On the Interdependence of International Asset Markets

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This chapter considers some possible volatility overspills on finely sampled asset market data. We review some recent work on both stock markets and foreign exchange rates and illustrate some of the ideas with hourly data on the foreign exchange market.

I. INTRODUCTION

Conventional wisdom, as affirmed by accounts in the media, is that global financial markets are becoming more integrated. The development of similar financial instruments in different major markets and the apparent increasing interdependence of the world macroeconomy are highly suggestive of this fact. Econometric work has attempted to examine the degree of interrelatedness; in particular, Dwyer and Hafer (1988) examine the degree of correlation between different stock market prices and Eun and Shim (1989) use analysis based on vector autoregressions (VARs) to identify the effects of shocks in different markets on other market indices. Interest in the degree of interdependence of the world's major asset markets was increased by the events occurring around the Great Crash of October 1987. Despite the apparent simultaneous downturn of the world's equity markets, Roll (1988, 1989), in his surveys of research on the Great Crash, notes that estimates of cross-correlations between the world's stock market indices are surprisingly low.

One apparent difficulty in dealing with the relationship between asset markets is that asset prices determined on speculative auction markets tend to exhibit martingale behavior, consistent with weak form efficiency (e.g., see Fama, 1965, 1970). Hence changes in asset prices are nearly uncorrelated with own past changes, while prices in levels are strongly determined by a unit root process. The
empirical finding by Rogers (1991) and others that innovations in different asset markets are relatively uncorrelated could be due to a variety of reasons. First, different stock market indices have a varying composition of common assets, implying that aggregate indices may not be particularly informative. Also, the full degree of information concerning linkages of returns is unlikely to be determined by examining the means of returns. As noted by Mandelbrot (1963), asset price changes tend to be non-Gaussian distributed and exhibit excess kurtosis. Furthermore, such price changes tend to have time-dependent heteroskedasticity, with sudden bursts of volatility followed by relatively tranquil periods. Although increases in volatility may be associated with sluggish price adjustments, a more reasonable explanation in this context is that the arrival of new information is lumpy or autocorrelated. This has led Stock (1987) to consider the notion of time deformation, where it may be more appropriate to record economic and financial data after a certain number of transactions have occurred rather than at regular intervals of calendar time. Lamoureux and Lastrapes (1990) note that persistence of volatility on futures options data is reduced once volume effects are introduced.

Following the initial work of Engle (1982), a large literature has developed on the presence of autoregressive conditional heteroskedasticity (ARCH) effects in asset price data. For example, Bollerslev (1987), French et al. (1987), Chou (1988), and Baillie and DeGennaro (1990) have documented such effects on stock returns; Engle et al. (1987) on interest rates; and Domowitz and Hakkio (1985), McCurdy and Morgan (1987), Hsieh (1988, 1989), and Baillie and Bollerslev (1989b) on exchange rates. Whereas own volatility effects and the persistence thereof are now well established, there has until recently been relatively little work on cross-effects between asset markets.

The plan of this chapter is as follows. After a brief description of volatility in single markets, we consider the motivation for examining cross-effects in both conditional means and conditional variances.

II. HOURLY EXCHANGE RATE DATA

In order to illustrate some of the preceding ideas on the nature of different asset markets, we now turn to an example based on nearly 7 months of hourly exchange rate data.

One of the attractions of the foreign exchange market is that, unlike the different stock exchanges and securities markets around the world, the foreign exchange market is virtually continually active with the same asset being traded in many different locations. Money market services (MMSs) have recorded the value of the spot exchange rate for the British pound (BP), the West German deutsche mark (DM), the Swiss franc (SW), and the Japanese yen (Yen) vis-à-vis the U.S. dollar on an hourly basis from 0:00 a.m. January 2, 1986 through 11:00 a.m. July 15, 1986, where local time is London, or Greenwich mean time. The data set consti-
tutes a total of 3191 trading hours and is taken from the average of the last five bid rates recorded each hour by the 50 largest banks in the foreign exchange market; for further details of the data see Goodhart and Giugale (1991). We denote the exchange rate for currency $i$ at day $t$ and hour $\tau$ by $s(i)_{t\tau}$, where $i =$ BP, DM, SF, Yen; $t = 1, 2, \ldots, 132$; and $\tau = 1, 2, \ldots, 24$. All rates are quoted as the amount of currency $i$ per U.S. dollar, with the exception of the BP, which is quoted as the number of U.S. dollars per BP.

