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Asymmetric volatility transmission in international stock markets

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The transmission mechanism of price and volatility spillovers across the New York, Tokyo and London stock markets is investigated. The asymmetric impact of good news (market advances) and bad news (market declines) on volatility transmission is described by an extended multivariate Exponential Generalized Autoregressive Conditionally Heteroskedastic (EGARCH) model. Using daily open-to-close returns, we find strong evidence that volatility spillovers in a given market are much more pronounced when the news arriving from the last market to trade is bad. A before and after October 1987 crash analysis reveals that the linkages and interactions among the three markets have increased substantially in the post-crash era, suggesting that national markets have grown more interdependent. (JEL C15).

It is fairly well established that stock traders in a given market incorporate into their 'buy' and 'sell' decisions not only information generated domestically but also information produced by other stock markets. Such behavior is consistent with the efficient markets hypothesis, provided that news generated by international stock markets is relevant for the pricing of domestic securities. This is the result of the increased globalization of financial markets, brought about by the relatively free flow of goods and capital as well as the revolution in information technology. Understanding the ways in which stock markets interact permits investors to carry out hedging and trading strategies more successfully. Likewise, regulatory proposals can be properly evaluated when linkages and interactions across national stock markets are taken into account.

Most of the research effort so far has focused on the interdependence and interaction of major stock markets in terms of the conditional first moments of

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the distribution of returns. For example, Koch and Koch (1991) use a dynamic simultaneous equations model to investigate the evolution of contemporaneous and lead/lag relationships among eight national stock markets. Their results point to a growing regional interdependence over time and to an increasing influence of the Tokyo market at the expense of the New York market. Becket *et al.* (1990) use regression analysis to study the intertemporal relation of the US and the Japanese stock markets. Their results show that information generated in the US market could be used to trade profitably in Japan, contrary to the market efficiency hypothesis. However, when transaction costs and transfer taxes are included into the analysis, excess profits vanish. Eun and Shim (1989) study the transmission of stock market movements using VAR methods. They document dynamic responses to innovations that are generally consistent with the notion of informationally efficient international stock markets. King and Wadhwani (1990) provide support for the hypothesis of 'contagion' effects in the three major markets. In such a setting, 'mistakes' in one market can be transmitted to other markets.[1]

More recent research explores stock market interactions in terms of both first and second moments. The list of such studies is rapidly growing, but the following sample serves to illustrate the extant literature. To wit, Hamao *et al.* (1990) examine price spillovers (*i.e.* first-moment interdependencies) and volatility spillovers (*i.e.* second-moment interdependencies) in the three major stock markets (New York, Tokyo, and London) using univariate GARCH models. For the period after the October 1987 worldwide stock market crash, they find volatility spillovers from New York to Tokyo, London to Tokyo, and New York to London. In contrast, no such spillovers are found in the pre-crash period. Hamao *et al.* (1991) test for structural changes and non-stochastic time trends in the spillover mechanism. They find that the spillover effect from the Japanese market to the US market has increased steadily over time. Lin *et al.* (1991) use a signal extraction model with GARCH processes to study the interaction of the US and the Japanese stock markets. Their findings suggest that price and volatility spillovers are generally reciprocal, in the sense that the two markets influence each other. Theodossiou and Lee (1993), using a multivariate GARCH-M model, find that the US market is the major 'exporter' of volatility. Ng *et al.* (1991) provide evidence on volatility spillovers in the stock markets of the Pacific-Basin. Finally, Susmel and Engle (1994) examine price and volatility spillovers between New York and London using hourly returns. They conclude that these spillovers are, at best, small and of short duration.

Despite the extensive investigation of the linkages and interactions of major stock markets, no attempt has been made to investigate the possibility that the quantity of news (*i.e.* the size of an innovation), as well as the quality (*i.e.* the sign of an innovation) may be important determinants of the degree of volatility spillovers across markets.[2] Studies dealing with the US market, however, suggest that such a possibility is very likely. For example, Black (1976) finds that current returns and future volatility are negatively related. Christie (1982) finds that this negative relationships is to a large part due to the leverage effect, *i.e.* a reduction in stock prices automatically produces a higher debt to equity ratio and hence higher volatility.

Nelson (1991) develops the exponential GARCH model (EGARCH) in an attempt to capture the asymmetric impact of shocks on volatility. His findings confirm that, for the US market, negative innovations increase volatility more than positive ones. Cheung and Ng (1992) find a significant leverage effect in a sample of individual stocks that persists even after conditioning on past volume. In terms of foreign stocks markets, Koutmos (1992) finds a significant leverage effect in the stock returns of Canada, France and Japan, as do Poon and Taylor (1992) for the UK. The evidence that volatility in the US and other stock markets is responding asymmetrically to own past innovations suggests that volatility spillovers themselves may be asymmetric, in the sense that negative innovations in a given market produce a higher volatility spillover in the next market to trade, than do positive innovations of an equal magnitude.

This paper contributes to the ongoing debate about stock market interactions by providing new evidence on price and volatility spillovers across the three major stock markets, *i.e.* New York, Tokyo and London. Unlike most previous research in this area, this paper explicitly models potential asymmetrics that may exist in the volatility transmission mechanism. The method employed is a multivariate extension of Nelson's (1991) univariate EGARCH model. Modeling the returns of the three markets simultaneously has several advantages over the univariate approach that has been used so far. First, it eliminates the two-step procedure, thereby avoiding problems associated with estimated regressors. Second, it improves the efficiency and the power of the tests for cross market spillovers. Third, it is methodologically consistent with the notion that spillovers are essentially manifestations of the impact of global news on any given market. The multivariate EGARCH model is ideally suited to test the possibility of asymmetries in the volatility transmission mechanism because it allows own market and cross market innovations to exert an asymmetric impact on the volatility in a given market. In other words, news generated in one market is evaluated in terms of both size and sign by the next market to trade.

