorrelated with X; and
(A4) $nk(n)(\gamma(q+1) - \gamma(q)) \to 0$ and $n \to \infty$ for sufficiently large q, where $k(n)$ is a slow varying function at infinity.

Because of the importance of the integrity of estimator (4) to this paper it is appropriate to have some further remarks on it. First, assumptions (A1) to (A4) allow flexible models for both X_t and ε_t. Assumption (A1) is a weak version of the random walk model. Assumption (A2) is a convergence condition on the accumulated variance in order to have Equation 3 meaningful. It is satisfied by a wide variety of stochastic processes, including diffusion-type processes with or without jumps. Assumption (A3) requires that the pricing error is stationary and independent of the process X_t. Assumption (A4) is a mixing condition for dependent sequences. It characterizes the 'smoothness' of the pricing error.

Second, the consistency of an estimator for Equation 3 is understood in the sense of continuous asymptotics (see, for example, Phillips, 1987. More precisely, an estimator is said to be consistent if for fixed T, as $\delta_n = \min_i(t_i - t_{i-1}) \to 0$ or equivalently, $n \to \infty$, it converges to $\text{limit}_{\to\infty}\sigma_n^2$ in probability.

Third, estimator (4) is, in general, inconsistent for (3). In fact, it can be shown that increasing the sample size within a fixed time interval does not necessarily improve the accuracy of volatility estimation. Therefore, to eliminate the pricing error effect we sample data at every k ticks. As in Fang (1998) and Zhou (1996), we choose $k = 5$, 3, and 1 for three series, respectively.

In order to estimate the truncation lag q, we calculate autocorrelations and autocovariances up to 20 lags for the three series analysed. Results are reported in Table 1. Among all 20 autocovariances, first-order autocovariances for the three series are negative and have the highest absolute values. Autocovariances for other lags are less statistically significant. To be safe q is taken to be 10 for all three series estimation in Section IV.

IV. SEASONALITY

Seasonality is known to play an important role in foreign exchange volatility. Among different seasonal effects detected in Reuters FXFX quotes, two of most interesting are daily and intraday seasonality. Both appear closely tied to the activity cycle of major organized stock exchanges.

We compute daily and hourly volatilities for three FXFX quotes from 1 October 1992 to 30 September 1993. The computation is based on estimator (4) with $q = 10$ and $k = 5$, 3, and 1 for the three series, respectively. Table 2 reports average daily volatilities with standard deviations listed aside. Panel A is the overall mean of the one-year sample period, Panels B and C report daily mean volatilities by month and by the day-of-the-week, respectively. Overall, daily volatilities for mark/dollar and yen/

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[6] The quadratic variation is defined by $\hat{\sigma}^2 \equiv \sum_{i=1}^{n}(Y_i - Y_n)^2$, where $\bar{Y}_n$ is the sample mean of the Y_is.

Table 1. *Sample autocorrelations and autocovariances*

	mark/dollar		yen/dollar		yen/mark	
Lag	ρ	γ	ρ	γ	ρ	γ
0	1.0000	1.074e-07	1.0000	1.786e-07	1.0000	1.220e-07
1	−0.2671	−2.870e-08	−0.2901	−5.183e-08	−0.1048	−1.279e-08
2	0.0008	8.770e-11	0.0050	8.908e-10	0.0184	2.243e-09
3	−0.0061	−6.569e-11	−0.0018	−3.221e-10	0.0061	7.382e-10
4	0.0084	9.044e-10	−0.0060	−1.077e-09	0.0098	1.201e-09
5	0.0046	4.935e-10	−0.0022	−4.000e-10	0.0019	2.322e-10
6	0.0026	2.742e-10	−0.0030	−5.380e-10	−0.0062	−7.571e-10
7	−0.0035	−3.716e-10	0.0016	2.794e-10	−0.0018	−2.145e-10
8	0.0006	5.973e-11	−0.0051	−9.079e-10	−0.0024	−2.883e-10
9	−0.0001	−1.116e-11	−0.0004	−7.195e-11	−0.0034	−4.147e-10
10	−0.0008	−8.451e-11	−0.0028	−5.007e-10	−0.0020	−2.429e-10
11	−0.0027	−2.855e-10	−0.0026	−4.588e-10	−0.0053	−6.500e-10
12	0.0002	1.687e-11	−0.0016	−2.940e-10	−0.0047	−5.720e-10
13	−0.0002	−2.266e-11	0.0045	8.101e-10	−0.0018	−2.184e-10
14	−0.0029	−3.121e-10	−0.0004	−6.612e-11	0.0038	4.595e-10
15	−0.0034	−3.696e-10	−0.0031	−5.477e-10	−0.0003	−3.846e-11
16	−0.0022	−2.328e-10	0.0026	4.622e-10	0.0025	3.097e-10
17	−0.0032	−3.489e-10	0.0005	8.219e-11	0.0010	1.262e-10
18	−0.0046	−4.913e-10	0.0002	4.338e-11	−0.0059	−7.244e-10
19	−0.0020	−2.195e-10	−0.0041	−7.361e-10	0.0063	7.659e-10
20	−0.0009	−1.009e-19	0.0009	1.659e-10	0.0029	3.508e-10