Although the foreign exchange market is active 24 hours a day, the vast majority of trading is concentrated in the three major markets of London, New York, and Tokyo. Of these three markets, the New York and London markets are by far the largest in terms of total volume traded. The U.S. dollar, the BP, the DM, the SF, and the Yen are the most actively traded currencies on both markets. The Tokyo market remains relatively restricted. More than 90% of the Tokyo market deals in the Yen/U.S. dollar, but there is also some activity in the other currencies included in this study.

For the subsequent analysis we have divided the world into the three time zones of the Asian (A) market, which is defined as being open between hour 23 and hour 7, the European (E) market, which is open from hour 8 through 16; and the United States (U) market, which is open between hours 14 and 22.

As a preliminary data analysis, the results of applying the unit root tests of Phillips (1987) and Phillips and Perron (1988) to the logarithm of $s(i)_{t\tau}$, are given in Table 1. These tests require estimating the regressions

\begin{equation}
\log(s(i)_{t\tau}) = \bar{\mu}(i) + \beta(i)(t - T/2) + \alpha(i) \log(s(i)_{t\tau-1}) + \bar{\mu}(i)_{t\tau} \tag{1}
\end{equation}

\begin{equation}
\log(s(i)_{t\tau}) = \mu^*(i) + \alpha^*(i) \log(s(i)_{t\tau-1}) \log(s(i)_{t\tau-1}) + u^*(i)_{t\tau} \tag{2}
\end{equation}

\begin{equation}
\log(s(i)_{t\tau}) = \hat{\mu}(i) \log(s(i)_{t\tau-1}) + \hat{\mu}(i)_{t\tau} \tag{3}
\end{equation}

where $T$ denotes the overall sample size and $s(i)_{t\tau-24} = s(i)_{t\tau-1}$. Also, if the market was closed at hour $t, \tau - 1$ the first observation preceding hour $t, \tau$ for which the market was open was taken as observation $t, \tau - 1$.

| Table 1 Phillips–Perron Tests for a Unit Root* |
|-----------------|----------------|----------------|----------------|
|                 | BP             | DM             | SF             |
| $Z(t_u)$        | -2.799         | -2.129         | -2.505         | -1.950         |
| $Z(\Phi_u)$     | 3.122          | 2.460          | 2.724          | 2.039          |
| $Z(\alpha_u)$   | -1.620         | -1.469         | -1.100         | -0.985         |
| $Z(\bar{t})$    | 0.117          | -1.144         | -1.400         | -2.157         |

*Key: The 5% critical values for $Z(t_u)$, $Z(\Phi_u)$, $Z(\alpha_u)$, and $Z(\bar{t})$ are -3.41, 6.25, -2.86, and -1.95, respectively. A truncation lag of 24 and Newey–West type adjustment was used in the calculation of all the test statistics.
The innovations $u(i)\tau r$, $u*(i)\tau r$, and $u(i)\tau r$, are assumed to satisfy regularity conditions which ensure the existence of a nondegenerate asymptotic distribution for a suitably normalized function of their sums, as stated by Phillips (1987). The hypotheses to be tested from Eq. (1) are given by $H_{0a}^\bullet$: $\delta(i) = 1$ and $H_{0b}^\bullet$: $\delta(i) = 0$, which are tested by means of the modified test statistics $Z(t_0)$ and $Z(t_3)$, respectively. The null hypothesis $H_{0c}^\bullet$: $\alpha*(i) = 1$ on Eq. (2) and the null $H_{0c}^\bullet$: $\delta(i) = 1$ on Eq. (3) are tested by $Z(t_{2a})$ and $Z(t_3)$. All these test statistics involve long algebraic expressions and are omitted for reasons of space; their precise form is given in Perron (1988). In calculating each of the test statistics, a consistent estimate of the variances of the sum of the innovations is required. The results reported in Table 1 were computed using a Newey and West (1987) type of correction and a maximum lag of 24 hours, or one trading day. Very similar results were obtained for other lag lengths. From the table, it is apparent that the unit root hypothesis cannot be rejected for any of the four currencies. This is consistent with the analysis in Goodhart and Giugale (1991) and also in accord with the findings for daily and weekly exchange rates in Corbouc and Ouliaris (1986) and Baillie and Bollerslev (1989a).