A competing model that also allows volatility to respond asymmetrically to innovations is the Quadratic GARCH model proposed by Engle (1990) and used by Campbell and Hentschel (1992). However, on the basis of several diagnostics, Engle and Ng (1993) find that the EGARCH model performs better than the Quadratic GARCH model because the latter tends to underpredict volatility associated with negative innovations. An additional advantage of the EGARCH model is that no parameter restrictions are required to insure positive variances at all times. This is important because Hamao *et al.* (1990) report that some of the coefficients in the conditional variance specification violate the non-negativity assumption.

The remainder of this paper is organized as follows: Section I discusses the methodology; Section II describes the data and analyzes the empirical findings for the entire sample period, as well as the pre-crash and the post-crash periods; Section III offers a summary and concluding remarks.

I. The multivariate EGARCH model

The New York and Tokyo stock markets open and close sequentially, as do the Tokyo and London markets. There is therefore, no overlap in the daily open-to-close returns of these two market pairs. Between New York and London, however, there is approximately a two hour overlap (*i.e.* late trading in London corresponds to early trading in New York). Nevertheless, to simplify the analysis we assume that all three markets open and close sequentially but we discuss possible biases resulting from the two-hour overlap between New York and London in Section III. Non-overlapping trading implies that the estimation of the means and variances in each market is conditional on own past information as well as information generated by the last two markets to close.

Let $R_{i,t}$ be the open-to-close return at time t for market i, ($i = 1,2,3$ where, $1 =$ New York, $2 =$ London and $3 =$ Tokyo), I_{t-1} the information set at time $t-1$, $\mu_{i,t}$ and $\sigma_{i,t}^2$ the conditional mean and the conditional variance respectively, $\sigma_{i,j,t}$ the conditional covariance, $\epsilon_{i,t}$ the innovation at time t (*i.e.* $\epsilon_{i,t} = R_{i,t} - \mu_{i,t}$) and $z_{i,t}$ the standardized innovation (*i.e.* $z_{i,t} = \epsilon_{i,t}/\sigma_{i,t}$). Then, the multivariate EGARCH model used to describe price and volatility spillovers across markets may be written as follows:

$$\langle 1 \rangle \qquad R_{i,t} = \beta_{i,0} + \sum_{j=1}^{3} \beta_{i,j}\epsilon_{j,t-1} + \epsilon_{i,t}, \quad \text{for } i,j = 1,2,3;$$

$$\langle 2 \rangle \qquad \sigma_{i,t}^2 = \exp\left\{ \alpha_{i,0} + \sum_{j=1}^{3} \alpha_{i,j} f_j(z_{j,t-1}) + \gamma_i \ln\left(\sigma_{i,t-1}^2\right) \right\}, \text{ for } i,j = 1,2,3;$$

$$\langle 3 \rangle \qquad f_j(z_{j,t-1}) = \left(|z_{j,t-1}| - E\left(|z_{j,t-1}|\right) + \delta_j z_{j,t-1}\right), \quad \text{for } j = 1,2,3;$$

$$\langle 4 \rangle \qquad \sigma_{i,j,t} = \rho_{i,j}\, \sigma_{i,t}\, \sigma_{j,t}, \quad \text{for } i,j = 1,2,3 \text{ and } i \neq j.$$

The time subscripts in equations $\langle 1 \rangle$–$\langle 4 \rangle$ correspond directly to trading time but not necessarily to calendar time. For example, if $i =$ New York, the information set for traders in New York at the opening of the market in a given day includes past New York innovations as well as innovations from London and Tokyo during the same day. In terms of trading time all this is past information (*i.e.* part of the information set $I_{i,t-1}$). However, in terms of calender time innovations in Tokyo and London are contemporaneous.

Equation $\langle 1 \rangle$ describes the open-to-close returns of the three markets as a vector moving average (VMA), whereby the conditional mean in each market is influenced by own past innovations as well as innovations coming from the two markets to close. The term $\beta_{i,j}\epsilon_{j,t-1}$ for $i = j$ in $\langle 1 \rangle$ allows for autocorrelation in the returns due to non-synchronous trading (*e.g.* Hamao *et al.*, 1990; French *et al.*, 1987), even though the use of value weighted indices should minimize this problem.

Innovations in market j enter the information set of traders in market i. Take, for example, the Tokyo market, which opens after the closing of the New York and London markets. To the extent that innovations coming from these two markets are useful for the evaluation of domestic securities (*i.e.* reflect global information), they will be exploited by traders in Tokyo so that the domestic closing price incorporates its own as well as cross market information. The same can be said to be true of the other two markets. Coefficients $\beta_{i,j}$, for $i \neq j$, then measure the extent of price spillover across markets.

The conditional variance process given by ⟨2⟩ follows an extended EGARCH process that allows its own lagged standardized innovations as well as cross market standardized innovations to exert an asymmetric impact on the volatility of market i. Asymmetry is modeled by equation ⟨3⟩, with the partial derivatives being

$$\langle 5\rangle \qquad \partial f_j(z_{j,t})/\partial z_{j,t} = 1 + \delta_j \text{ for } z_j > 0 \text{ and,}$$
$$\partial f_j(z_{j,t})/\partial z_{j,t} = -1 + \delta_j \text{ for } z_j < 0.$$

Asymmetry is present if δ_j is negative and statistically significant. The term $|z_{j,t}| - E(|z_{j,t}|)$ measures the size effect and $\delta_j z_{j,t}$ measures the corresponding sign effect. If δ_j is negative, a negative $z_{j,t}$ tends to reinforce the size effect, whereas a positive $z_{j,t}$ tends to partially offset it. This phenomenon has been attributed to the aforementioned leverage effect. The relative importance of the asymmetry, or leverage effect, can be measured by the ratio $|-1+\delta_j|/(1+\delta)$. Volatility spillovers across markets are measured by $\alpha_{i,j}$ for $i,j = 1,2,3$ and $i \neq j$. A significant positive $\alpha_{i,j}$ coupled with a negative δ_j implies that negative innovations in market j have a higher impact on the volatility of market i than positive innovations, *i.e.* the volatility spillover mechanism is asymmetric.