The table displays sample autocorrelations (ρ) and sample autocovariances (γ) for mark/dollar, yen/dollar and yen/mark with lags from 0 to 20. The results are based on data sampled at every 5, 3, and 1 ticks for three exchange rates, respectively. The sample period is 1 October 1992 to 30 September 1993.

Table 2. *Summary statistics of daily volatilities*

	mark/dollar		yen/dollar		yen/mark	
Panel A	Mean	SD	Mean	SD	Mean	SD
Full sample	4.738038e-05	4.459519e-05	4.733903e-05	5.107097e-05	4.396292e-05	4.218276e-05
Panel B						
October 92	1.070994e-04	7.988904e-05	3.925006e-05	2.774192e-05	5.945324e-05	4.709000e-05
November 92	6.032214e-05	5.294013e-05	2.366789e-05	2.359601e-05	3.202647e-05	2.675466e-05
December 92	3.918081e-05	3.494810e-05	1.542136e-05	1.642272e-05	2.079710e-05	1.878899e-05
January 93	3.722156e-05	2.810590e-05	1.614950e-05	1.643248e-05	1.945856e-05	1523114e-05
February 93	5.454603e-05	4.052520e-05	5.478324e-05	4.365331e-05	5.697630e-05	4.202553e-05
March 93	3.469591e-05	2.709999e-05	4.039425e-05	3.206488e-05	3.683022e-05	2.707150e-05
April 93	4.284008e-05	3.467017e-05	5.877980e-05	5.420551e-05	5.095639e-05	4.509834e-05
May 93	2.959896e-05	2.292516e-05	3.724244e-05	3.736227e-05	2.561709e-05	1.931875e-05
June 93	4.443679e-05	3.112021e-05	6.860331e-05	5.906283e-05	4.632467e-05	3.538557e-05
July 93	3.404734e-05	2.727843e-05	8.313200e-05	6.488324e-05	5.874151e-05	5.015853e-05
August 93	3.383713e-05	2.596773e-05	6.911204e-05	8.451538e-05	5.614186e-05	6.142020e-05
September 93	5.174883e-05	4.292557e-05	6.305110e-05	5.144628e-05	6.612252e-05	5.464641e-05
Panel C						
Monday	5.563854e-05	4.150203e-05	5.055805e-05	3.335768e-05	4.925652e-05	2.653014e-05
Tuesday	6.165136e-05	3.260986e-05	6.387573e-05	4.313163e-05	5.902381e-05	3.864764e-05
Wednesday	6.081522e-05	3.291108e-05	6.152211e-05	3.772460e-05	5.651751e-05	2.574585e-05
Thursday	7.368568e-05	4.014994e-05	7.944318e-05	7.478037e-05	7.573688e-05	5.432463e-05
Friday	7.370181e-05	5.179535e-05	6.759597e-05	5.092617e-05	6.188273e-05	3.826055e-05
Saturday	0.00000e+ 00	0.00000e+ 00	1.573658e-08	1.134781e-07	0.00000e+ 00	0.00000e+ 00
Sunday	5.665156e-06	6.979896e-06	7.745037e-06	7.644504e-06	4.711931e-06	5.296771e-06

Daily volatilities are estimated under $\hat{\sigma}_q^2$ with $q = 10$ for mark/dollar, yen/dollar and yen/mark. Panel A reports the overall means. Panels B and C report daily means for each month of the year and each day-of-the-week, respectively. Standard deviations (SD) are given next to the mean. The full sample period is 1 October 1992 to 30 September 1993.

