Journal of International Money and Finance (1991), **10**, 23–52

Every minute counts in financial markets

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This paper represents an introductory study of ultra high frequency, minute-by-minute data, for forex spot rates (bid–ask Reuters quotes) on three days, Autumn 1987. The frequency of price revision, size of spread, and statistical characteristics are measured. The series exhibit (time varying) leptokurtosis, unit roots, and first-order negative correlation, the latter especially in disturbed 'jumpy' markets. The effect of time aggregation on these characteristics is examined, and variance ratios are analyzed. Multivariate analysis revealed significant relationships between lagged exchange rates, both the own rate and the key deutsche mark/US dollar rate, and the current spot rate.

This paper reports the results of a study of the statistical characteristics of time series of spot foreign exchange rates, taken at intervals of a minute from Reuters' screens in London on three working days in the autumn of 1987. This is a preliminary exercise, in advance of a more ambitious study of a far longer continuous series of forex rates. Even with this smaller data set, we can report some interesting findings, *e.g.*, on spreads, on the prevalence of negative auto-correlation, especially in disturbed, jumpy markets, and on interactions between the forex series.

The foreign exchange market is the broadest, most active, financial market in the world. It is currently structured as an electronic/telephone market. The prices that the main players, the large international banks, are prepared to bid and offer for the various currencies (in all cases bilateral with the US dollar) can be observed by watching the relevant screen pages of the main news services, *i.e.*, Reuters and Telerate. (Cross rates are derived from the basic bilateral spot rates.) Given such publicly available information on the bid–ask rates on offer, a market trader can telephone around (either to a bank which has recently quoted bid–ask rates, or to any other bank/trader or foreign exchange market broker), to seek to negotiate a purchase, or sale, of a currency. This latter transaction, the price and amount of the deal, remains private information to the two parties concerned.

0261–5606/91/01/0023–30

There are currently no time series available on transactions data in the forex market. Reuters is, we understand, planning to introduce a facility whereby spot transactions can also be executed electronically. But, for the time being, the only data on *transactions* available are those obtained from the occasional sample surveys conducted by the Central Banks in the main centres, *e.g.*, as reported in news releases on September 13, 1989.

The frequency with which new quotes are put onto the relevant Reuters screen page (FXFX) is high. In the busiest, main forex spot market, for the deutsche mark/US dollar, there are on average some 5000 quotes per working day. It is our future intention to record, and then to analyze, the main forext spot series continuously over a long enough period to be regarded as representative. This, however, will represent a major research exercise. As a preliminary to that further exercise which is now being undertaken, we thought it prudent to undertake a trial practice run, to see whether we could handle such large data series and what the characteristics of the data were, so that we would have some experience when we came to exploring the, even larger, continuous time series to be assembled and analyzed at a future date.

For this purpose we obtained from Reuters, United Kingdom, snapshots of their foreign exchange screen, FXFX, taken every minute during the period when the London sector of the forex market was functioning on three days in the autumn of 1987. The market is, of course, open on a continuous round-the-clock, 24 hour basis, but the Reuters' data are supplied to the screens from Reuters offices in different financial centres as time passes through the day, and we only obtained our data during the period in which Reuters' London office was filing the data. We first asked for these minute by minute data for September 14 and 15, which turned out, in the event, to be rather calm days;[1] the dates were chosen, somewhat arbitrarily (but aimed to avoid potentially unrepresentative occasions, *e.g.*, on end-quarter), some weeks in advance, in order to give Reuters time to set up the arrangements; subsequently in view of our interest about how markets worked during more disturbed periods, Reuters was kind enough to provide similar minute by minute snapshops for October 21, 1987, a couple of days after the crash, when all asset markets were perturbed.[2]

It may help readers unfamiliar with the working of the forex market to see a snapshot of what the screen page (FXFX) from Reuters of the main eight currencies, bilateral with the US dollar, looks like. An example is shown in Table 1.

TABLE 1. Typical foreign exchange screen page from Reuters.

13:07	CCY	Page	Name	*	Reuters Spot Rates	* CCY	Hi*Euro	** Lo FXFX
13:06	DEM	DGXX	DG BANK	FFT	1.8528/33*DEM		1.8538	1.8440
13:06	GBP	AIBN	AL IRISH	N.Y.	1.7653/63*GBP		1.7710	1.7630
13:06	CHF	CITX	CITYBANK	ZUR	1.5749/56*CHF		1.5750	1.5665
13:06	JPY	CHNY	CHEMICAL	N.Y.	128.53/58*JPY		128.70	128.23
13:07	FRF	MGFX	MORGAN	LDN	6.3030/60*FRF		6.3080	6.2750
13:06	NLG	MGFX	MORGAN	LDN	2.0920/30*NLG		2.0925	2.0815
13:00	ITL	MGFX	MORGAN	LDN	1356.45/6.58*ITL		1356.45	1349.00
13:02	XEV	PRBX	PRIVAT	COP	1.1259/68*XEV		1.1304	1.1255

XAV	UBXO	402.00/402.50	*	ED3	9.31 / 9.43	*	FED PREB	*	LFDA MAR
XAG	CSGL	6.08/6.10	*	US30Y	YTM 8.78	*	9.12–9.18		B 9108

The left hand column gives the time of entry of the latest quote to the nearest minute (British Standard Time), the time being 13:07 when the snapshot was taken. The next column refers to the currency (bilateral with the US dollar), in terms of dollars per unit of pound sterling and ECU—European currency unit—and units of domestic currency per US dollar otherwise; CHF is Swiss franc; NLG Netherlands guilder. The fourth column gives the name of the trading bank inputting the quotes, and the fifth shows the branch location of that bank from which the quote has emanated (so that an enquiring trader can telephone the correct branch). Only spot rates are reported on FXFX; the mnemonic of each inputting bank is shown in column three, so that an enquiring trader on the Reuters network can dial up the relevant screen page, say DGXX for the DG bank, on which page the trader could see the full set of spot and forward quotes for this (and other) currencies being offered by this bank. The final two columns report recent extremes, high and low in prices being quoted, and the data below the line record gold and silver prices (respectively XAV and XAG), and certain (US) interest rates.

When a bank wants to advertise its willingness to do business in the forex (spot) market, it keys the bid–ask prices which it is prepared to offer directly (subject to various gateways) on the Reuters (or Telerate) screen. The screen, therefore, records a series of individual bank quotes. Our first statistical task was to translate the data series shown on FXFX into usable time series for individual currencies.[3] Table 2 may be helpful in showing what such a series looks like.

There are certain potential problems with these data. They indicate the prices at which banks advertise that they would deal, but they are not themselves firm transactions data. Particularly in a fast moving market, *e.g.*, after a news flash, many dealers may be too busy making deals on the phone to update their own quotes, though there is no reason to believe that the quotes actually made on such occasions are biased. Again, banks may at times make quotations that they hope may influence the subsequent course of the market, *e.g.*, to quote higher bid–ask prices in the hopes of encouraging a general rise in the market. Since the actual deals are made subsequently over the phone, that bank *could* avoid the immediate consequences of being 'hit' as a consequence of such a strategic move—should the market not follow that lead—simply by not answering the

TABLE 2. An example of DM/$ time series.

13:19	Danske	COP	1.7003/10
13:20	Bk Ire	DBN	1.7000/10
13:21	Bk Bos	NY	1.7000/10
13:22	Bk Mtl	TOR	1.7000/10
13:23	Natwest	NY	1.7003/08
13:24	Scotia	NY	1.7002/12
13:25	Amex	LDN	1.7000/10
13:26	Natwest	LDN	1.7002/12
13:27	Natwest	LDN	1.7002/12
13:28	Barclays	NY	1.7000/10
13:29	Std Chtd	NY	1.7010/15
13:30	Can Impl	TOR	1.7005/12

phone, or claiming that the quote had been input in error, or refusing to deal except in very small amounts. If such behaviour was repeated at all frequently, however, it would result in the loss of reputation, and we rely on the importance that banks and traders attach to their reputation to keep these indicative data in line with the underlying prices at which banks would actually deal. On inspection of the raw data, it did, however, also become clear that there were a very few occasions on which plain errors were made in keying in the data. Our method of identifying, and removing, such errors is described in the note.[4]

Whatever may be the biases, if any, that arise because the data relate to indicative quotes, rather than to actual transactions, they are the raw material from which *all* other forex data time series are derived. Thus the figures quoted for the spot exchange rate (or the forward rate) at a particular time, say at the end of a day, will normally be an average of the rates then being quoted on the screens by the last five, or six, banks to update their quotes, or the latest quotes of some subset of local banks.

With such high frequency data, one obtains a large number of observations even when the data set is restricted to part of the working day on three particular calendar days. In Table 3, we note the precise minutes, British Standard Time (BST), of our available opening and closing observations. The latter differed for the Italian lira, since the spot market for lira shut at 16:30 BST.

Nevertheless the question obviously remains whether the behaviour of the forex market on these three days is representative. That question *will* be answered in due course, when the much longer continuous time series becomes available. Why then should anyone concern themselves with our preliminary, and possibly unrepresentative, findings?

We believe that we can, even now, throw some light on some interesting issues, despite the possibility that some of these initial results may have to be amended subsequently. First, we have not seen any previous studies of spreads (between bid and offer prices) in the forex market; as is apparent from Table 2, our time series provides us with direct evidence on such spreads, and we report our study of how such spreads varied over time and between markets in Section I. A testable hypothesis is that spreads would widen in more disturbed markets, and we sought

TABLE 3. Opening and closing times.