The conditional covariance specification in ⟨4⟩ assumes constant correlation coefficients along the lines suggested in Bollerslev (1990). This assumption significantly reduces the number of parameters to be estimated. Its validity of course must be assessed empirically. Some caution should be exercised when interpreting these cross market correlation coefficients. This is because the returns are not contemporaneous in trading time. Thus, they cannot be interpreted as measuring contemporaneous relationships. Instead they should be interpreted as measuring intraday lead/lag relationships.

The persistence of volatility implied by equation ⟨2⟩ is measured by γ_i. The unconditional variance is finite if $\gamma_i < 1$ (see Nelson, 1991). If $\gamma_i = 1$, then the unconditional variance does not exist and the conditional variance follows an integrated process of order one. As noted by Hsieh (1989), the exponential specification is less likely to produce integrated variances.

Assuming the conditional joint distribution of the returns of the three markets is normal, the log likelihood for the multivariate EGARCH model can be written as

$$\langle 6\rangle \qquad L(\Theta) = -(1/2)(NT)\ln(2\pi) - (1/2)\sum_{t=1}^{T}\left(\ln|S_t| + \epsilon_t' S_t^{-1} \epsilon_t\right),$$

where N is the number of equations, T is the number of observations, Θ is the 33×1 parameter vector to be estimated, $\epsilon_t' = [\epsilon_{1,t}\ \epsilon_{2,t}\ \epsilon_{3,t}]$ is the 1×3 vector of innovations at time t, S_t is the 3×3 time varying conditional variance–covariance matrix with diagonal elements given by equation ⟨2⟩ for $i = 1,2,3$ and cross diagonal elements are given by equation ⟨4⟩ for $i,j = 1,2,3$ and $i \neq j$. The log-likelihood function is highly non-linear in Θ, and, therefore, numerical maximization techniques have to be used. We use the Berndt *et al.* (1974) algorithm, which utilizes numerical derivatives to maximize $L(\Theta)$.

II. Empirical findings

II.A. Data, preliminary statistics and univariate analysis

Data used in this paper are the daily opening and closing figures for the aggregate stock price indices of the US, UK and the Japanese stock markets. The indices used are the S&P 500 for the USA, obtained from Tick Data Inc., the Financial Times 100 Share Index (FTSE-100) for the UK, obtained from Commodity Systems Inc. (CSI) and the Nikkei 225 Stock Index for Japan also obtained from CSI. The S&P 500 and the FTSE-100 are value weighted indices representing approximately 76 and 70 percent of total market capitalization, respectively. The Nikkei 225 is a price weighted index and it represents approximately 52 percent of total market capitalization. Hamao *et al.* (1990) provide a useful description of these indices. The daily open-to-close returns for each index are the continuously compounded percentage returns calculated as $R_{i,t} = 100^* \log(P_{i,\text{close},t}/P_{i,\text{open},t})$. To assess the size of the bias introduced by the two-hour overlap between London and New York, we also calculate the noon-to-close return for the S&P 500. The period under examination extends from September 3, 1986 to December 1, 1993. The number of observations across markets is 1,700, which is less than the total number of observations because joint modeling of three markets requires matching returns.

Table 1 reports summary statistics for the daily returns of the three markets as well as statistics testing for normality and independence. The sample means for all three markets are not statistically different from zero. The measures for skewness and excess kurtosis show that all return series are negatively skewed and highly leptokurtic with respect to the normal distribution. Likewise, the Kolmogorov–Smirnov statistic rejects normality for each of the return series at the 5 percent level of significance, a level that is used throughout this paper. The Ljung–Box statistic for up to 12 lags, calculated for both the return and the squared return series, indicate the presence of significant linear and non-linear dependencies, respectively, in the returns of all three markets. Linear dependencies may be due either to non-synchronous trading of the stocks that make up each index (see Scholes and Williams, 1977; Lo and MacKinley, 1988) or to some form of market inefficiency. Non-linear dependencies may be due to autoregressive conditional heteroskedasticity, as documented by several recent studies for both US and foreign stock returns (*e.g.* Nelson, 1991; Akgiray, 1989; Booth *et al.*, 1992, among others).

We first estimate the model given by equations ⟨1⟩–⟨4⟩ by restricting all cross-market coefficients, measuring price and volatility spillovers, as well as

TABLE 1. Preliminary statistics. Daily open-to-close stock returns.
Period: 9/3/86 to 12/01/93 (1,700 days).

	Tokyo	London	New York
Sample mean (μ)	−0.0387	0.0179	−0.0006
Standard deviation (σ)	1.3848	0.7332	1.0874
Skewness (S)	−0.5124*	−0.4407*	−5.9507*
Excess kurtosis (K)	16.7012*	5.3353*	115.9237*
Kolmogorov–Smirnov (D)	0.0456*	0.0906*	0.0626*
LB(12)	19.2985*	43.7211*	70.9938*
$LB^2(12)$	89.9047*	208.9816*	51.0496

* Denotes significance at the .05 level at least. All returns are expressed in percentages. The test statistic for skewness and excess kurtosis is the conventional t-statistic. LB(n) and $LB^2(n)$ is the Ljung–Box statistic for returns and squared returns respectively distributed as χ^2 with n degrees of freedom. The critical value at the .05 level is 21.026 for 12 lags. The assumed density for the Kolomogorov–Smirnov statistic is the normal; sample critical value at the .05 level is 0.032.