Table 3. *Summary statistics of hourly volatilities*

	mark/dollar		yen/dollar		yen/mark	
Panel A	Mean	SD	Mean	SD	Mean	SD
Full Sample	1.844913e-06	3.598416e-06	1.852864e-06	3.795529e-06	1.44511e-06	2.814701e-06

	mark/dollar		yen/dollar		yen/mark	
Panel B	Mean	SD	Mean	SD	Mean	SD
0:00–1:00 GMT	1.462957e-06	2.562554e-06	2.544047e-06	4.263767e-06	1.863751e-06	2.718511e-06
1:00–2:00 GMT	1.027441e-06	1.747940e-06	2.004609e-06	2.977433e-06	1.306316e-06	2.071644e-06
2:00–3:00 GMT	1.069945e-06	1.856471e-06	1.939621e-06	3.818946e-06	1.027401e-06	1.658593e-06
3:00–4:00 GMT	3.918789e-07	1.071125e-06	5.937953e-07	2.064921e-06	5.879187e-08	3.414582e-07
4:00–5:00 GMT	6.845289e-07	9.476381e-07	1.482647e-06	2.827278e-06	5.927940e-07	1.339604e-06
5:00–6:00 GMT	1.252372e-06	1.388665e-06	2.126863e-06	3.349075e-06	1.112666e-06	1.746348e-06
6:00–7:00 GMT	1.831025e-06	1.939724e-06	2.344293e-06	3.314544e-06	1.511537e-06	2.312377e-06
7:00–8:00 GMT	2.356242e-06	2.450609e-06	2.439236e-06	5.192287e-06	1.810967e-06	2.425210e-06
8:00–9:00 GMT	2.086701e-06	2.411863e-06	2.102030e-06	3.584987e-06	1.697449e-06	2.161316e-06
9:00–10:00 GMT	2.071691e-06	2.881103e-06	1.646147e-06	2.447502e-06	1.809440e-06	3.128240e-06
10:00–11:00 GMT	1.718883e-06	2.362490e-06	1.411603e-06	2.373632e-06	1.558801e-06	2.784215e-06
11:00–12:00 GMT	1.771429e-06	2.345976e-06	1.272671e-06	1.804648e-06	1.277076e-06	1.867110e-06
12:00–13:00 GMT	3.878179e-06	8.417835e-06	2.933821e-06	5.421928e-06	2.532466e-06	6.328685e-06
13:00–14:00 GMT	4.223888e-06	6.254669e-06	3.031552e-06	4.120237e-06	2.836041e-06	4.452605e-06
14:00–15:00 GMT	4.605128e-06	5.347430e-06	3.429800e-06	6.694137e-06	3.028759e-06	3.979099e-06
15:00–16:00 GMT	4.079151e-06	4.835704e-06	2.684456e-06	3.773456e-06	2.616808e-06	3.098771e-06
16:00–17:00 GMT	3.258936e-06	5.896196e-06	2.075718e-06	3.493470e-06	2.061248e-06	3.133472e-06
17:00–18:00 GMT	1.771097e-06	3.233903e-06	1.721662e-06	3.848366e-06	1.518247e-06	2.461539e-06
18:00–19:00 GMT	1.404887e-06	2.740451e-06	1.656504e-06	4.764354e-06	1.348524e-06	2.481336e-06
19:00–20:00 GMT	9.092835e-07	1.611533e-06	9.953681e-07	2.234691e-06	9.387762e-07	2.822492e-06
20:00–21:00 GMT	6.482237e-07	8.765894e-07	1.092734e-06	5.744410e-06	4.870788e-07	7.347346e-07
21:00–22:00 GMT	6.160132e-07	1.209905e-06	7.288367e-07	1.216428e-06	4.557313e-07	1.009465e-06
22:00–23:00 GMT	4.714791e-07	8.096076e-07	8.281356e-07	1.408078e-06	4.596050e-07	8.933551e-07
23:00– 0:00 GMT	6.875579e-07	1.424387e-06	1.382594e-06	2.455293e-06	7.723724e-07	1.462783e-06