Date	Hour: British Standard Time Open	Close	Number of observations
	(All currencies except Italian lira)		
9/14	8:23	17:03	521
9/15	8:10	17:04	535
10/21	8:32	17:23	532
		(Italian lira)	
9/14	8:23	16:30	488
9/15	810	16:30	501
9/21	8:32	16:30	479

to examine that by comparing spreads in the calm days of September 14 and 15 with those on October 21.

Work with hourly forex data series (Goodhart and Giugale, 1988; Baillie and Bollerslev, 1989) has already shown that volatility in forex markets is time dependent. Such time dependence may well be associated with variations in the frequency of price adjustments in the forex market. In Section II we examine how market activity, as measured by the frequency of price adjustments (as compared with no change observations), varied over time and between currencies on these days.

Data observed at discrete low frequencies, weekly, daily, even hourly, involve the aggregation of a very large number of intervening price changes. How does such time aggregation alter the basic characteristics of the series? One can study this question either by comparing the characteristics of this series, *e.g.*, the four main moments, with those obtained from studies of lower frequency series (as done in Section II), or, more ambitiously, by undertaking time aggregation on the same series; thus in Section VI, following the approach adopted by Poterba and Summers (1988), we explore how the measured variance of the series alters as the observations are aggregated into increasingly lower frequencies. If the series was, in fact, a pure random walk the variance ratio test would show that the ratio of the variances would be exactly proportional to the ratio of the frequencies, and that hypothesis is, of course, testable.

The question of whether the spot exchange rate is a stationary series or has a unit root is, of course, one of the key econometric issues. We examine this in Section III by running not only an augmented Dickey–Fuller (ADF) equation, but also, because of the non-normality (lepto-kurtotic) and heteroscedasticity of the series, a Phillips–Perron test.

One of our findings, from the augmented Dickey–Fuller test, is that these series generally exhibit significant first-order negative autocorrelation. In earlier studies using hourly data (Ito and Roley, 1986; Goodhart and Giugale, 1988), such negative autocorrelation had been found to be most evident around the occasion of large 'jumps' in the exchange rate. In Section V we examined whether the same result appeared in our higher frequency data series.

As already stated, one of our main objectives was to study the effect of time aggregation on the characteristics of the data series. As one facet of that study, in Section V we repeated the augmented Dickey–Fuller equations, but now using five and ten minute intervals; this involved overlapping observations, which we treated by using the Hansen and Hodrick approach.

Another of our main concerns has been to examine the efficiency of the forex market. We have already noted that the minute-by-minute time series exhibit first-order negative autocorrelation. In Section VII we examine whether changes in (first differences in the log of) spot exchange rates are partially predictable on the basis of prior changes in *other* forex spot rates.

We had also hoped to examine the effect of 'news' on forex quotes. For that purpose we also obtained, for September 14 and 15, records, taken at 15 minute intervals, of the main economic and other, *e.g.*, political, 'news' transmitted by Reuters over their page of news items intended for financial and forex market traders, their AAMM page, with the timing of such news recorded to the nearest minute. In addition, on September 15 we received the complete Reuters' news printout from 12:30 to 17:00 BST. Knowing the timing of each news announcement on these two days to the nearest minute, we could examine the associated minute by minute forex time series to see, both visually and by examination of the statistical characteristics of the series immediately after the news announcements, whether, and how, the forex market responded to 'news' on these two days; we did not, however, also obtain similar 'news' reports on October 21. In fact, as we report in Section VIII, we found it difficult to observe any clear response, or any 'jumps', in our forex series in response to the 'news' on these two days, but this may, of course, be largely due to the absence of any startling 'news' on a couple of days that were generally characterized as being calm (see note 1).

One of our referees, with personal experience on the trading floor, commented that such a lack of identifiable market reaction to news, might be

> ... the rule rather than the exception. Measurable reactions appear to be rather few, to depend upon not just the data relative to expectations but whether these bits of data fit into any sort of important pattern, one that tips the weight of the evidence in favor of one view or another with regard to actual economic performance or central banks's reactions thereto. Sometimes, moreover, the reactions are seemingly perverse or quickly reversed, as new information makes it clear that what initially seemed to be the signal in the news was not real. A CPI figure dominated by one relative price is an example. Only after several minutes had elapsed from the time of the release of the overall figure would it become apparent what had happened.That we are sometimes able to find measurable responses should not blind us to the fact that most of the information that moves markets is not of the same variety as the US money data in the early 1980s, statistics that swamped much else of what was going on.

He then went on to suggest that what would be needed would be a much larger sample, which would encompass many more items of news held to be important for forex markets, *e.g.*, monthly trade figures with outcomes differing from expectations, and (associated) 'jumps' in the exchange rate. That will, indeed, be the first exercise to be done on our forthcoming much longer and larger continuous database to be assembled. In this latter exercise we shall also compare economic 'news' announcements with prior expectations, which we were not able to do on our two days in this preliminary study. But one has to start somewhere, and this paper represents our own start on a longer research project.

I. The spread

The spreads for each individual currency exhibited on the screens almost always took one out of a few conventional values. The statistics showing the recorded size of the spread at each end-minute observation for each currency on each day is available on request from the authors. For the deutsche mark, pound sterling, Japanese yen, and the Netherlands guilder[5] the main three conventional values (in their respective units, *i.e.*, basis points of pfennigs, cents, yen, etc.) were 5, 7, and 10. While there is some residual evidence of the 5, 7, 10 pattern for the Swiss franc, the overwhelming number of recorded observations are for 10 basis points of centimes. The main French pattern is to have spreads of 20, 25, or 30 basis points for centimes, with 20 and 30 being more frequent than 25. The two most frequent values of spread for the ECU were 4 or 5 basis points.

This is a clear case of round number syndrome. The most common standard spread, if it seems at all appropriate, will be 10 (or 20, or 30) units. If the 'appropriate' spread deviates from such a round number, a unit in multiples of 5 will be the next most commonly chosen. Then, between 5 and 10, the order of preference will generally be 7, 8, 6, 9 for obvious reasons. There was not a single spread of 9 recorded during this whole period. There were not enough cases of spreads falling into the range 0–5 (apart from the ECU) to record a similar order of preference in that range.

If the 'appropriate' spread is close to 10, as in the case of the Swiss franc, or yen, the vast majority of quotes will remain at that conventional level. In other cases, deutsche mark, pound sterling, French franc, Netherlands guilder, the distribution was basically trimodal, in most cases 5, 7, 10, in a majority of cases with the central peak (7, or 25 in the case of the French franc) being lower than that of the surrounding round number peak. The ECU distribution was bimodal (4 or 5).

It is not currently clear what determines the choice, and thus the distribution, between these conventional alternatives. As already noted, we obtained data for October 21, partly to examine differences in market behaviour between disturbed and quiet periods, and we looked for signs of spreads on average being wider on October 21 than on September 14 and 15. There were no such signs at all. Instead, if there was *any* pattern to the differences between the days, it shadowed a reversion to a more extreme form of the round number syndrome with both 5 and 10 (or 20 and 30 French francs) gaining at the expense of 7 (25 French francs), with even perhaps some marginal tendency for there to be more additional *low* spreads on October 21, but these differences are very slight and not statistically significant.

Although the pattern of spreads showed little difference between the three *days*, there was a clear intraday temporal pattern in two currencies, the French franc and ECU. The North American, especially the New York, market in these currencies is not as active as the European market, and, during the final half hour, or so, of our observations each day, with New York becoming the dominant market, *i.e.*, from 16:30 BST onwards, spreads in these two currencies widened markedly. No such effect was visible in other markets. Finally, right at the start of the European day, around 08:30 BST, there were again a very few cases of bid–ask quotes with higher (than conventional) spreads, in several cases emanating from Far East countries.

We have, therefore, no evidence here that posted spreads in the forex market are sensitively responsive to changes in market conditions, although it does appear that in some cases the conventional spread for a currency may vary from market to market (*e.g.*, from Europe to North America), and thus be time dependent. Instead, it is perhaps more likely that banks will respond to changing perceived risk by shifting the amounts in which they will subsequently be prepared to deal over the telephone. Given that the size of the spreads was largely conventionally determined, and appears to remain roughly constant on average, despite shifts in market conditions over the three days of our data set, we felt that we could work, in the rest of our exercise, just with the series for the ask price in each case.

II. Characteristics of the time series

Next, we report the basic characteristics of the series for the change, the first

TABLE 4. Basic statistics.

	Mean	Standard deviation	Kurtosis	Skewness
September 14	6.5X−06	0.00023	5.87	0.11
September 15	−8.2X−06	0.00019	5.71	−0.24
October 21	3.3X−06	0.00026	7.34	0.27

difference, from minute to minute of the logarithmic value of each (of the eight) currency series for the ask price for each day, *i.e.*, the mean, standard deviation, kurtosis, and skewness. The figures for each currency on each day are available from the authors on request. The data averaged over all currencies on each day are shown in Table 4, with the mean in each case calculated in terms of units of domestic currency per US dollar.

The means were, as would be expected, very low. None was significantly different from zero. All of the signs of the mean per cent change, after adjusting the pound sterling and ECU into terms of domestic units per US dollar, were the same on each day, implying that the common cause of trend was a similar move against the US dollar with all currencies depreciating against the US dollar on September 14 and October 21, and appreciating on September 15: the one exception was a slight trend appreciation in the lira on October 21, against the run of all the other currencies.