the correlation coefficients to be zero. This restriction reduces the multivariate model to three univariate EGARCH models. The restricted model is used as the benchmark model, and its estimates are presented in Table 2. The moving average coefficients, $\beta_{i,i}$, are statistically significant for the Japanese and the UK markets, indicating that either non-synchronous trading or market inefficiency induces autocorrelation in the return series. For the US market $\beta_{i,i}$ is insignificant. Conditional heteroskedasticity is perhaps the single most important property describing the short-term dynamics of all three markets. The conditional variance is a function of past innovations and past conditional variances. The relevant coefficients $\alpha_{i,i}$ and γ_i are statistically significant. The leverage effect, or asymmetric impact of past innovations on current volatility, is significant in all instances lending support to our assertion that volatility spillovers may also be asymmetric. The degree of asymmetry, on the basis of the estimated δ_i coefficients, is highest for the Japanese market (negative innovations increase volatility approximately 4.34 times more than positive innovations), followed by the UK market (approximately 3.27 times) and the US market (approximately 2.14 times). Volatility persistence, measured by γ_i, is highest for New York, followed by London and Tokyo.[3] The hypothesis that the return series are homoskedastic (*i.e.* $\alpha_{i,i} = \delta_i = \gamma_i = 0$) is rejected at any sensible level of significance on the basis of the likelihood ratio test. The estimated Ljung–Box statistics for the standardized and the squared standardized residuals show that the benchmark EGARCH model successfully accounts for all linear and non-linear dependencies present in the return series. On the basis of the Kolmogorov–Smirnov statistic, the hypothesis of univariate normality is rejected for the US and the UK return series. Rejection of univariate normality, however, does not preclude multivariate normality of the joint distribution of returns.

TABLE 2. Results from benchmark EGARCH.
Full sample period: 9/3/86 to 12/01/93 (1,700 days).

	Tokyo		London		New York
$\beta_{3,0}$	00048	$\beta_{2,0}$	0.0228	$\beta_{1,0}$	−0.0011
	(0.0223)		(0.0166)		(0.0213)
$\beta_{3,3}$	0.0549	$\beta_{2,2}$	−0.0855	$\beta_{1,1}$	0.0110
	(0.0244)*		(0.0284)*		(0.0313)
$\alpha_{3,0}$	0.0301	$\alpha_{2,0}$	−0.0385	$\alpha_{1,0}$	0.0141
	(0.0072)*		(0.0093)*		(0.0031)*
$\alpha_{3,3}$	0.3811	$\alpha_{2,2}$	0.1526	$\alpha_{1,1}$	0.2305
	(0.0125)		(0.0176)*		(0.0208)*
δ_3	−0.6256	δ_2	−0.3637	δ_1	−0.5314
	(0.0466)*		(0.0973)*		(0.0794)*
γ_3	0.9267	γ_2	0.9355	γ_1	0.9535
	(0.0073)*		(0.0133)*		(0.0057)*

Log-likelihood = −6,624.12, LR(9) = 1,541.08* (H_0: $\alpha_{i,j} = \delta_i = \gamma_i = 0$ for $i = 1,2,3$.)

Diagnostics on standardized residuals

	Tokyo	London	New York
D	0.0296	0.0384*	0.0364*
LB(12)	18.4949	16.1858	12.3609
$LB^2(12)$	4.6693	10.4229	3.5153

* Denotes significance at the .05 level at least. Numbers in parentheses are standard errors. LR(9) is the likelihood ratio statistic distributed as $\chi^2_{(9)}$. The .05 critical value is 16.191. LB(n) is the Ljung–Box statistic for the standardized residuals distributed as $\chi^2_{(n)}$ (see Table 1 notes). $LB^2(n)$ is the Ljung–Box statistic for the squared standardized residuals distributed as $\chi^2_{(n-j)}$, where j is number of own EGARCH parameters (two in this case); thus, the .05 critical value is 18.037 for 12 lags. D is the Kolmogorov–Smirnov statistic testing for normality. Sample critical value at the .05 level is 0.032.

II.B. Price and volatility spillovers

The maximum likelihood estimates of the multivariate model with no parameter restrictions are reported in Table 3. The full model considers both price and volatility spillovers from the last two markets to close to the next market to trade.[4] In terms of first moment interdependencies, there are significant price spillovers from New York to Tokyo as well as from Tokyo and New York to London. Despite the two hour overlap, there is no significant price spillover from London to New York. This is because the correlation coefficients $\rho_{1,2}$ accounts for most of the overlap effect. When we re-estimate the model using noon to close returns for the US market, the value of $\rho_{1,2}$ drops from 0.3748 to 0.1772. The rest of the coefficients, however, are not materially altered. Thus, the impact of the overlap is to almost double the correlation coefficient. Since the pairwise correlations are not the focus of our study, we continue the analysis using US open-to-close returns.[5]

Turning to second moment interdependencies (volatility spillovers), it can be seen from Table 3 that these are far more extensive and reciprocal. In addition to own past innovations, the conditional variance in each market is also affected by innovations coming from the last two markets to close. Thus, there are significant volatility spillovers from New York and London to Tokyo, from Tokyo and New York to London and from London and Tokyo to New York.[6] More importantly, the volatility transmission mechanism is asymmetric in all instances. The coefficients measuring asymmetry, δ_i are significant for all three

TABLE 3. Multivariate EGARCH model. Price and volatility spillovers.
Full sample period: 9/3/86 to 12/01/93 (1,700 days).