Hourly volatilities are estimated under $\hat{\sigma}_q^2$ with $q = 10$ for mark/dollar, yen/dollar and yen/mark. Panel A reports the overall means. Panel B reports the mean for each hour. Standard deviations (SD) are given next to the mean. The full sample period is 1 October 1992 to 30 September 1993.

dollar are at a similar level (4.73 to 4.74e-05). The daily volatility in yen/mark is about 4.40e-05, which is relatively lower during the one-year time period considered. As we proceed through the panels to the results summarized by month, there are no clear patterns uniformly across all three series. The lowest volatilities are those of May for mark/dollar, December and January for yen/dollar and yen/mark. October, July and September are months in which the three series have their highest average daily volatilities, respectively. On the other hand, patterns of average daily volatilities for each day of the week are strong. The average daily volatilities have a tendency to increase from Monday to Friday. They reach peaks on either Thursday (for yen/dollar and yen/mark) or Friday (mark/dollar). Volatilities on weekends are low; there is virtually no activity on Saturdays for both mark/dollar and yen/mark.

To study intraday volatility patterns, Table 3 reports hourly volatilities for three FXFX quotes. From Panel A, average hourly volatilities for mark/dollar and yen/dollar are about 1.84e-06 to 1.85e-06. The average volatility for yen/mark is 1.45e-06. Panel B reports hourly volatilities during the course of the day. Hourly volatilities vary significantly, ranging from 5.88e-08 (3:00-4:00 GMT in yen/mark) to 4.61e-06 (14:00-15:00 GMT in mark/dollar). As documented in earlier studies, hourly volatilities for all three FXFX quotes reach their peaks during the overlap of the London and New York trading hours (about 13:00–17:00 GMT). Volatilities are low during lunch hours in Asia (3:00–5:00 GMT).[7] We also find evidence of decreased volatilities between 20:00 and 24:00 GMT, the gap between the close of the New York and the open of the Tokyo market. Results obtained here are consistent with those documented in the previous studies.

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[7] The drop during the Asian lunch time is largely related to the prohibition against yen trading in Tokyo (Ito *et al.* 1998).

Table 4. *Significance of seasonal components*

Panel A F-value	mark/dollar	yen/dollar	yen/mark
α	208.2459	145.2367	207.2791
β	63.3122	15.9411	38.2415
Panel B Effect	mark/dollar	yen/dollar	yen/mark
μ	1.844913e-06	1.852864e-06	1.445110e-06
α_1	1.007017e-07	2.683251e-07	8.608190e-08
α_2	3.992477e-08	8.261029e-08	3.164960e-08
α_3	1.252197e-07	1.854093e-07	1.647625e-07
α_4	5.429826e-08	3.555808e-08	−2.806129e-10
α_5	−4.178629e-07	−4.251030e-07	−3.304998e-07
α_6	−2.767754e-07	−2.696023e-07	−2.216995e-07
β_1	−2.355644e-07	−2.683423e-07	−2.865469e-07
β_2	−5.793624e-08	−1.102471e-07	−1.756703e-07
β_3	−1.941169e-07	−3.920421e-07	−3.305476e-07
β_4	−6.004621e-08	−5.540939e-08	−9.187798e-08
β_5	5.492982e-08	6.975638e-08	2.423537e-08
β_6	1.192290e-07	8.020063e-08	7.291707e-08
β_7	1.559566e-07	7.253316e-08	9.275600e-08
β_8	9.237015e-08	1.779613e-08	6.131670e-08
β_9	7.342188e-08	−3.014541e-08	5.988165e-08
β_{10}	2.821885e-08	−4.541055e-08	2.692610e-08
β_{11}	2.485087e-08	−5.023686e-08	−1.603360e-09
β_{12}	1.631114e-07	8.284221e-08	7.739892e-08
β_{13}	1.832837e-07	8.119996e-08	1.046151e-07
β_{14}	1.777669e-07	9.488824e-08	1.009666e-07
β_{15}	1.264234e-07	3.705232e-08	6.204213e-08
β_{16}	6.482047e-08	−3.101243e-09	2.483277e-08
β_{17}	−2.219098e-08	−2.142765e-08	−7.624157e-08
β_{18}	−3.882257e-08	−2.268329e-08	−1.544768e-08
β_{19}	−5.950915e-08	−5.399640e-08	−3.511685e-08
β_{20}	−6.674354e-08	−4.387837e-08	−5.311642e-08
β_{21}	−6.283869e-08	−5.683213e-08	−5.006502e-08
β_{22}	−6.304027e-08	−4.815459e-08	−4.554961e-08
β_{23}	−4.895065e-08	−2.053016e-08	−0.843992e-08