The other moments, standard deviation (SD), kurtosis, and skewness all exhibit some indication of time dependence. Markets were disturbed in the week beginning October 19. It also appears that, even in the quieter period of September 14 and 15, the latter day was the more placid. Anyhow, the average (over all currencies) estimates of SD, kurtosis, and skewness are highest on October 21 and lowest on September 15. This is not true, however, for all individual cases, *e.g.*, the SD for the yen and Netherlands guilder is highest on September 14, lira kurtosis lowest on October 21, yen kurtosis highest on September 15, etc.

These moments, for the series at minute intervals, may be compared with the moments for lower periodicities, such as those already estimated by Diana Whistler (1988) for a set of hourly, daily, weekly, and monthly spot exchange rates.

Whistler's earlier work indicated that lepto-kurtosis rose as periodicities became shorter and frequencies higher. This finding, however, did *not* carry through to the minute by minute data, where the estimates of kurtosis (themselves time dependent) were lower on average than those found by Whistler for hourly and daily data.

Overall our skewness estimates do not appear to differ from those reported in other financial markets, as reported by Taylor (1986) or Hsieh (1988). They are, however, somewhat larger than those obtained on daily and hourly forex data, respectively, by Whistler (1988) and Goodhart and Giugale (1988).

The amount of activity in each market also appeared, not surprisingly, to vary over time, *i.e.*, falling at midday at the time of the European lunch hour, BST 12:00–13:00. One measure of this is the number of minutes in each hour in which the ask remained unchanged, data for each hour in each currency in each day are available on request from the authors.

A summary (excluding data for the lira, since this market closed earlier each

TABLE 5. Number of no-change observations.[1]

(By hour)									
8–9	9–10	10–11	11–12	12–13	13–14	14–15	15–16	16–17	17–18
271	479	504	572	699	500	426	451	618	80
Ratios to total observations									
2.3	2.7	2.8	3.2	3.9	2.8	2.4	2.5	3.4	1.8

(By currency)							
Deutsche mark	British pound	Japanese yen	Swiss franc	French franc	Italian lira	Netherlands guilder	XEV
304	518	661	639	509	599	756	615

[1] Total number of observations: 1599.

day) showing the comparative numbers of no change observation by hour and by currency over all three days is appended in Table 5 (N.B. a high figure indicates low activity and vice versa).

Beware that the opening and closing hours (8:00–9:00, 17:00–18:00 BST) contain a (daily varying) number of minutes. To adjust for this the hourly no change data were expressed also as a ratio to the number of minutes in each hourly period (180 except for the opening and closing hours). Even so, we would advocate caution in interpreting the figure for the final hour. The data were predominantly only taken from October 21 (37 out of 44 observations), and the low ratios (high apparent frequency) may be particular to that single hour. For the rest, the hourly pattern is straightforward, low figures/high activity at the market opening, with activity falling slowly to a large lunchtime trough (an apt simile!), picking up smartly as New York enters around 1:30 p.m., but falling away again after 16:00 hours. The hourly averages in the afternoon are somewhat misleading, however, since they disguise the tendency for the North American currency markets to be comparatively inactive in the Netherlands guilder and ECU markets. This biases the no-change numbers up, especially after 16:00 hours, so that the summary table understates the afternoon activity in the other currency markets.

As expected, the deutsche mark market is clearly the most active, and the Netherlands guilder the least active. We were, however, surprised by some of the other currency results. The French franc appeared on this basis the second most active currency market, closely followed by the pound sterling. The ECU appeared a more active market than the yen or Swiss franc. This latter ranking is clearly decisively reversed later in North America, but even for Europe this comparative ranking surprised us. Perhaps it arises from certain peculiarities in our small sample of days? In any case, we have further addressed the question of the geographical location of the forex market in our companion paper (Goodhart and Figliuoli, 1988).

Since these results show that none of these markets operated absolutely continuously, and also that the pace of activity is time dependent, it would be desirable to utilize statistical methods that allow for occasional activity, and wherein that activity is time-varying. Bringing to bear more complex econometric methodology on these times series remains, however, an exercise for the future.

So, for the time being, we shall ignore the above complications, together with the other features that make these series non-normal, *i.e.*, lepto-kurtosis and, in some cases as will be reported, heteroscedasticity; and we shall start by treating these series, for the first difference of the log of the ask quotations, for each currency/day, as an ordinary time series, to which we can apply OLS.

III. Univariate time series properties

Our first step then was to examine the univariate time series properties of each series. We began by examining a Dickey–Fuller equation of the form:

$$\text{Per cent } \Delta \text{ currency (ask)} = a + b \text{ level currency (ask)}_{t-1}.$$

An example of the results that were obtained for each currency on each day (*i.e.*, 24 regressions) is given below; the full set is available from the authors on request.

DM September 14	Constant	Ask − 1	Dickey–Fuller
Coefficients	0.007	−0.011	1.91
(t-values)	(1.88)	(−1.87)	

In all the exercises in which a Dickey–Fuller, or an augmented Dickey–Fuller, type regression was run, we recorded, among other statistics, the values of the standard t-statistic for the coefficient on the lagged level of the log; these are to be compared with the critical values of Fuller (1976), p. 373, Table 8.52 for the case when a constant is included in the regression (*i.e.*, the τ_μ statistics in Fuller's notation). Such values, for a sample size of $n = 500$, are, in relationship to the one-sided alternative hypothesis of stationarity, as follows:

0.01	0.05	0.10
−3.44	−2.87	−2.57

Therefore in our data set, for all currencies/days, the null hypothesis of a unit root cannot be rejected at standard significance levels. If we were, however, prepared to follow the argument of Poterba and Summers (1988) further discussed in Section VII in reference to variance ratios, particularly given the high number of observations available here, we might be prepared to accept a higher significance level (0.25 for instance), in which case some day currencies would exhibit evidence of *stationary* behaviour.

In these regressions, and above, under the heading Dickey–Fuller (DF) was also reported the values of the statistic:

$$\phi = \frac{\left[\sum_{2}^{n}{}_{t} \left(Y_t - Y_{t-1}\right)^2 - SSR\right] \Big/ 2}{SSR/n},$$

where n is the sample size, $t = 1, \ldots, n$, and SSR is the residual sum of squares obtained in the regression of $Y_t - Y_{t-1}$, on Y_{t-1}, with an intercept included in the regression. It can be used to test the joint null hypothesis that $(a, b) = (0, 1)$, being of the F-test type. From Table 4 of Dickey and Fuller (1979) the value of this statistic will exceed 3.79 about 10 per cent of the time.

Therefore the null joint hypothesis that $(a, b) = (0, 1)$ is easily accepted at significance values for all days-currencies in our sample, with the exception of the Italian lira on October 21, when the rejection is clearly due to the anomalous high value estimated for the constant. The appropriate statistics for the alternative specification:

$$(Y_t - Y_1) = b(Y_{t-1} - Y_1) + u_t$$

have also been computed and are available on request. The results are analogous.

Although this test indicated that we could not dismiss the hypothesis of the existence of a unit root, the non-normality of the series made the power of the significance tests doubtful. So, we then applied a Phillips Z-test, or Phillips–Perron test, to the series of the exchange rates for the various currencies and days considered. This is an extension of the Dickey–Fuller test. The latter should be confined to those cases where the sequence of innovations in the data set being modelled is independent with common variance. In the original paper—see Dickey (1976)—it is assumed that these are *iid* $(0, \sigma^2)$. Independence and homoscedasticity are strong assumptions to make about the errors in most empirical econometric work. Our tests for detecting the presence of heteroscedasticity and/or ARCH effects in the distribution of the returns confirm that such assumptions do not hold for our data, and similar findings characterize most other empirical research on high frequency data for asset prices.

The values of the statistics which we used in this test to examine the significance of the intercept and the presence of a unit root are available on request.[6]

It was evident anyhow that the hypothesis of the presence of a unit root could not be rejected for any currency or day considered; and the same applied to the joint hypothesis of the presence of a unit root and a null intercept.

We then examined the auto-correlative properties of the system by running an augmented Dickey–Fuller equation, including up to 29 own lags of the per cent change in the series, as well as a constant, and the single lagged level:

$$\text{Per cent } \Delta \text{ currency (ask)} = a + b_1\text{(ask) level}_{t-1} + \text{b}_2$$

$$\text{Per cent } \Delta \text{ (ask)}_{t-1} + b_3 \text{ per cent } \Delta \text{ (ask)}_{t-2} \cdots \quad + b_{30} \text{ per cent } \Delta \text{ (ask)}_{t-29}.$$

The results for the first three regressions that we ran (out of 24) are shown in Table 6; the remainder are available on request. We have reported here only those lagged values in the series for which $t > 2$.

In 22 cases out of 24, there was significant first-order negative correlation with t-values more negative than -1.98 (of which 16, < -3; 12, < -4; 7, < -5).[7] The exceptions were for the yen on October 21 (-1.68), and the Dutch guilder on the same day ($+2.80$!).

On the basis of these results we considered the optimal length of lag to run in our subsequent regressions. Three criteria, Akaike's,[8] F, and the apparent significance of additional lags beyond first-order were considered. In the majority of cases it was clear from all three criteria that the appropriate order of lag was restricted to first. The details of these tests are available on request: the remaining cases, in which there was some doubt over the optimal lag length, are shown in note 8.

The extent to which the minute-by-minute fluctuations in spot exchange rates can be explained (predicted) by their immediately preceding time path is not large. The adjusted R^2 values in the full set of 24 regressions tended to fall in the range 0.05 to 10. Even though the average size of the negative first-order

TABLE 6. Augmented Dickey–Fuller regressions.