From New York ($\beta_{3,1}$, $\alpha_{3,1}$) & London ($\beta_{3,2}$, $\alpha_{3,2}$) to Tokyo		From Tokyo ($\beta_{2,3}$, $\alpha_{2,3}$) & New York ($\beta_{2,1}$, $\alpha_{2,1}$) to London		From London ($\beta_{1,2}$, $\alpha_{1,2}$) & Tokyo ($\beta_{1,3}$, $\alpha_{1,3}$) to New York	
$\beta_{3,0}$	0.0695 (0.0104)*	$\beta_{2,0}$	0.0382 (0.0144)*	$\beta_{1,0}$	0.0249 (0.0182)
$\beta_{3,1}$	0.1519 (0.0249)*	$\beta_{2,1}$	−0.0400 (0.0184)*	$\beta_{1,1}$	0.0204 (0.0258)
$\beta_{3,2}$	0.0562 (0.0339)	$\beta_{2,2}$	−0.0815 (0.0249)*	$\beta_{1,2}$	−0.0529 (0.6724)
$\beta_{3,3}$	0.0422 (0.0247)*	$\beta_{2,3}$	−0.0858 (0.0358)*	$\beta_{1,3}$	0.0736 (0.0270)
$\alpha_{3,0}$	0.0605 (0.0042)*	$\alpha_{2,0}$	−0.0116 (0.0051)*	$\alpha_{1,0}$	0.0314 (0.0029)*
$\alpha_{3,1}$	0.0890 (0.0122)*	$\alpha_{2,1}$	0.0521 (0.0106)*	$\alpha_{1,1}$	0.1118 (0.0130)*
$\alpha_{3,2}$	0.0764 (0.0194)*	$\alpha_{2,2}$	0.0951 (0.0140)*	$\alpha_{1,2}$	0.1440 (0.0138)*
$\alpha_{3,3}$	0.2407 (0.0172)*	$\alpha_{2,3}$	0.0767 (0.0105)*	$\alpha_{1,3}$	0.0249 (0.0106)*
δ_3	−0.5121 (0.0557)*	δ_2	−0.2545 (0.0797)*	δ_1	−0.4447 (0.1077)*
γ_3	0.9676 (0.0050)*	γ_2	0.9756 (0.0049)*	γ_1	0.9834 (0.0047)*
		Correlation coefficients			
$\rho_{1,3}$	0.0407 (0.0417)	$\rho_{2,3}$	0.2305 (0.0526)*	$\rho_{1,2}$	0.3748 (0.0498)*
Log-likelihood = −6,306.44, LR(15) = 636.36* (H_0; $\alpha_{i,j} = \delta_j = \gamma_j = \rho_{i,j} = 0$ for $i,j = 1,2,3$.)					
		Diagnostics on standardized and cross standardized residuals			
D	0.0296		0.0305		0.0248
LB(12)	12.8428		11.9184		7.1424
$LB^2(12)$	5.0891		12.5879		6.5658
$LB^a(12)$	8.2562		7.3230		8.4049

* Denotes significance at the .05 level at least. Numbers in parentheses are standard errors. LR(15) is the likelihood ratio statistic distributed at $\chi^2_{(15)}$. The .05 critical value is 24.996. LB(n) and $LB^2(n)$ are the Ljung–Box statistics for the standardized and the squared standardized residuals respectively. $LB^a(12)$ is the Ljung–Box Statistic for the cross product of the standardized residuals *i.e.* $z_{i,t}$ $z_{j,t}$. See also Table 1 and Table 2 notes.

markets. This finding confirms our assertion that both the size of the innovations are important determinants of volatility spillovers.

The extent to which negative news (innovations) in one market increase volatility more than positive news in the next market to trade can be assessed using the estimated coefficients. Thus, a negative innovation in (i) New York, (ii) London, (iii) Tokyo increases volatility in the other two markets by (i) 2.6, (ii) 1.68, (iii) 3.12 times more than a positive innovation.[7] The final impact of an innovation from market i on the conditional variance of market j is determined by the size of $\alpha_{i,j}$ and δ_j (see equations ⟨2⟩ and ⟨3⟩). On the basis of these estimates we calculate the impact of a $\pm 5\%$ innovation in market i on the conditional variance of market j assuming all other innovations are zero.[8] The results are given in Table 4. As expected, the impact of an innovation in market i is mostly felt in the next market to trade. The impact is still felt in the following market to open but it is typically reduced. For example, a -5% ($+5\%$) innovation in New York increases volatility by 0.6414% (0.2471%) in Tokyo and by 0.3763% (0.1446%) in London the next day. Similarly, a -5% ($+5\%$) innovation in Tokyo increases volatility by 0.5798% (0.1870%) in London and by 0.1882% (0.0607) in New York the same day.

Comparing the estimates of the benchmark model to those of the unrestricted model (*i.e.* Tables 2 and 3, respectively), we can see that the degree of asymmetry implied by the benchmark model is invariably higher. This is because the benchmark model does not take into account volatility spillovers from the other markets. Also, the parameters measuring volatility persistence γ_i are much closer to unity than the estimates of the benchmark model. In fact, simple t-tests fail to reject the hypothesis that there is a unit root in the conditional variances of the three stock markets (*i.e.* $\gamma_i = 1$ for $i = 1,2,3$). Thus, current innovations remain important for all future forecasts of the conditional variance.

We use the likelihood ratio statistic to test the hypothesis that price and volatility spillovers from the last two markets to close to the next market to trade are jointly zero (*i.e.* the benchmark versus the unrestricted model). The null hypothesis is rejected at any plausible level of significance. The existence of first and second moment interdependencies points to the presence of a global marketplace, whereby news affecting asset pricing are not purely domes-

TABLE 4. Impact of innovations on volatility.

Innovations	%Δ in New York volatility	%Δ in London volatility	%Δ in Tokyo volatility
+5% New York		0.1446	0.2471
−5% New York		0.3763	0.6415
+5% London	0.5367		0.2848
−5% London	0.9032		0.4792
+5% Tokyo	0.0607	0.1870	
−5% Tokyo	0.1882	0.5798	

tic in nature but, to a considerable extent, international. In this respect our findings support the 'meteor shower hypothesis' of Engle *et al.* (1990) who find that in foreign exchange markets news follows a process like a meteor shower hitting the earth as it revolves. The impact of such a process is manifested in the form of volatility spillovers from one market to the next.