Although all four series appear to contain a unit root in their univariate time series representations, it is possible that these roots are common among the series, so that they are cointegrated in the sense of Engle and Granger (1987). The techniques developed in Johansen (1988, 1989) provide a formal test for the number of such linearly independent cointegrating vectors, or stochastic trends, in the multivariate system. The procedure involves estimating two separate vector autoregressions of order $p - 1$, i.e., VAR $(p - 1)$, for the full four-dimensional vector of the logarithm of the exchange rates, say $Y_{cr} = (\log(s(BP)*), (\log(s(DM)*), \log(s(SF)*), \log(s(Yen)*))$. One VAR uses the differences of $Y_{cr}, \Delta Y_{cr}$, as the vector of dependent variables; the other uses $Y_{cr-p}, \Delta Y_{cr-p-1}, \ldots, \Delta Y_{cr-p}$, together with a vector of constants are the explanatory variables in both VARs. The Johansen test for at most $r$ linearly independent cointegrating vectors, or equivalently $4 - r$ common unit roots, in the full four-dimensional system, is then computed from the squared canonical correlations of the sample second-moment matrices from the two sets of VAR residual vectors (for a more detailed discussion, see Johansen, 1988, 1989). The results of implementing this procedure with a fourth-order VAR, i.e., $p = 4$, are given in Table 2. Hence the multivariate tests for cointegration indicate the appropriateness of dealing with each of the hourly exchange rates over this 6-month period on a univariate basis.

This result is particularly intriguing because it is contrary to the analysis reported in Baillie and Bollerslev (1989a), who on analyzing 1245 daily exchange rates over a longer 6-year period found evidence of one cointegrating factor in a system of seven exchange rates vis-à-vis the U.S. dollar. However, as illustrated by Shiller and Perron (1985), for univariate tests of unit roots the power is more closely related to the sampling interval as opposed to the number of observations, which equals the length of the sampling interval times the sampling frequency;
Table 2  Johansen Trace Test for the Presence of 
$\rho$ Linearly Independent Cointegrating Vectors
(4 - $\rho$ Common Unit Roots)*

<table>
<thead>
<tr>
<th>$r$</th>
<th>$-2 \log Q_r$</th>
<th>95% quantile</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>0.768</td>
<td>3.962</td>
</tr>
<tr>
<td>2</td>
<td>9.035</td>
<td>15.197</td>
</tr>
<tr>
<td>1</td>
<td>18.146</td>
<td>29.509</td>
</tr>
<tr>
<td>0</td>
<td>36.088</td>
<td>47.181</td>
</tr>
</tbody>
</table>

*Key: The Johansen trace statistic $-2 \log Q_r$ is calculated from the squared canonical correlations of the sample second-moment matrices from two sets of VAR residuals:

$$\Delta Y_{t,r} = c + \sum_{j=1}^{\rho} \Phi_j \Delta Y_{t-r,j} + \varepsilon_t$$

$$Y_{t-r,p} = c + \sum_{j=1}^{\rho} \Phi_j \Delta Y_{t-r,j} + \varepsilon_t'$$

hence with only 133 daily observations the difference might be due to lack of power.

In light of the foregoing unit root tests, subsequent analysis in this study will only consider the first differences for each of the four exchange rates,

$$y(t)_{it} = 100[\log(s(t)_{it}) - \log(s(t)_{it-1})]$$

(4)

It should be noted that $y(t)_{it}$ is approximately equal to the percentage nominal return in currency $i$ obtained from an investment from time $t, t-1$ to $t, t$.