	September 14				
	Constant	Ask_{-1}	Percent Δ ask_{-1}	Other 'significant' lags	
				$((t-21)$	$(t-29))$
Deutche mark	0.008	−0.013	−0.243	−0.128	0.111
	(2.02)	(−2.01)	(−5.45)	(−2.66)	(2.33)
Pound sterling	0.004	−0.009	−0.164		
	(1.48)	(−1.49)	(−3.49)		
Japanese yen	0.047	−0.009	−0.209		
	(1.55)	(−1.55)	(−4.48)		
	R^2	DW	TRSQ	TRSQ1	
Deutsche mark	0.06	1.99	19.6	27.2	
Pound sterling	0.01	1.98	8.9	3.2	
Japanese yen	0.03	1.99	24.4	13.7	

coefficient is quite large in absolute size, around 0.18 on average, given the tiny size of the average minute by minute change; the fact that this series represents quotations, not actual trading prices, and the existence of trading costs, the discovery of such an econometric relationship is not going to make anyone, least of all the authors, rich.

The final figures recorded, under the headings TRSQ and TRSQ1 above, are two test statistics for the presence of heteroscedasticity.[9] Unlike Diana Whistler's results, showing significant heteroscedasticity at frequencies higher than one month, *e.g.*, one hour or one day, the minute-by-minute currency data only show mild heteroscedasticity through the course of the day on September 14 and 15. With the curious exception of the French franc market, where heteroscedasticity appeared on September 15 but not on October 21, the currency markets, not surprisingly, exhibited much more significant heteroscedasticity during the disturbed market conditions of this latter day.

IV. Negative autocorrelations around jumps

A possibly more serious concern, than the need to account for the *regular* negative low order autocorrelation, was that the scale of negative autocorrelation appeared to be greater in those cases when the exchange rate had its largest changes, *i.e.*, 'jumps', more than two or three times the standard deviation. This phenomenon had been observed before in studies of hourly data, *e.g.*, by one of the authors (Goodhart and Giugale, 1988) and by Ito and Roley (1986). Now we were in a position to test for this same feature using even higher frequency data. We approached this by examining separately the autocorrelation properties around the 'jump' as compared with the autocorrelation properties of the series when centred on 'non-jump' observations, which represented, of course, the vast majority of observations.

We began by looking at the latter, the autocorrelation properties of the series centred on the non-jump observations. In particular we examined the autocorrelations centred on all those observations whose change was *less* than three times the standard deviation, examining the moments, covariance and correlation matrix of the form,

$$\begin{array}{l} Z10 \ldots Z1, \quad X, \quad W1 \ldots W10 \\ \vdots \\ Z1, \\ X \\ W1, \\ \vdots \\ W10 \end{array}$$

where $Z10$ are the observations 10 minutes earlier, $Z1$ one minute earlier, X the non-jump observations, $W1$ the one minute later observations, $W10$ the tenth minute later observations. The number of such non-jump observations whose autocorrelation properties we could examine was about 500 for each currency in each day.

Inspection showed that the coefficients in the correlation matrix tended to be almost the same along each diagonal, though varying markedly from diagonal to diagonal. Thus the correlation between Z_{10} and Z_9 had very nearly the same value as the correlation between Z_1 and X, or X and $W1$, or W_9 and W_{10}. Similarly the correlation between Z_{10} and Z_8 was very nearly the same value as that between Z_2 and X, or X and W_2, or W_8 and W_{10}, but the latter second-order correlations would differ markedly (usually being positive) from the first-order correlation, which were negative and usually highly significant.

As an example, the average values of these common crosscorrelations for the first, second and third order, and an N test of their significance,[10] are shown for the deutsche mark on all three days in Table 7 (data for all the other currencies are available on request).

In comparison with such benchmark correlations, we examined similar matrices for moments, covariances and crosscorrelations, but this time centered on 'jump' observations, with changes greater than 2 or 3 standard deviations. In practice

TABLE 7. Average cross correlations around non-jumps for the Deutsche mark.

Lead time:	$t+1$	$t+2$	$t+3$
14th N-test	-0.24	0.08	-0.03
	(-5.5)	(1.9)	(-1.1)
15th N-test	-0.32	-0.02	0.04
	(-7.0)	(-0.5)	(1.4)
21st N-test	-0.23	0.12	-0.05
	(-4.2)	(2.3)	(-1.0)

in these series the number of 'jump' observations larger than three standard deviations was small: in all cases examined, fewer than 11 observations out of a series of about 520. This was too small a sample to expect to obtain useful results. So, instead, we concentrated on the crosscorrelations centred around those observations whose changes were, in absolute value, more than twice the SD. There were usually about 30 such observations for each currency on each day. The results of examing these latter crosscorrelations (full data available on request indicated that the absolute size of the negative first-order crosscorrelation increases, compared with the non-jump observations, not only on the occasion of the jump itself, but also in the two minutes before the jump, and in the minute afterwards. Thus not only does the 'jump' itself tend to be followed by a partial reversal, but so do immediately surrounding changes.

We have calculated the ratio of the size of the negative first-order crosscorrelation in 'jump' situations to those under non-jump conditions, for each currency averaged over three days, and present this in Table 8. In a few cases the crosscorrelation was of the wrong (positive) sign: here we took the ratio as being zero.

What this shows is unusually large negative crosscorrelations between the 'jump' and the subsequent observation, but also between the observation before the 'jump' and the 'jump' itself, and similarly between $t-2$ and $t-1$, and $t+1$ and $t+2$. As the length of time, in both directions, from the 'jump' widens, the size of the first-order crosscorrelations returns to normal; indeed the negative crosscorrelations between $t-3$ and $t-2$, and between $t+2$ and $t+3$, are less in absolute size than average, when centred on a 'jump' observation.

The finding that the negative first-order autocorrelation is unusually large not only on the occasion of a 'jump', but also immediately adjacent to such a 'jump', is not easy to explain. Nevertheless there does appear to be some evidence, as will be recorded in the following section on time aggregation, for negative autocorrelation to be a more persistent feature in disturbed markets, and the heteroscedastic nature of the forex market suggests that 'jumps' will normally occur in the course of periods of disturbance.

Another more institutional consideration is that 'jumps' may occur as a result of major (unanticipated) news being announced. The timing of such announcements is often known exactly. Possibly the disparity between the information

TABLE 8. Ratio of first-order negative correlation coefficients of the change in the log from $t+i$ to $t+i+1$ in jump (SD$>$2) compared with nonjump (SD$<$3) occasions.

Average of three days	$t-3$	$t-2$	$t-1$	t	$t+1$	$t+2$
Deutsch mark	0.2[1]	1.2	1.5	2.0	0.9[1]	0.1[1]
Pound sterling	0.9[1]	2.4	2.5	2.2	2.8	0.1[1]
Japanese yen	0.1	1.0	2.2	2.1	1.9	0.4[1]
Swiss franc	0.4[1]	1.6	1.2	1.9	2.0	0.7[1]
French franc	0.6[1]	0.0	1.6	1.3	0.8	0.5

[1] These averages are biased *upwards* by entering incorrect signs as a zero ratio.

sets of differing agents is particularly large just ahead of such moments; or alternatively, in conditions of such uncertainty, agents are particularly keen to square their books, so that underlying 'bulls' and 'bears' will quote sharply different bid/ask prices in order to reduce the size of their differing positions. We do not, however, find either of these explanations convincing, and we leave the finding of large negative autocorrelation both immediately after, and adjacent to, a 'jump' as a puzzle still to be explained.

V. The effect of time aggregation on the characteristics of the time series

Moving from an hour by hour to a minute by minute set involves a major jump in frequency. It seemed, therefore, of some interest to investigate the effect of intermediate time aggregation. So, we examined what would happen to the augmented Dickey–Fuller equations if the data were time-aggregated into five and ten minute intervals. Rather than throw observations away, this implied the use of overlapping observations. This automatically introduces autocorrelation in the error terms, as indicated by the dramatically lower Durbin–Watson (DW) ratios, and, in particular, biases the standard significance tests.

So we had to adjust for this, following the approach pioneered by Hansen (1979) and by Hansen and Hodrick (1980). Let us consider a multivariate time series (y_t, t_t), $t=1,, \ldots, T$, where y_t is the scalar dependent variable and x_t a vector (l-dimensional) of predetermined variables. We assume that the relationship between y_t and x_t can be depicted by:

$$\langle 1 \rangle \qquad y_t = \beta x_t + u_t,$$

where $E(x_t u_t)=0$ and u_t is i.i.d.

If we are interested in the variables $y_{t,k}$ and $x_{t,k}$ obtained from (y_t, x_t) as their aggregated counterparts relative to k periods, the functional link between them, derived from $\langle 1 \rangle$, is again a similar form:

$$\langle 2 \rangle \qquad y_{t,k} = \beta_k x_{t,k} + u_{t,k},$$

but now the disturbances $u_{t,k}$ are serially correlated whenever $t=k$, a positive integer. As a consequence the usual formulae for the asymptotic standard errors are no longer valid. Thus, in testing hypotheses concerning 'aggregated' equations, one alternative is to define the sampling interval to be equal to the aggregation interval. In the context of tests of exchange market efficiency, Cornell (1977), Frenkel (1977, 1978a and b, 1979), Levich (1978), and Geweke and Feige (1979), have all used nonoverlapping samples to avoid the serial correlation problem, being forced to accept a severe sacrifice of observations in the process.