Residual based diagnostic tests show that the multivariate EGARCH model satisfactorily explains the interaction of the three major stock markets. The Ljung–Box statistics show no evidence of linear and non-linear dependence in the standardized residuals. The validity of the assumption of constant conditional correlations can be assessed by testing for serial correlation in the cross product of the standardized residuals. The Ljung–Box statistics up to 12 lags show no evidence of serial correlation. Moreover, on the basis of the Kolmogorov–Smirnov statistic, conditional multivariate normality is not rejected.

II.C. Pre- and post-crash analysis

Bollerslev *et al.* (1992) suggest that the asymmetric response of volatility to innovations may be the result of a few extreme observations such as those associated with the October 1987 crash. To investigate this possibility, as well as possible changes in the nature of price and volatility spillovers in the period following the 1987 crash, we estimate the unrestricted model for the pre- and post-crash periods.

The results for the unrestricted model for the pre-crash period are reported in Table 5. There is evidence of price spillovers from New York to Tokyo and London. There is also evidence of volatility spillovers from London to New York. These spillovers are symmetric since the coefficient measuring asymmetry for the London market is insignificant. There are no significant spillovers from Tokyo to either London or New York. Conditional volatility of the returns in New York and Tokyo respond asymmetrically to own past innovations but there is no evidence of asymmetric volatility transmission in any direction. These findings suggest that market interactions were limited in the pre-crash period with the New York market being the major producer of information. Nevertheless, these results should be interpreted carefully because of the small size of the pre-crash period.

The picture changes substantially when we look at the estimates of the model for the post-crash period, which are reported in Table 6. The interactions now are very similar to those documented for the entire period. In all three markets the leverage effect is significant. There are significant price spillovers from New York to Tokyo and London, from Tokyo to London and New York and from London to New York. In terms of second moment interactions, there are significant asymmetric volatility spillovers from New York to Tokyo, from London to New York, and from Tokyo to both London and New York.

A comparison of the results from the pre- and post-crash period reveals that national markets have grown more interdependent in the sense that information affecting asset prices has become more global in nature. The New York and London markets have become more sensitive to news originating in Tokyo

TABLE 5. Multivariate EGARCH model. Price and volatility spillovers.
Pre-crash period: 9/3/86 to 9/3/87 (257 days).

From New York ($\beta_{3,1}$, $\alpha_{3,1}$) & London ($\beta_{3,2}$, $\alpha_{3,2}$) to Tokyo		From Tokyo ($\beta_{2,3}$, $\alpha_{2,3}$) & New York ($\beta_{2,1}$, $\alpha_{2,1}$) to London		From London ($\beta_{1,2}$, $\alpha_{1,2}$) & Tokyo ($\beta_{1,3}$, $\alpha_{1,3}$) to New York	
$\beta_{3,0}$	0.0959 (0.0650)	$\beta_{2,0}$	0.1051 (0.0458)*	$\beta_{1,0}$	0.0681 (0.0633)
$\beta_{3,1}$	0.2436 (0.0548)*	$\beta_{2,1}$	−0.0312 (0.0522)*	$\beta_{1,1}$	0.0906 (0.0573)
$\beta_{3,2}$	0.0897 (0.0918)	$\beta_{2,2}$	−0.0186 (0.0688)	$\beta_{1,2}$	−0.0157 (0.1858)
$\beta_{3,3}$	0.0627 (0.0711)	$\beta_{2,3}$	−0.1657 (0.2276)	$\beta_{1,3}$	0.1154 (0.1162)
$\alpha_{3,0}$	−0.0426 (0.0169)*	$\alpha_{2,0}$	−0.2296 (0.0340)*	$\alpha_{1,0}$	−0.0179 (0.0091)*
$\alpha_{3,1}$	0.0004 (0.0147)	$\alpha_{2,1}$	−0.0001 (0.0047)	$\alpha_{1,1}$	0.1241 (0.0465)*
$\alpha_{3,2}$	−0.0236 (0.0885)	$\alpha_{2,2}$	0.0674 (0.0314)*	$\alpha_{1,2}$	−0.0184 (0.0438)*
$\alpha_{3,3}$	0.1474 (0.0701)*	$\alpha_{2,3}$	−0.0023 (0.0169)	$\alpha_{1,3}$	−0.0479 (0.0344)
δ_3	−0.1107 (0.0538)*	δ_2	−0.2352 (0.7247)	δ_1	−0.5699 (0.2157)*
γ_3	−0.9287 (0.0339)*	γ_2	0.6553 (0.0498)*	γ_1	0.9703 (0.0117)*
		Correlation coefficients			
$\rho_{1,3}$	−0.0554 (0.1479)	$\rho_{2,3}$	0.2518 (0.2722)	$\rho_{1,2}$	0.2948 (0.1558)
		Diagnostics on standardized and cross standardized residuals			
D	0.0275		0.0413		0.0280
LB(12)	13.2479		8.2737		13.5966
$LB^2(12)$	14.2138		17.5794		7.6513
$LB^a(12)$	7.7435		8.2186		8.0665

* Denotes significance at the .05 level at least. Numbers in parentheses are standard errors. Sample critical value for D at the .05 level is 0.082. See also Table 3 notes.

in agreement with the findings of Hamao *et al.* (1991). Most striking is the finding that the volatility transmission mechanism is asymmetric in the sense the bad news (market declines) in one market has a greater impact on the volatility of the next market to trade.

III. Summary and concluding remarks

This paper investigates the dynamic interaction of the three major stock markets, *i.e.* Tokyo, London and New York. Price and volatility spillovers are

TABLE 6. Multivariate EGARCH model. Price and volatility spillovers. Post-crash period: 11/2/87 to 12/01/93 (1,424 days).