Results are based on the following model

$$\sigma_{ijk} = \mu + \alpha_i + \beta_j + \varepsilon_{ijk}$$

where σ_{ijk} are hourly volatilities, μ is the overall mean, α is the day-of-week effect with $i = 1,2,\ldots,6$, and β is the hourly effect with $j = 1,2,3,\ldots,23$. k is taken to be 52. Panel A reports F-values and Panel B lists the overall means and treatment effects. The full sample period is 1 October 1992 to 30 September 1993.

To test for significance of seasonality, the following model is estimated[8]

$$\sigma_{ijk} = \mu + \alpha_i + \beta_j + \varepsilon_{ijk} \tag{5}$$

where σ_{ijk} are hourly volatilities, μ is the overall mean, α is the day-of-week effect with $i = 1,2,\ldots,6$, and β is the hourly effect with $j = 1,2,3,\ldots,23$. The number of replications, k, is 52. This two-way layout with replicates is useful to test for the following two null hypotheses:

I. H_0: There is no day-of-week effect; vs H_a: There is a day-of-week effect.
II. H_0: There is no hour-of-day effect; vs H_a: There is an hour-of-day effect.

Table 4 reports estimation results of Equation 5. Panel A provides F-values for the two hypotheses for the three FXFX quotes. It is clear that both null hypotheses are rejected at a 1% level of significance for all three series.[9] This implies statistical significance of both day-of-week and hour-of-day seasonalities in volatility.

We end the section by assessing the economic significance of the seasonality. Panel B reports treatment effects, α_i and β_j, which reflect changes in response due to the combination of treatments. In our parameterization, an effect is the difference between treatment levels. The base level for the day-of-week factor is Monday. The base level for the hour-of-day factor is 00:00–1:00 GMT. Hence, in the case of day-of-week effect entries in columns 2 to 6 in Panel B are the differences between Monday and other days numbered as 1 (Tuesday) to 6 (Sunday). Entries in the last 23 columns in Panel B are the differences between the 00:00–1:00 GMT and the other 23 hours. These estimates are readily interpreted. For example, the estimate of α_1 for yen/dollar is 2.683251e-07. Thus, volatility from Monday to Tuesday increases by 2.683251e-07, or about 14.48%. This effect applies uniformly to each week during the one-year period considered. Assessment of the hour-to-day effect is also astonishing. For example, the estimate of β_3 for yen/mark is −3.305476e-07. Consequently, the difference between 0:00–1:00 and 3:00–4:00 GMT (the lunch hour in Asia) amounts to −3.305476e-07, or a reduction in volatility of about 22.87%

V. CONCLUSION

This paper provides further empirical evidence on seasonality in foreign exchange volatility. We used a two-step approach. First, daily and hourly volatilities were estimated using a signal and noise model. The model is an alternative to ARIMA-GARCH and it is useful in estimating the volatility at the actual market level. Second, we analysed seasonality in estimated daily and hourly volatilities for mark/dollar, yen/dollar and yen/mark. We found that there were significant day-of-week and hour-of-day seasonal effects. These patterns appear to be related to the activity cycle of major organized stock exchanges. Seasonality in foreign exchange volatility has non-trivial

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[8] The additive model with two factors, the day-of-week and the hour-of-day, and 52 replicates per cell is used. The diagnostic tests show the model is reasonable. We have omitted diagnostic results to conserve space.