One might think it possible to circumvent the serial correlation problem by the use of generalized least squares (GLS), but this is not the case in our exercise and in most time series research. In fact GLS requires strict econometric exogeneity of the x_t process in $\langle 1 \rangle$ ($x_{t,k}$ in $\langle 2 \rangle$). If the x_t vector contains variables which are not strictly exogenous, GLS estimation distorts the orthogonality conditions and leads to an inconsistent estimator (see Hansen, 1979). Such exogeneity would imply that knowledge of future x_ts (x_t, ks) would be useless in determining the optimal forecast for y_t ($y_{t,k}$), and it is clearly not satisfied by our choice of x_t (see below). Following Hansen (1979) and Hansen and Hodrick (1980), our strategy is to estimate β_k consistently with OLS procedures using the full data set available, *i.e.*, data sampled more finely than the aggregation interval, but adopting the appropriate modifications[11] in the estimation of the asymptotic covariance matrix derived by Hansen (1979). Note however that this estimation method is not fully efficient, as would instead be the MLE procedure in the Appendix of Hansen and Hodrick (1980); the latter however is computationally burdensome.

As described in note 12, we derive and use the same statistic to test efficiency as originally obtained by Hansen and Hodrick (1980) in the present context. This statistic, here termed *HH*, replaces the standard t-value of an estimate of significance, and is used for all the exercises here involving time aggregations. The results of running an augmented Dickey–Fuller equation on the time series aggregated to five minutes observations, and then to ten minute observations, suggest that the clear pattern of negative first-order autocorrelation observable in the minute by minute data diminishes as time aggregation increases to five and then ten minutes, but that the rate of diminution appears to depend on whether the market is calm or excited. On the calm days, September 14 and 15, the first-order negative correlation is often much less for the five minute intervals, and has totally disappeared with ten minute intervals (September 15 only) —though there still remained a usual pattern of longer lagged negative coefficients with t-values around -1.5. On the other hand on the excited day, October 21, first-order negative correlations are not only again often apparent in the five minute interval case, but also still marginally observable in the ten minute interval case. Moreover, in the rapidly moving markets of October 21, the lagged *level* of the exchange rate had in several cases in these latter regressions a significant positive coefficient, implying a strong extrapolative trend through the day.

In order to illustrate how the size, and significance, of the negative first-order autocorrelation declined with time aggregation, we report in Table 9 the coefficient on the first lagged change in the exchange rate in the augmented Dickey–Fuller (ADF) equations, and its t-value (minute by minute) or *HH* value (five and ten minute aggregation) for the deutsche mark, pound sterling, Japanese yen, and French franc on all three days. Full results of the ADF equations aggregated over five and ten minutes respectively are available on request.

The effect of time aggregation from one minute to five minute intervals also sharply increases the extent of heteroscedasticity in the data sets, dramatically so for the TRSQ1 statistic; there is less difference between the five and ten minute aggregation in this respect; the TRSQ statistic in several cases even fell slightly with the longer (ten minute) time interval, but the TRSQ1 number rose even higher to extremely high values, occasionally over 300. This effect of time aggregation on heteroscedasticity is illustrated in Table 10.

What emerges from this is that heteroscedasticity does not increase monotonically as frequency rises; instead it reaches a peak level, perhaps over frequencies of about 10–15 minutes, before falling back again as frequencies rise even higher.

One extremely tentative implication of this exercise is that there may be *two* forms of negative autocorrelation in the data, the first being a *very* high frequency regular pattern that occurs continuously, but diminishes and, perhaps, in some cases disappears, with quite limited time aggregation. We examine a hypothesis to account for this in our related paper, Goodhart and Figliuoli (1988). The second source of negative autocorrelation appears to be associated with excited

TABLE 9. Coefficient, and significance on first lagged change.

	1 minute		5 minutes		10 minutes	
			(Deutsche mark)			
September 14	−0.24	(−5.25)	−0.07	(−0.94)		
September 15	−0.35	(−7.69)	−0.06	(−0.89)	0.03	(0.25)
October 21	−0.19	(−4.02)	−0.19	(−2.20)	−0.21	(−1.68)
			(Pound sterling)			
September 14	−0.16	(−3.49)	−0.19	(−2.23)		
September 15	−0.28	(−6.12)	−0.13	(−1.70)	0.02	(0.20)
October 21	−0.09	(−2.05)	−0.11	(−1.33)	−0.12	(−1.00)
			(Japanese yen)			
September 14	−0.21	(−4.48)	−0.14	(−1.72)		
September 15	−0.13	(−2.85)	−0.13	(−1.62)	0.05	(0.44)
October 21	−0.07	(−1.68)	−0.21	(−2.51)	−0.25	(−2.09)
			(French franc)			
September 14	−0.30	(−6.39)	−0.18	(−2.43)		
September 15	−0.30	(−6.53)	−0.14	(−1.86)	−0.05	(−0.49)
October 21	−0.27	(−5.75)	−0.08	(−0.22)	−0.25	(−1.99)

TABLE 10. Heteroscedasticity and time aggregation.

	September 14	September 15	October 21	September 14	September 15	October 21
		(Deutsche mark)			(Pound sterling)	
TRSQ 1	19.6	11.3	66.3	8.9	7.7	19.1
5	37.2	11.7	51.5	23.5	14.3	32.8
10		21.0	48.0		14.0	24.0
TRSQ1 1	27.2	6.2	67.8	3.2	5.9	24.3
5	78.1	42.6	195.4	121.1	99.3	144.9
10		103.5	300.1		153.8	225.6
		(Japanese yen)			(French franc)	
TRSQ 1	24.4	17.0	64.9	17.1	43.4	5.1
5	24.1	23.9	81.0	22.9	40.6	38.1
10		15.4	59.5		29.1	25.3
TRSQ1 1	13.7	10.4	66.0	4.2	25.1	13.5
5	143.4	139.0	195.4	60.4	71.8	187.4
10		151.7	232.6		106.5	193.6

forex markets, reversals following 'jumps'. As already noted, one of us has observed that feature persisting in hour by hour data sets. We are uncertain, at this moment, how to explain this latter phenomenon.

VI. Variance ratios

Our preliminary results suggest that a number of the characteristics of the foreign exchange market are frequency dependent. In particular, negative (first-order) autocorrelation appears to be prevalent at ultra-high frequencies, *i.e.*, minute by minute; appears to persist over ten minute and hourly periodicities during periods of market disturbance—though not generally—being specially marked around 'jump' observations; but appears to die out altogether at lower frequencies a day, a month, etc. Again, heteroscedasticity and lepto-kurtosis are *not* such a marked feature of the ultra-high frequency data, but rise rapidly with time aggregation to peak (around ten minutes?) before declining gently as the frequency of observation falls further.

A further way of exploring such frequency dependent characteristics is to look at the change in the variance of the series as the frequency of observation shifts. This is, perhaps, particularly useful since, as already noted, if the series were random walk, then the ratio of the variance when observed only at interval of length n units would be n times that observed at each unit of time.

In this part of our paper, we have closely followed the approach adopted by Poterba and Summers (1988).

Our variance ratios exploit the fact that if the logarithm of the exchange rate (or of a state price) follows a random walk, then the return variance should be proportional to the return horizon. Such tests have been recently applied to the study of efficiency in financial markets by Fama and French (1986a and b), Lo and MacKinlay (1987), and Poterba and Summers (1988). In particular we study the variability of returns, defined as the first difference between the logarithms of the exchange rates for the various currencies/days in our sample, relative to the variation over a ten minute period, using the latter as our reference point.

For minute by minute returns, the variance ratio statistic is therefore:

$$VR(k) = [\mathrm{Var}(R_t^k)/k]/[\mathrm{Var}(R_t^{10})/10], \tag{3}$$

where

$$R_t^k = \sum_{0}^{k-1}{}_i\, R_{t-1},$$

R_t denoting the return in minute t.

The statistic converges to unity if returns are uncorrelated through time. If some of the price variation is due to transitory (or mean reverting) factors, however, autocorrelations at some lags will be negative and the variance ratio will tend to be smaller than unity: per contra, if there is persistence, a positive autocorrelation, in returns, the variance ratio would exceed unity. The said statistics have been corrected throughout for small sample bias by dividing by $E(VR(k))$.[12]

The power and size of the variance ratio test has been studied by Poterba and Summers (1986) and compared with that of alternative testing procedures. They conclude that for most of the tests taken into consideration (including the variance ratio), the type II error rate would be between 0.85 and 0.95 if the type I error rate were set at the conventional 0.05 level. In particular, for the variance ratio test, a 0.40 significance test is appropriate, if the objective is to minimize the sum of type I and type II errors and, it should be noted, in order to justify the conventional 0.05 level test, three times as great a weight should be attached to type I as opposed to type II errors.

Accordingly, Poterba and Summers suggest that 'since there is little basis for strong attachment to the null hypothesis that stock prices follow a random walk, significance levels in excess of 0.05 seem appropriate in evaluating the importance of transitory components in stock prices.'

The main empirical finding of Poterba and Summers (1988) is that positive autocorrelation over short lags is followed by negative autocorrelation over longer lags for observed returns (remembering that they were studying much lower periodicities than being examined here). Given the base they adopted (12 months) this is reflected in an increasing variance ratio at first, followed by a rather consistent decline back towards unity.

We first examined the variance ratios taking ten minutes as the reference point and proceeding in steps of this length. When the results of this are viewed, it should be noted that consistent negative autocorrelation would lead to the variance ratio being lower than unity when comparing *longer* periods of time (*e.g.*, a multiple of ten minutes, say one hour), with the reference point, but *greater* than unity when comparing shorter periods of time (*e.g.*, comparing variances over one minute intervals), with the reference point. Partly as a cross-check, partly in order to simplify interpretation, we redid the same exercise using one minute as the reference point, *i.e.*, allowing for a more fine partition of the high frequency band (one to ten lags). The two procedures, as might be expected, show the same results.