From New York ($\beta_{3,1}$, $\alpha_{3,1}$) & London ($\beta_{3,2}$, $\alpha_{3,2}$) to Tokyo		From Tokyo ($\beta_{2,3}$, $\alpha_{2,3}$) & New York ($\beta_{2,1}$, $\alpha_{2,1}$) to London		From London ($\beta_{1,2}$, $\alpha_{1,2}$) & Tokyo ($\beta_{1,3}$, $\alpha_{1,3}$) to New York	
$\beta_{3,0}$	−0.0241 (0.0188)	$\beta_{2,0}$	0.0290 (0.1515)	$\beta_{1,0}$	0.0197 (0.0199)
$\beta_{3,1}$	0.1447 (0.0268)*	$\beta_{2,1}$	−0.0456 (0.0187)*	$\beta_{1,1}$	0.0235 (0.0249)
$\beta_{3,2}$	0.0244 (0.0371)	$\beta_{2,2}$	−0.0712 (0.0272)*	$\beta_{1,2}$	−0.2634 (0.1075)*
$\beta_{3,3}$	0.0382 (0.0289)	$\beta_{2,3}$	0.1222 (0.0329)*	$\beta_{1,3}$	0.0769 (0.0300)*
$\alpha_{3,0}$	0.0540 (0.0048)*	$\alpha_{2,0}$	−0.0092 (0.0032)*	$\alpha_{1,0}$	−0.0844 (0.0187)*
$\alpha_{3,1}$	0.0834 (0.0223)*	$\alpha_{2,1}$	0.0157 (0.0093)	$\alpha_{1,1}$	0.0402 (0.0107)*
$\alpha_{3,2}$	0.0051 (0.0197)	$\alpha_{2,2}$	0.0521 (0.0105)*	$\alpha_{1,2}$	0.0629 (0.0098)*
$\alpha_{3,3}$	0.2061 (0.0212)*	$\alpha_{2,3}$	0.0583 (0.0091)*	$\alpha_{1,3}$	0.0356 (0.0071)*
δ_3	−0.6336 (0.0707)*	δ_2	−0.4776 (0.1493)*	δ_1	−0.5301 (0.1791)*
γ_3	0.9728 (0.0046)*	γ_2	0.9851 (0.0036)*	γ_1	0.9927 (0.0051)*
		Correlation coefficients			
$\rho_{1,3}$	0.0111 (0.0542)	$\rho_{2,3}$	−0.0951 (0.0577)	$\rho_{1,2}$	0.5182 (0.0637)*
		Diagnostics on standardized and cross standardized residuals			
D	0.0309		0.0329		0.0244
LB(12)	14.9328		12.0051		7.8428
$LB^2(12)$	5.0891		12.5879		6.5658
$LB^a(12)$	8.2122		13.8560		9.6631

* Denotes significance at the .05 level at least. Numbers in parentheses are standard errors. Sample critical value for D at the .05 level is 0.035. See also Table 3 notes.

examined in the context of an extended multivariate Exponential Generalized Autoregressive Conditionally Heteroskedastic (EGARCH) model. Unlike previous related studies, this paper fully takes into account potential asymmetries that may exist in the volatility transmission mechanism, *i.e.* the possibility that bad news in a given market has a greater impact on the volatility of the returns in the next market to trade. We find evidence of price spillovers from New York to Tokyo and London, and from Tokyo to London. More extensive and reciprocal, however, are the second moment interactions. We document significant volatility spillovers from New York to London and Tokyo, from London to New York and Tokyo and from Tokyo to London and New York. In all instances the volatility transmission mechanism is asymmetric, *i.e.* negative innovations in a given market increase volatility in the next market to trade considerably more than positive innovations. These findings suggest that stock markets are sensitive to news originating in other markets, especially when the news is adverse. A pre- and post-crash analysis reveals that the stock markets in New York and London have become more sensitive to innovations originating in Tokyo.

Notes

1. Several other studies provide empirical evidence on first-moment (mean) interactions among national stock markets, *e.g.* Von Furstenberg and Jeon (1989), Becker *et al.* (1992), and Bennet and Kelleher (1988).
2. Susmel and Engle (1994) allow for a leverage effect in their univariate GARCH representation, but this effect is not linked to the volatility transmission mechanism. A related study by Kroner and Ng (1991) shows that bad news from portfolios of large firms spills over to portfolios of small firms, but not vice versa.
3. For the US market, the univariate results are very similar when noon-to-close returns are used.
4. 'Price spillover' is the impact of an innovation from market i on the conditional mean of market j, whereas 'volatility spillover' is the impact of an innovation from market i on the conditional variance of market j.
5. The results of the multivariate model that uses noon-to-close returns for the US are available from the authors upon request.
6. Related studies report fewer volatility spillovers across markets, *e.g.* Hamao *et al.* (1990, 1991) and Susmel and Engle (1994). Some of the differences can undoubtedly be attributed to different sample periods. This paper employs a much larger data set covering a six-year post-crash period. Differences can also be attributed to different methodologies since all of the aforementioned studies use univariate ARCH type models. Koch and Koch (1991) use a simultaneous equation approach but they do not examine volatility spillovers.
7. These figures also measure the differential impact of own past innovation on the current conditional variance of any given market.
8. From a theoretical point of view, an additional assumption is required namely that the persistence coefficients γ_i are unity. From Table 3 it can be seen that all persistence coefficients are very close to unity.

References

Akgiray, V., 'Conditional heteroskedasticity in time series of stock returns: evidence and forecasts,' *Journal of Business*, January 1989, **62**: 55–80.

Becker, K.G., J.E. Finnerty and M. Gupta, 'The intertemporal relation between the U.S. and Japanese stock markets,' *Journal of Finance*, September 1990, **45**: 1297–1306.

Becker, K.G., J.E. Finnerty and A.L. Tucker, 'The intraday interdependence between U.S. and Japanese equity markets,' *Journal of Financial Research*, Spring 1992, **15**: 27–37.