III. MODELING TIME-VARYING VOLATILITY

Given the unit root test results discussed in Section II, the hourly return on each exchange rate can be represented as a martingale with the addition of an MA(1) term to account for slight autocorrelation, which is probably due to the data being averages of the last five bid rates. Following Baillie and Bollerslev (1989b), Hsieh (1989), and Baillie and DeGennaro (1990) a reasonable model to account for the second-moment properties of the hourly returns data is the linear GARCH (1,1) process, which was originally developed by Bollerslev (1986). The full model is then

$$y_{it} = \mu + \epsilon_{it} + \theta \epsilon_{it-1}$$

(5)

$$\epsilon_{it} \mid \Omega_{it-1} \sim N(0, \sigma_{it}^2)$$

(6)

$$\sigma_{it}^2 = \omega + \alpha \epsilon_{it-1}^2 + \beta \sigma_{it-1}^2$$

(7)
Table 3

\[ Y_{t+1} = \mu + \epsilon_{t+1} + \theta \epsilon_{t}, \]
\[ \epsilon_{t}|\Omega_{t-1} \sim N(0, \sigma_{\epsilon}^2) \]
\[ \sigma_{\epsilon}^2 = \omega + \alpha \epsilon_{t-1}^2 + \beta \sigma_{\epsilon,t-1}^2 \]

<table>
<thead>
<tr>
<th></th>
<th>BP</th>
<th>DM</th>
<th>SF</th>
<th>Yen</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \mu )</td>
<td>.001</td>
<td>.032</td>
<td>.023</td>
<td>.057</td>
</tr>
<tr>
<td>( \theta )</td>
<td>-.028</td>
<td>.022</td>
<td>-.057</td>
<td>-.046</td>
</tr>
<tr>
<td>( \omega )</td>
<td>1.141</td>
<td>.1027</td>
<td>.785</td>
<td>1.800</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>-.213</td>
<td>.182</td>
<td>.266</td>
<td>.174</td>
</tr>
<tr>
<td>( \beta )</td>
<td>.475</td>
<td>.539</td>
<td>.529</td>
<td>.395</td>
</tr>
</tbody>
</table>

Skewness    : -.19, .19, -.18, .12
Kurtosis    : 8.80, 10.99, 13.63, 8.65
\( Q(20) \)  : 34.61, 16.23, 25.65, 14.38
\( Q(10) \)  : 32.07, 22.94, 23.61, 33.20

The results of estimating this model on each of the four exchange rate returns series by approximate maximum likelihood estimation based on the Berndt et al. (1974) algorithm are given in Table 3. As in studies of daily exchange rate series, there is evidence of substantial persistence in the time-varying volatility, with \( \alpha + \beta \) estimated between .57 and .78 for the four currencies. The estimated moving average coefficient appears small but significant and could be due to the averaging of the data or to a small time-varying risk premium. However, there is evidence of extreme kurtosis in the data, which is sufficiently large to cast doubt on the validity of standard inferential procedures. In particular, Bollerslev and Wooldridge (1992) show that this may cause particular problems when conducting inference on parameters in the conditional variance equation of the model. One possible solution to the problem is to estimate the model based on a non-Gaussian conditional density, such as the Student \( t \), which Bollerslev (1987) and Baillie and Bollerslev (1989b) found to be particularly useful in describing daily exchange rate data. However, attempts to use this model on hourly data generally gave rise to an estimated degree-of-freedom parameter of under 4, which implies an undefined or infinite kurtosis. Full details of these results are available from the authors on request. An alternative and probably more reasonable approach in the presence of such extreme kurtosis is to estimate the model given by Eqs. (5) through (8) assuming conditional normality and then to adjust the standard errors of the parameter estimator using robust inference which allows for departures from normality. This technique can be described as quasi-maximum likelihood estimation (QMLE) and the results of applying these methods to the same hourly exchange rate series are given in Baillie and Bollerslev (1991), who also extend Eq. (7) by allowing the intercept \( \omega \) to vary across the different hours of the day and allow the lagged squared innovation 24 hours previously, \( \epsilon_{t-1,t}^2 \), to enter the equation. These changes introduce an element of daily seasonality within the volatility.
IV. INTERACTIONS BETWEEN VOLATILITY

Many studies have found contemporaneous movements between different asset prices. Also, Bollerslev (1986) and Baillie (1989) have found daily exchange rates and daily commodity prices, respectively, to possess one cointegrating vector so that the levels of prices appear tied together in one long-run equilibrium relationship. However, little evidence has appeared for lagged innovations to Granger cause the change in asset prices in other markets.

However, evidence has emerged for volatility to be autocorrelated within its own market and also to be cross-correlated with volatility in other asset markets. In particular, the autocorrelation in the conditional second moments of each of the four currencies (i.e., GARCH effects) is consistent with the “meteor shower” and “heat wave” hypotheses in the terminology of Engle et al. (1990). According to the meteor shower hypothesis, news about the same currency is transmitted through time and different market locations as the globe turns on its axis, whereas in the heat wave hypothesis news is country or market specific.