Tables collecting the results of both these exercises are available on request. The results indicate that there are considerable signs of negative autocorrelation in the ultra-high frequency band on all days (except for the NLG on October 21). Consideration of the more detailed exercise with one minute returns as a base shows that this transitory component manifests its presence mainly in the first few lags, after which the variance ratio remains fairly steady for long intermediate spans of frequencies for all days and currencies.

Thereafter the findings differed for the various days (in particular for the more disturbed day October 21, on one side, and the two calmer days, September 14 and 15). On September 14 nothing more happens, apart from oscillations. On September 15, lowering the frequency, after 90 minutes, the variance ratio falls further. However, consideration of even lower frequency lags indicated that this was not a lasting effect: indeed it soon then returned to about the values assumed soon after the initial drop. On October 21, the variance ratio falls less far below one than on the other days in the sample and starts to climb to values around unity when compared with the one period frequency (deutsche mark, pound sterling, Japanese yen) or slightly below it (French franc, ECU). The Swiss franc, although showing the same pattern, exhibits more evidence of a permanent pattern of negative autocorrelation.

Just as Poterba and Summers found (1986, pp. 8 and ff.), the standard deviation applicable to these variance ratios also rises as the frequency falls, so it is not possible to state, using traditional confidence levels, that the ratios, except at the ultra-high frequencies, are significantly different from unity (nor even with great confidence that the ratios on September 25 are significantly different from those obtained on October 21). However, as argued by Poterba and Summers, there is a strong case in this kind of exercise to apply significance levels which make it easier to rebut the null hypothesis.

VII. Multivariate relationships between exchange rates

That concluded our study of the univariate characteristics of our forex time series;

we then turned to a multivariate study to examine whether there were any multivariate relationships whereby prior (in time) changes in other exchange rates might have an effect on the movements of the particular exchange rate being studied, in addition to its own lags. This amounted to running a VAR, vector autoregression, on all our exchange rates.

Initially we regressed the first difference of the log of the ECU on its own lags and on the lags of each of the other currencies in the same format, taking them one at a time (since the movements in the currencies are highly collinear); we also examined the inter-relationships between the four main currencies, deutsche mark, pound sterling, Japanese yen, and Swiss franc, again relating each currency to its own lags and the lags of one other currency (of the other three) at a time; finally we regressed each of the minor currencies on its own lags and lags of the DM, treating the latter as the key currency. We did this for all three days separately. This generated a vast number of regressions. In order to save space, we only show a small subsample of these results below. In general, when the (changes in) the other exchange rates were entered one at a time, the addition of lags of the deutsche mark had the greatest effect on the fit of the equation (in the case of the deutsche mark itself, the Japanese yen and Swiss franc had roughly equal explanatory power as measured by the improvement in fit). So, we show below the small subset of equations, and only for one day, September 15, with the deutsche mark as the extra variable (Japanese yen in the case of the deutsche mark itsef). The general form of the equation is:

$$\begin{aligned}\%\,\Delta\, Acur_t = a + b_1\ \%\ \Delta\ Acur_{t-1} + \cdots\quad + + b_n\ \%\ \Delta\ Acur_{t-n}\\ + c_1\ \%\ \Delta\ Bcur_{t-1} + \cdots\quad + + c_n\ \%\ \Delta\ Bcur_{t-n} + u_t,\end{aligned}$$

where $\%\ \Delta\ Acur$ and $\%\ \Delta\ Bcur$ are respectively the per cent change in the own and the other currency, u_t is the error term, a, the bs, and cs are constant coefficients.

We ran up to 20 lags on both own and other currencies, and in a few cases found significant lags up to $t-9$, when the equation was run in this way. Again to save space, we only report in Table 11 the coefficients (and t-values) on the first two significant lags ($t-1$ and $t-2$ in all cases). The full results are, once again, available on request.

What emerges from these results is that the inclusion of lags on other exchange rate per cent changes strongly improves the fit of the equation. We were, however, omitting potential information by only using the lags of one other exchange rate at a time; on the other hand all the exchange rates tended to move together leading to problems of multicollinearity. We sought to cope with this by including in the equation, besides the own lag in unchanged form, the *difference* between the per cent change in the dependent variable and in the per cent change of each of the other exchange rates at the appropriate lag, *e.g.*, we would calculate at lag i, say for the deutsche mark, the difference between the per cent change in the deutsche mark and in the pound sterling, and use the latter as an independent variable, along with similar differences with respect to the other currencies. We thought that such differencing would sufficiently reduce multicollinearity to allow us to enter all other (lags in) per cent currency changes in the equation for each currency in turn. We excluded the Italian lira from this exercise, since it had a different, shorter data period on each day. This left us with seven currencies

TABLE 11. Improvement in fit on September 15 when past changes in other currency (Deutsche mark) added to simple autoregression (A = Without other currency added; B = With other currency).

	Own lag		Other lag			
	$t-1$	$t-2$	$t-1$	$t-2$	R^2	F-Test
A ECU[1]	−0.19	−0.11			0.06	2.13
	(−4.20)	(−2.4)				
B	−0.37	−0.18	−0.31	−0.33	0.19	6.75
	(−8.11)	(−3.46)	(−7.80)	(−7.00)		
A Pound sterling	−0.28	−0.15			0.06	2.07
	(−6.13)	(−3.09)				
B	−0.15	−0.31	−0.23	−0.23	0.17	6.15
	(−9.05)	(−6.00)	(−5.89)	(−5.14)		
A Deutsche mark	−0.35	−0.15			0.13	3.48
	(−7.69)	(−3.15)				
B [2]	−0.48	−0.33	0.20	0.18	0.18	6.60
	(−10.14)	(−5.94)	(5.67)	(4.40)		
A French franc	−0.30	−0.18			0.09	2.66
	(−5.53)	(−3.77)				
B	−0.13	−0.39	0.39	0.34	0.22	7.81
	(−9.15)	(−7.64)	(9.11)	(6.82)		
A Netherlands guilder	−0.16	−0.13			0.07	2.18
	(−3.46)	(−2.86)				
B	−0.24	−0.33	0.26	0.29	0.17	5.97
	(−5.15)	(−6.67)	(7.14)	(6.80)		
A Italian lira	−0.31	−0.16			0.02	2.71
	(−6.52)	(−3.27)				
B	−0.14	−0.31	0.31	0.28	0.22	7.45
	(−8.75)	(−6.02)	(6.97)	(5.34)		

[1] ECU and pound sterling expressed in reverse form to all other currencies, so sign of other currency effect will be reversed from the norm.
[2] Other currency here is the Japanese yen.

(equations) on each of the three days. In Table 12 we show the improvement in the fit of the equation when the lags in the other currencies were allowed to enter the equation in this way (*i.e.*, differenced from the own lag). The set of other significant currencies are reported in rough order of relative importance (this could have been done formally but the exercise would have taken more time than it was worth). In the simple ADF equations, the DW statistic ranged from 1.98 to 2.01; in the equation with other currencies added DW ranged from 1.95 to 2.06.

At first sight these results look remarkable. We can explain on average some 25 per cent of the minute-by-minute changes in exchange rates on the basis of currently known data for the exchange rates in our data set. The value of R^2 varies between a low of 0.134 (pound sterling, September 14) and a high of 0.40 (French franc, October 21). This could appear superficially to be inconsistent with efficiency. Yet a large number of qualifications are in order. First, the minute-by-minute average changes are small; so even if one is able to achieve some

TABLE 12. Improvement in fit when lags on all other currencies added (A = September 14; B = September 15; C = October 21).

	R^2 (ADF)	R^2 (with other currencies)	Other currencies significant[1]
Deutsche mark	A 0.06	0.16	SF, NG, BP, ECU
	B 0.13	0.28	SF, BP, NG, JY
	C 0.09	0.16	SF, FF, NG, BP, ECU, JY
Pound sterling	A 0.01	0.13	DM, NG, ECU
	B 0.06	0.24	JY, FF, SF, ECU, DM
	C 0.01	0.21	DM, FF, JY
Japanese yen	A 0.03	0.21	DM, BP, ECU
	B 0.05	0.21	DM, BP, ECU, SF, FF
	C 0.04	0.24	DM, SF, NG, FF
Swiss franc	A 0.04	0.21	DM, BP, JY
	B 0.04	0.21	DM, NG, BP, ECU
	C 0.02	0.26	DM, FF, JY, NG, BP
French franc	A 0.11	0.29	DM, BP, ECU, SF
	B 0.09	0.27	DM, BP, JY, SF
	C 0.09	0.40	DM, BP, SF, JY, ECU
Netherlands guilder	A 0.09	0.22	DM, BP, SF, FF, ECU
	B 0.07	0.24	DM, BP, JY, SF
	C 0.00	0.30	DM, SF, JY
ECU	A 0.03	0.25	DM, SF, JY, BP
	B 0.06	0.25	DM, FF, SF, JY
	C 0.04	0.29	DM, NG, FF, SF, BP

[1] BP: British pound; NG: Dutch guilder; DM: deutsche mark; FF: French franc; SF: Swiss franc; ECU: European Currency Unit; JY: Japanese yen.

predictive ability, it may still not offset the various forms of transaction cost. Second, many of the highly significant coefficients appear in the immediately preceding minute, $t-1$. It takes some minimum of time to react to news and to adjust one's market actions. If the change in an exchange rate from, say, 11.58 to 11.59 is partially predictable on the basis of exchange rates changes between 11.57 and 11.58, is it really valid to claim this as evidence of inefficiency? It might, however, indicate some role for programmed computer trading on the basis of very high frequency data. Third, the pattern of coefficients shows only limited stability in each currency equation from day to day. This can be observed even from the limited results shown in Table 12; apart from the continual significance of the deutsche mark (or Swiss franc in the deutsche mark equation), the set of other currencies whose lagged changes appear 'significant' varies somewhat from day to day. Fourth, the sum of the negative own coefficients on pound sterling on all three days, and on the ECU for September 15, amount to a figure more negative than -1; it is hard to make economic behavioural sense of that, and it may well imply some misspecification. Fifth the TRSQ statistic (though *not* the TRSQ1 statistic) rises to a high level, and is considerably above the values found in the simpler augmented Dickey–Fuller equations reported, *e.g.*, in Table 6; this may again suggest misspecification, and may have been due to our attempt to overcome multicollinearity by entering all other exchange rates in a form in which their per cent change is differenced from the per cent change in the dependent variable. A look, however, at the regression results where such constraints were *not* imposed, as in the runs partially reported in Table 11, reveals that the sum of the coefficients on the own lags of both pound sterling and ECU remains too negative (often < -1) to be behaviourally plausible. We have no explanation for this latter finding.