Bennett, P. and J. Kelleher, 'The international transmission of stock price disruption in October 1987,' *Federal Reserve Bank of New York Quarterly Review*, Summer 1988, 17–33.

BERNDT, E.K., H.B. HALL, R.E. HALL AND J. A. HAUSMAN, 'Estimation and inference in nonlinear structural models,' *Annals of Economic and Social Measurement*, 1974, **4**: 653–666.

BLACK, F., 'Studies of stock market volatility changes,' *Proceedings of the American Statistical Association, Business and Economics Studies Section*, 1976, 177–181.

BOLLERSLEV, T., 'Modelling the coherence in short-run nominal exchange rates: a multivariate generalized ARCH model,' *The Review of Economics and Statistics*, August 1990, **72**: 498–505.

BOLLERSLEV, T., R.Y. CHOU AND K.F. KRONER, 'ARCH modeling in finance: a review of the theory and empirical evidence,' *Journal of Econometrics*, April/May 1992, **52**: 5–59.

BOOTH, G.G., J. HATEM, I. VITRANEN AND P. YLI-OLLI, 'Stochastic modeling of security returns: evidence from the Helsinki stock exchange,' *European Journal of Operational Research*, January 1992, **56**: 98–106.

CAMPBELL, J.Y. AND L. HENTSCHEL, 'No news is good news: an asymmetric model of changing volatility in stock returns,' *Journal of Financial Economics*, June 1992, **31**: 281–318.

CHEUNG, Y.-W. AND L.K. NG, 'Stock price dynamics and firm size: an empirical investigation,' *Journal of Finance*, December 1992, **47**: 1985–1997.

CHRISTIE, A.A., 'The stochastic behavior of common stock variances: value, leverage and interest rate effects,' *Journal of Financial Economics,* 1982, **10**: 407–432.

ENGLE, R.F., 'Discussion: stock volatility and the crash of '87,' *Review of Financial Studies*, 1990, **3**: 103–106.

ENGLE, R.F., T. ITO AND W.-L. LIN, 'Meteor showers or heat waves? Heteroskedastic intra-daily volatility in the foreign exchange market,' *Econometrica*, 1990, **58**: 525–542.

ENGLE, R.F. AND V.K. NG, 'Measuring and testing the impact of news on volatility,' *Journal of Finance*, December 1993, **48**: 1749–1778.

EUN, C.S. AND S. SHIM, 'International transmission of stock market movements', *Journal of Financial and Quantitative Analysis*, June 1989, **24**: 241–256.

FRENCH, K.R., G.W. SCHWERT AND R.F. STAMBAUGH, 'Expected stock returns and volatility,' *Journal of Financial Economics*, September 1987, **19**: 3–29.

HAMAO, Y.R., R.W. MASULIS AND V.K. NG, 'Correlation in price changes and volatility across international stock markets,' *The Review of Financial Studies,* 1990, **3**: 281–307.

HAMAO, Y.R., R.W. MASULIS AND V.K. NG, 'The effect of the 1987 stock crash on international financial integration,' in Ziemba, W.T., W. Bailey and Y.R. Hamao, eds, *Japanese Financial Market Research*, Elsevier Science Publishers B.V., 1991: 483–502.

HSIEH, D., 'Modeling heteroskedasticity in daily foreign exchange rates,' *Journal of Business and Economics Statistics*, July 1989, **7**: 307–317.

KING, M.A. AND S. WADHWANI, 'Transmission of volatility between stock markets,' *The Review of Financial Studies*, 1990, **3**: 5–33.

KOCH, P.D. AND T.W. KOCH, 'Evolution in dynamic linkages across daily national stock indexes,' *Journal of International Money and Finance*, June 1991, **10**: 231–251.

KOUTMOS, G., 'Asymmetric volatility and risk return tradeoff in foreign stock markets,' *Journal of Multinational Financial Management*, 1992, **2**: 27–43.

KRONER, K.F. AND V.K. NG, 'Modelling the time-varying comovement of asset returns,' Unpublished manuscript, Department of Economics, University of Arizona, 1991.

LIN, W.L., R.F. ENGLE AND T. ITO, 'Do bulls and bears move across borders? International transmission of stock returns and volatility as the world burns,' *National Bureau of Economic Research*, 1991, Working Paper No. 3911.

LO, ANDREW, W. AND A.C. MACKINLEY, 'Stock market prices do not follow random walks,' *Review of Financial Studies*, 1988, **1**: 41–66.

NELSON, D., 'Conditional heteroskedasticity in asset returns: a new approach,' *Econometrica*, March 1991, **59**: 347–370.

NG, V.K., P.R. CHANG AND R.Y. CHOU, 'An examination of the behavior of Pacific-Basin stock market volatility,' in Ghon, R. and R.P. Chang, eds, *Pacific-Basin Capital Markets Research*, Elsevier Science Publishers BV, 1991: 245–260.

POON, S-H. AND S.J. TAYLOR, 'Stock returns and volatility: an empirical study of the U.K. stock market,' *Journal of Banking and Finance*, February 1992, **16**: 37–59.

SCHOLES, M. AND J. WILLIAMS, 'Estimating betas from nonsynchronous data,' *Journal of Financial Economics*, 1977, **5**: 309–327.

SUSMEL, R. AND R.F. ENGLE, 'Hourly volatility spillovers between international equity markets,' *Journal of International Money and Finance*, February 1994, **13**: 3–25.

THEODOSSIOU, P. AND U. LEE, 'Mean and volatility spillovers across major national stock markets: further empirical evidence,' *Journal of Financial Research*, Winter 1993, **16**: 337–350.

VON FURSTENBERG, G.M. AND B.N. JEON, 'International stock price movements: links and messages,' *Brookings Papers on Economic Activity*, 1989, **1**: 125–179.