[9] If we delete all weekends and holidays, results for hypotheses I and II still hold at any conventional significant level.

implications for many empirical studies including the evolution of volatility premia through time and volatility persistency across markets. The conclusion drawn from the evidence documented in this paper is that seasonality is an important component in volatility at high frequencies and any empirical analysis not taking into account these patterns is biased and will be virtually meaningless.

REFERENCES

Andersen, T. G. and Bollerslev, T. (1998) Deutschmark-dollar volatility: intraday activity patterns, macroeconomic announcements, and longer run dependencies, *Journal of Finance,* **53**, 219–65.

Baillie, R. T. and Bollerslev, T. (1991) Intra day and inter market volatility in foreign exchange rates, *Review of Economic Studies,* **58**, 565–85.

Baillie, R. T. and Bollerslev, T. (1997) High frequency data in finance, *Journal of Empirical Finance,* **4**, 69–73.

Bollerslev, T. and Domowitz, I. (1993) Trading patterns and prices in the interbank foreign exchange market, *Journal of Finance,* **48**, 1421–43.

Bollerslev, T. and Melvin, M. (1994) Bid–ask spreads and volatility in the foreign exchange market: an empirical analysis, *Journal of International Economics,* **36**, 355–72.

Dacorogna, M. M., Müller, U. A., Nagler, R. J., Olsen, R. B. and Pictet, O. V. (1993) A geographical model for the daily and weekly seasonal volatility in the foreign exchange market, *Journal of International Money and Finance,* **12**, 412–38.

DeGennaro, R. P. and Shrieves, R. E. (1997) Public information releases, private information arrival and volatility in the foreign exchange market, *Journal of Empirical Finance,* **4**, 295–315.

Ederington, L. H. and Lee, J. H. (1993) How markets process information: news releases and volatility, *Journal of Finance,* **48**, 1161–91.

Evans, M. D. (1998) The microstructure of foreign exchange dynamics. Working paper, Georgetown University.

Fang, Y. (1998) Intraday volatility and the informational role of quote arrivals in foreign exchange markets. Working paper, University of Oregon.

Goodhart, C. and Figiuoli L. (1991) Every minute counts in financial markets, *Journal of International Money and Finance,* **10**, 23–52.

Goodhart, C. and Figiuoli, L. (1992) The geographical location of the foreign exchange market: A test of an island hypothesis, *Journal of International and Comparative Economics,* **1**, 13–28.

Goodhart, C., Ito, T. and Payne, R. (1995) One day in June, 1993: a study of the working of Reuters 2002-2 Electronic Foreign Exchange Trading System, in Frankel, J. A., Galli, G. and Giovannini, A. (eds), *The Microstructure of Foreign Exchange Markets*, The University of Chicago Press, Chicago, IL.

Guillaume, D. M., Dacorogna, M. M., Davé, R. R., Müller, U. A., Olsen, R. B. and Pictet, O. V. (1997) From the bird's eye to the microscope, *Finance and Stochastics,* **1**, 95–129.

Ito, T., Lyons, R. and Melvin, M. (1998) Is there private information in the FX market? The Tokyo experiment, *Journal of Finance,* **53**, 1111–30.

Martens, M. and Kofman, P. (1998) The inefficiency of Reuters foreign exchange quotes, *Journal of Banking and Finance,* **22**, 347–66.

Müller, U. A., Dacorogna, M. M., Olsen, R. B., Pictet, O. V., Schwarz, M. and Morgenegg, C. (1990) Statistical study of foreign exchange rates, empirical evidence of a price change scaling law and intraday analysis, *Journal of Banking and Finance,* **14**, 1189–208.

Newey, W. and West, K. (1987) A simple, positive semi-definite, heteroskedasticity and auocorrelation consistent covariance matrix, *Econometrica,* **55**, 703–8.

Phillips, P. C. B. (1987) Time series regression with a unit root, *Econometrica,* **55**, 277–301.

Tanner, G. (1997) A note on economic news and intraday exchange rates, *Journal of Banking and Finance,* **21**, 573–85.

Zhou, B. (1996) High-frequency data and volatility in foreign-exchange rates, *Journal of Business and Economic Statistics,* **14**, 45–52.