Even after all such qualifications have been made, there do remain some patterns in the results which suggest some shortfall from complete efficiency. Thus, if the deutsche mark moves away from most of the other currencies, there is a weak tendency for it to revert over the next minute or two. Generally, however, the regularity and 'explanatory' power of this equation was otherwise comparatively weak. For all other currencies there were clear and strong indications that any move away from the path of the deutsche mark would be partially reversed over the course of the next few minutes. This is our main finding here. It *does* suggest inefficiency in so far as traders in other currencies do not react quickly enough to the overriding pull of the deutsche mark. In the study by Goodhart and Giugale (1988) of hourly trading exactly the same source of inefficiency appeared in the case of the Swiss franc.

For the rest, we have already mentioned the oddly large negative own lag coefficients on pound sterling and ECU. Apart from the deutsche mark, there are some rather faint and variable signs of other currencies having 'pulling power,' in the sense that if currency X deviates from the path of currency Y, then currency X will revert towards that path. This is, perhaps, most apparent for the pound sterling, and somewhat less so for French franc and Swiss franc, but, even so, the force of such 'pulling power' is *much* smaller than that of the deutsche mark.

The main conclusion of this section is straightforward. Traders specializing in other currencies have been a bit slow to adjust their own currencies into line with the overriding power of the deutsche mark/US dollar exchange rate. In this respect the forex market has been, on the occasions observed here, inefficient.

VIII. The impact of 'news' on the forex market

Since the source of our forex data was Reuters, London office, it seemed sensible to try to relate movements in the exchange rates at this high frequency to Reuters 'news' announcements. Indeed at one time we thought that that might prove the main focus of the paper. In order to try to relate 'news' to exchange rate movements, we also obtained snapshots every quarter of an hour of Reuters AAMM file, the screen page reporting those news announcements thought most likely (by Reuters editors) to interest market (forex) traders, time-stamped to the nearest minute. We received the AAMM file for the full (London) day on September 14 and 15, but *not* for October 21.

As already noted, September 14 and 15 were rather quiet days in the forex market, but the days were not void of (economic) news. Yet it proved extraordinarily difficult to relate movements in the forex markets to such announcements, either prior, concurrently or immediately afterwards. We examined all the relevant series, *e.g.*, pound sterling in case of United Kingdom news, deutsche mark for the Federal Republic of Germany news, deutsche mark, pound sterling, and Japanese yen with United States news, both visually and by looking for much larger than average changes, 'jumps', in the data around the timing of the news release. There were no signs at all of sudden major jumps on the receipt of 'news.' There were a few cases that might have represented market reactions. The one that seemed the most likely candidate involved a depreciation in the Dutch guilder, which trended downwards starting almost five minutes after the reported tax cut there on September 15, with the trend then continuing for some ten minutes. Again there was some strengthening of the deutsche mark in the morning of September 15 about five minutes after Reuters news report of some rise in the Federal Republic of Germany's interest rates, and a strengthening in pound sterling, but *not* in the other currencies, shortly after the reported US quarterly current account deficit. For the rest, it was not possible for us to see any clear relationship between our news items on these two days and forex market reactions. It may well be that such news announcements as appeared gave reports that were largely in line with prior expectations, or were not regarded—for one reason or another—as important for this market. Certainly we were unfortunate in our choice of sample days in that no major, unforeseen news announcement was made. Our sample, in this case effectively of only two days, is clearly too small to throw much, if any, light on the nature of the relationship between 'news' and forex market reactions. A study of this relationship will be one of the primary exercises to be undertaken on our *much* larger continuous data set currently being assembled.

IX. Conclusions

We have examined minute-by-minute data for eight spot exchange rates for three European market days, which had been kindly provided to us by Reuters, United Kingdom, in London. There were a very few errors in keying the bid–ask quotes onto the screens. The spread between the bid and ask quote normally took one of a few, conventional round-number values. There was no sign of the spread widening in the more disturbed market conditions of October 21, but in some cases it differed from market to market. There is less lepto-kurtosis and heteroscedasticity at the minute by minute frequency than at lower frequencies, *e.g.*, one hour, one day. The lepto-kurtosis, skewness, and heteroscedasticity were all time varying, being more marked on October 21 than on the quieter days of September 14 and 15. Activity in forex markets varied markedly from hour to hour, being highest at the European and North American opening and lowest at the European lunch hour; it also varied by currency; as expected the deutsche mark was the most active, but the ranking in this sample of the French franc and ECU was higher than we had expected.

The series showed clear signs of first-order negative autocorrelation, with some series having also faint higher order negative autocorrelation. In earlier work on hourly data, such first-order correlation had been particularly pronounced following 'jumps' in the exchange rate. An examination of correlations around the occasion of a 'jump' suggests that there is abnormally high negative autocorrelation not just following a jump but also preceding it.

We examined the effect of time aggregation on the series, studying the series observed at five and ten minute intervals. Time aggregation appeared to diminish the first-order negative autocorrelation apparent in the minute by minute frequency, but there still remained considerable signs of negative autocorrelation, especially in the more disturbed markets on October 21. There appear to be two forms of such autocorrelation in operation, a short-lived ultra-high frequency form, possibly connected with the normal process of market readjustment to news flow, and a rather more persistent version which only occurred during periods of market disturbance.

We then explored the variance ratio of the series, comparing the variances at differing frequencies, following the approach of Poterba and Summers (1988). The existence of transitory movements, implying negative autocorrelation, at ultra high frequencies, was given further support. We did not, however, find any signs of more persistent, lower frequency, negative autocorrelation during the more disturbed conditions of October 21 than on September 15, rather the reverse.

When we studied multivariate relationships between exchange rate changes and lagged changes in both own and other currencies, we obtained startling good fits, with values of R^2 averaging 0.25. Even after a number of qualifications have been made, there does seem evidence of inefficiency, notably that traders in currencies other than the deutsche mark have taken insufficient notice of the 'pulling power' of the deutsche mark on their own currencies.

We had started this exercise hopeful that we could use Reuters data for news announcements, on their AAMM file, to relate such news to forex market movements. Apart from some signs of a depreciation in the Dutch guilder following a tax cut in their budget, there was little sign of any such relationship, but that may be mainly because on the two days for which we had the AAMM file there was little important, unanticipated news. We hope to be able to return to this latter topic in future research.

Appendix A

In our exercise in Section V, y_t and x_t in equation $\langle 1 \rangle$ are present and lagged returns (*i.e.*, differences of the logarithm) of exchange rates vs. the dollar of various currencies. Accordingly, $y_{t,k}$ and $x_{t,k}$ are present and lagged returns over k periods. The assumptions that we require in order to justify the use of Hansen's formulae are the following:

1. y_t is stationary and ergodic.
2. The best linear predictor is equivalent to the conditional expectation (this is, in the present instance, superfluous).
3. Letting $v_t = y_t - E(y_t/\Delta_{t-1})$ be the one-step-ahead forecast error for y_t using the information set Δ_{t-1}, generated by past values of y_t itself, we have:

$$E[v_t v_t^1/\Delta_{t-1}] = \Lambda,$$

a matrix of constants independent of the elements in Δ_{t-1}.

Under the above assumptions, Hansen demonstrates that $\sqrt{T}(\hat{\beta}_{k\ T} - \beta_k)$ converges in distribution to a normal random vector with mean zero and covariance matrix θ where T is the sample size, and $\hat{\beta}_{k,T}$ the OLS estimator of β_k. Here:

$$\theta = R_x(0)^{-1} C R_x(0)_{-1}$$

$$C = \sum_{-k+1}^{k-1} R_u(j) R_x(j)$$

with

$$R_u(j) = E(u_{t,k} u_{t+j,k})$$

and

$$R_x(j) = E(x_t' x_{t+j})$$

$R_u(j)$ and $R_x(j)$ are consistently estimated by:

$$\hat{R}_u^T(j) = 1/T \sum_{j+1}^{T} {}_t \, x_t' x_{t-j},$$

and

$$\hat{R}_x^T(j) = 1/T \sum_{j+1}^{T} {}_t \, \hat{u}_{t,k}^T \hat{u}_{t-j,k}^T,$$

where $\hat{u}_{t,k}^T$ is the OLS residual for observation t with sample size T.