Baillie and Bollerslev (1991) also find the inclusion of a holiday dummy in the conditional variance equation to be significant for all four currencies. If the amount of new information that accumulates is proportional to the length of time that the market is closed, then volatility should be approximately 38 times greater following vacations compared with the average volatility across the day, 38 being the average hourly length of a vacation in the sample. The effects as measured by the estimated vacation dummy are all much smaller, which is consistent with the notion of information as essentially a private phenomenon, with market participants acting on their own acquisition of new information. This is also consistent with the idea of “self-generating” trading suggested by French and Roll (1986). Baillie and Bollerslev (1991) also failed to find evidence of market inefficiencies, such as the lagged mean returns, or lagged conditional standard deviation in one currency Granger causing returns in another currency. This particular absence of GARCH in mean effects suggests that news in one market, which causes volatility, is rapidly incorporated into the mean of the other currencies. Hence increased volatility due to news is uninformative one hour later about the returns on all other currencies. Also, Baillie and Bollerslev (1991) find no evidence of causal relationships between the variances; there was no consistent pattern of lagged squared innovations (residuals) causing volatility in other markets. All these tests were computed by robust Lagrange multiplier tests. Hence no causal pattern of volatility spillovers were found.

Although the results of Engle et al. (1990) and Baillie and Bollerslev (1991) are suggestive of the relative efficiency of exchange rates, evidence on the equity market is mixed. The same type of hourly variation in stock returns as in exchange rates has been documented by Foster and Viswanathan (1988) and Wood et al. (1985) and is consistent with a segmented market of informed and liquidity traders, as developed by Admati and Pfleiderer (1988). French et al. (1987), Chou
(1988), and Baillie and DeGennaro (1990) have all documented their own GARCH effects and persistence of volatility on stock returns, although there has been some controversy about the validity of the simple market model, where volatility affects own returns.

V. SUMMARY AND CONCLUSIONS

The example used in this study consisted of hourly exchange rates, which possessed the typical asset price property of following a martingale. The fact that the rates did not appear to be cointegrated was probably due to the historical length of data, an aspect of unit root tests noted by Shiller and Perron (1985). If a set of exchange rates or asset prices is cointegrated while individually possessing the martingale property, it would appear that weak form efficiency might be violated. That is, from the Granger representation theorem, discussed by Engle and Granger (1987), a single equation of a VAR on the change in the exchange rates would look like

\[
\Delta \varepsilon_{tr} = z_{tr-1} + \varepsilon_{te}
\]

where \( z_{tr-1} \) is a linear combination of the levels of the exchange rates in the previous time period; it is known as the cointegrating vector or error correction term and is an I(0) process. For the right-hand side of Eq. (8) to be white noise, complicated restrictions of the individual exchange rates are required. Otherwise an apparent violation of weak form efficiency might occur. This aspect of cointegration and efficiency appears to deserve further investigation because cointegration of spot exchange rates and cash commodity prices has been noted by Baillie and Bollerslev (1989b) and Baillie (1989), respectively.

The further interdependence between asset prices concerns the links between their conditional variances. It seems reasonable for volatility to vary across time and space, so that volatility in one asset market moves contemporaneously or leads the volatility of other assets, possibly at different spatial locations. These effects are probably due to the processing and transmission of economic news and are frequently related to changes in the patterns of trading volume. Engle et al. (1990) have introduced the terminology of heat waves and meteor showers to describe these temporal and spatial patterns of volatility.

The presence of autocorrelated volatility does not necessarily have any implications for the possible efficiency of a financial market. Only where mean returns are dependent or Granger caused by lagged conditional standard deviation does efficiency become an issue. In the case of hourly exchange rates, Baillie and Bollerslev (1991) fail to find evidence of conditional standard deviations Granger causing mean returns. However, as noted previously, the effects in equity markets are mixed; Hamao et al. (1990) found possible volatility spillovers with volatility on the U.S. market index appearing to provide useful information on mean returns.
in Tokyo the following day. Further work on individual assets would be desirable to examine this hypothesis in more detail.

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References