Using the fact that $R_u(j) = R_u(-j)$ and $R_x(j) = R_x'(j)$, defining the 'explanatory' data matrix,

$$X_T = \begin{pmatrix} x_1 \\ \vdots \\ x_T \end{pmatrix},$$

and the $T \times T$ symmetric matrix $\hat{\Omega}_T$ whose lower triangular representation is:

$$\begin{bmatrix} \hat{R}_u^T(0) & & & & \\ \hat{R}_u^T(1) & & \hat{R}_u^T(0) & & \\ \vdots & \ddots & & \ddots & \\ \hat{R}_u^T(k-1) & \ddots & & \ddots & \\ 0 & & & & \\ \vdots & & & & \\ 0 & \dots\dots & 0 \; \hat{R}_u^T(k-1) & \dots\dots & \hat{R}_u^T(0) \end{bmatrix}$$

the required consistent estimator of θ is:

$$\hat{\theta}_T = T(X_T' X_T')^{-1} X_T' \hat{\Omega}_T X_T (X_T' X_T)^{-1}.$$

The diagonal elements of $\hat{\theta}_T$ are the required consistent asymptotic variance estimators of the OLS regression with overlapping observations corrected for serial correlation in the residuals.

Since we are also interested in performing tests of the hypothesis that $\beta_k = \beta_k^0$ $(\beta_k^0 = 0)$ in particular for the joint set of regression coefficients, from the asymptotic distribution theory of Hansen (1979) referred to above, we deduce that:

$$HH = T(\hat{\beta}_{kT} - \beta_k^0)' \hat{\theta}_T^{-1} (\hat{\beta}_{kT} - \beta_k^0)$$

is asymptotically χ^2 with l degrees of freedom.

Notes

1. Harris Bank, 'Foreign Exchange Weekly Review,' September 18, 1987, reported that, 'this week in foreign exchange many interbank traders were disappointed by the general lack of currency movement,' and 'the end result was a stalemate between the dollars bears and bulls.'
2. Harris Bank, 'Foreign Exchange Weekly Review,' October 23, 1987, noted that 'throughout the week the dollar continued to retrace its recent drop in often choppy trading.'
3. We were able to do this with the assistance of software developed by Philip Shearer in London.

4. After some early inspection and manipulation, a problem with the data became evident. In a few cases, *e.g.*, for pound sterling at 17:00 British Standard Time on the 14th, for the lira at 11:29 and 15:32 British Standard Time on September 15, there was an entry that implied an enormous change from previous levels that was 'corrected' in the next minute, or couple of minutes. It seemed implausible that a bank would really be prepared to trade at rates so out of line with the market, and much more likely that it represented an error, probably occurring in the process of keying the data onto the screen.

   Our, inevitably somewhat arbitrary, identification of such an error was a change in spot rate four times ($\times 4$) the standard deviation, which was then reversed in the next few minutes. So the filtering process adopted in order to deal with outliers (that might arise from incorrect basic observations in our data set) was first to identify all observations of changes (in the log of the level) more than four standard deviations from the average size. Then we arranged a program to select those cases where there was a *reverse* movement of broadly similar size (between $\frac{3}{4}$ and $1\frac{1}{2}$ times the original jump) in the following ten observations (minutes). In most cases where there was such a reversal, it came in the very next minute; but in some less frequently traded currencies (lira, guilder, Ecu), it was possible that errors might not be spotted and corrected for several minutes. Then, having identified potential cases of jumps and reversals caused by data error, we removed the original ('incorrect') observations and substituted a linear interpolation from the nearest 'true' observations on either side. We are aware that this procedure may lead to some slight artificial bias towards positive autocorrelation in the time series, but we would excuse that on two grounds.

   First, there are very few interpolated observations, rarely more than four per day per series. Those individual observations, which were interpolated, are available on request from the authors. Research workers can apply to us for copies either of the original series, or of the series as 'corrected' and used by us. We did not want simply to omit these data, since we needed continuous runs to test for various interrelationships.

   Second, one of our main findings, discussed in the text, is that the series of changes in the level of the logarithm of the spot market 'ask' quotations (approximately the series of per cent changes in the rate), from minute to minute exhibits low order negative autocorrelation. Although we are reasonably confident that such extreme outliers, where a 'jump' was immediately followed by a reversal, represented errors in variables, we are far less sure how far smaller reported changes may also represent errors in variables.
5. While the spreads were, indeed, mainly set at 5, 7, or 10 for the Netherlands guilder (NLG) on September 15 and October 21, 1987, for some unknown reason on September 14 there were no quotes of 7 at all. Instead there were a large number of quotes of 6 and 8. No attempt has been made to pursue this curious anomaly further.
6. See Phillips and Perron (1986), Phillips (1987a and 1987b) for a description of the tests; and Dickey (1976), Fuller (1976), Dickey and Fuller (1979), and Evans and Savin (1981, 1984) for a tabulation of the asymptotic distributions of the statistics involved. The procedure suggested by Newey and West (1987) has been used to obtain a positive definite autocorrelation consistent covariance matrix. Further details are available on request.
7. In general, on the quiet days (14 and 15), there was quite often a tendency for significant negative autocorrelation to persist for a further minute or two, and a tendency in a small number of these currency series for some subsequent positive autocorrelation around $t-10$ to $t-12$. This pattern, however, if it can be so called, was disturbed in the more volatile market of October 21. The size of the negative first-order coefficient tended to come down, and the frequency of observation of subsequent significant higher coefficients increases, in the more disturbed market conditions pertaining on this latter day.
8. The Akaike statistic is given by: $-2\log L+2p=AK$, where L is the likelihood function and p the number of paremeters in the model fitted under regularity conditions. The criterion can be shown to lead to an asymptotically correct model choice, by selecting the structure for which AK is a minimum. The values reported in our tables (available on request) are those of $AK1=-AK$ corresponding to various maximum lag orders and therefore the largest value should be chosen for every model (=number of lags included in the regression)/day/currency. The values of AK are rather unusual. This is due to the fact that the values of the log likelihood are comparatively large and this may well indicate some misspecification of the model class. Therefore, instead of relying entirely on the Akaike Information Criterion, we prefer to select the optimal lag by a combination of informal

assessment of the information provided by the three criteria. It would also be possible to use the t-tests in a multiple testing procedure as outlined in Savin (1984). In any case the instances where the optimal lag length may be greater than first order as shown below, with the possible higher order shown in parentheses.

14–9	15–9	21–10
DM($t-4$)	DM($t-2$)	DM($t-2$)
FF($t-2$)	GB($t-5$)	XE($t-5$)
XE($t-2$)	FF($t-2$)	
	NL($t-3$)	
	XE($t-2$)	

9. Our tests for heteroscedasticity are asymptotically equivalent to Lagrange multiplier tests and are based on running an auxiliary regression of the square of the residuals of our regression on appropriate functions of the explanatory variables (for 'classical' heteroscedasticity) or lagged values of the squared residuals (for autoregressive conditional heteroscedasticity ARCH).

   The former is the same as that proposed by White (1980). His test includes all the alternatives for which the least squares standard errors are biased.

   The heteroscedastic model includes all the squares and cross products of the data. That is, if the original model were $Y=\beta_0+\beta_1x_1+\beta_2x_2+\varepsilon$, the White test would consider x_1, x_2^2, x_1^2, x_2 and x_1x_2 as possible determinants of $\sigma^2=E(\varepsilon_t\varepsilon_t)$. It assumes the form of the TR^2 statistic for the regression of $\hat{u}^2$ ($\hat{u}$ residuals) on these variables plus an intercept, R^2 being the coefficient of determination and T the sample size. This is our TRSQ.

   TRSQ_1 is similarly computed as the $T.\ R^2$ of the regression of $\hat{u}_t^2$ on the lagged squared residuals (up to order 6), $\hat{u}_{t-1}^2, \ldots, \hat{u}_{t-6}^2$ and an intercept. The number of degrees of freedom in the resulting X^2 asymptotic distribution is given by the number of coefficients in the associated regression (including the intercept).

   Critical values at 5 per cent and 1 per cent level of significance (l.s) with 9/6 degrees of freedom (dg.f) are given below:

	0.05 l.s	0.01 l.s
TRSQ → 9 dg.f.:	16.919	21.666
	0.05 l.s	0.01 l.s
TRSQ → 6 dg.f.:	15.592	16.812

10. The N-tests were estimated as $T^{\frac{1}{2}}r(\tau)$ where T is the number of observations, and $r(\tau)$ sample autocorrelation, because under the null hypothesis of zero correlation among the returns the sample autocorrelations at any lag $\tau \neq 0$ will tend to be, in large samples, independently distributed, with a mean of zero and a variance of $1/T$. See Harvey (1979), p. 146.
11. See Appendix A for a description of the procedure that we employed.
12. This quantity can be computed noting, first, that Kendall and Stuart (1976) show that under weak restrictions, the expected value of the jth sample autocorrelation is $-1/(T-j)$, T being the sample size; and, second, that ⟨3⟩ can be very accurately approximated by:

$$\langle A\rangle \qquad VR(K) \simeq 1+2\sum_{1}^{k-1}{}_j\left(\frac{k-j}{k}\right)\hat{\rho}_j-2\sum_{1}^{9}{}_j\left(\frac{10-j}{10}\right)\hat{\rho}_j.$$

   The latter result is easily obtained using Cochrane's (1987) general result that the ratio of the k-period return variance to k single period return variance is approximately equal to a linear combination of sample autocorrelations. Similarly, using the result that the asymptotic variance at any lag of the serial correlation coefficient, under the null hypothesis of serial independence, is given by $1/T$ (see Harvey, 1979, p. 146) from equation (A) we can immediately derive the asymptotic variance (under the null) of the variance ratio statistic. The values reported in parentheses in Table 11 are the associated standard errors which are identical for all currencies on each day. A detailed Monte Carlo analysis of the behavior of the variance ratio statistic may be found in Lo and MacKinlay (1987).

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