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Price, Volume and Volatility Spillovers among New York, Tokyo and London Stock Markets

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The dynamic relationship among the U.S., Japan and U.K. daily stock market return volatility and trading volume is examined using a multivariate generalized autoregressive conditional heteroskedastic (GARCH) model. Significant return spillovers from New York and Tokyo to London, and from New York, London to Tokyo and from Tokyo to New York has been found. Volatility spillover seems to be far more extensive and reciprocal. A comparison of the results from the before and after October 1987 crash period reveals that national markets have grown more interdependent in the sense that information affecting asset prices has become more global in nature.

I. INTRODUCTION

Finance theory predicts that there are potential gains from international portfolio diversification if returns from investments in various national stock markets are not perfectly correlated and the correlation structure is stable. It appears that previous empirical studies of the interrelationship of the major world stock price indexes have not provided consistent results. The sizes and signs of correlation coefficients varied depending on the choice of markets, the sample period chosen, the frequency of observations (daily, weekly, or monthly), and the different methodologies employed to estimate the matrix of correlation coefficients.

Jaffe and Westerfield [16] suggest that the return correlation among different markets is positive and significant. Eun and Shim [10], who use vector autoregressions, find substantial cross-country interactions and also record an influential role for the U.S. market. King and Walhwani [19], in a significant study of the period surrounding the 1987 crash, document a "contagion effects" where a "mistake" in one market is transmitted to other markets.

Hamao, Masulis, and Ng [12] use an ARCH model to examine the linkage among the New York, Tokyo and London Stock markets. They find evidence of price volatility spillovers from New York to Tokyo, London to Tokyo, and New York to London but find no evidence of spillover effects in

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other directions for the period prior to the 1987 crash. Hamao, Masulis, and Ng [12], extend their previous study, and find volatility spillover effects of disproportionate size from one market to the next and these patterns have been relatively stable both prior to and after the crash. They find, however, some weak evidence of increasing volatility spillovers from the Tokyo market to other markets, which supports the growing importance of the Japanese market during this period.

To study the relationship between the New York and London stock markets, Susmel and Engle [24] use hourly data to estimate a modified ARCH model. While they find no evidence of mean spillovers if no overlapping periods are included, they do note some weak evidence of volatility spillovers.

Lin, Engle, and Ito [21], using a signal extraction model with GARCH processes, find that Tokyo (New York) daytime returns are, in general, significantly correlated with New York (Tokyo) overnight returns. They also observe that except for a lagged return spillover from New York to Tokyo for the period after the crash, there are no significant lagged spillovers in returns or volatility.

As evidenced by the studies referenced above since the stock market crash of October 1987, there has been substantial interest in research on why stock returns and volatility are interdependent across world markets. Two possible interpretations for such interdependence of stock returns and volatility are informational link hypothesis and contagion hypothesis. According to the informational link hypothesis, news revealed in one country is perceived as informative to fundamentals of stock prices in another. The interdependence can be attributed to real and financial linkage of economies. Market contagion hypothesis suggests that stock prices in one country be affected by changes in another country beyond what is conceivable by connections through economic fundamentals. According to this view, overreaction, speculation, and/or noise trading are transmissible across borders. The liquidity needs of uninformed traders in New York trigger selling pressure on NYSE, resulting in high volume. Subsequently, uninformed traders in Tokyo, observing a drop in New York stock prices, may increase selling pressure on the Tokyo stock exchange. In this scenario, correlation in international stock returns is caused by the contagious behavior of liquidity traders across borders. As in King and Wadhwanis' article [19], trading volume can be a proxy for a time-varying contagious coefficient.

Recently, some theoretical studies explicitly investigate the dynamic relationship among trading volume, stock returns and volatility. Blume, Easley, and O'Hara [2] present a model in which traders can learn valuable information about a security by observing both past price and past volume information. In their model, volume provides data on the quality or precision of information about past price movements, and thus traders who include volume measures in their technical analysis may be expected to perform better in the market than those who do not. Wang [27] analyzes dynamic relationships between volume and returns based on a model with information asymmetry. His model shows that volume may provide information about expected future returns. For this paper, the focus is on trading volume because authors' beliefs in this paper reflect the view that trading volume is a good proxy for the degree of heterogeneity in investors' opinions and beliefs. Most studies reported a positive relationship between volatility and trading volume in the domestic stock market. According to the mixture-of-distribution hypothesis (see for example Clark [4] and Tauchen and Pitts [25], this positive relationship is often attributed to the rate of information, which drives both volatility and volume. Lamoraux and Lastrapes [22] use this framework to test whether there are any GARCH effects remaining after the conditional volatility specification expands to include the contemporaneous trading volume, a proxy for information arrival. They find that for individual stocks, volatility persistence falls significantly once contemporaneous trading volume is included.

The principal objective of this study is to disentangle the two possible interpretations by examining the effect of trading volume on inter-market dependence on stock returns. First, if correlation between international stock returns is caused by international contagion of liquidity traders' sentiments or by resolution of heterogeneous interpretations of foreign news, such correlation will be positively influenced by foreign trading volume. Second, if international return interdependence is associated with the information containing in stock price changes in one market to another market, these interdependence are likely to be positively influenced by foreign price volatility but not by foreign trading volume. The use of trading volume allows for the assessment of the two possible channels of international transmission of international stock return and volatility by examining the causal relationship among the correlation of international stock returns, trading volume, and volatility.

In this paper, the dynamic relationship among the U.S., Japan and U.K. daily stock market return volatility and trading volume is examined using a multivariate generalized autoregressive conditional heteroskedastic (GARCH) model. The vultivariate GARCH model uses information from the history of more than one market. According to Conrad, Gultekin, and Kaul [5], multivariate models provide more precise estimates of the parameters because they utilize information in entire variance-covariance matrix of the errors. The remainder of the paper is organized as follows: Section 2 discusses data. Methodology is presented in Section 3. Section 4 reports the empirical results and Section 5 concludes the paper.

II. DATA

The data set comprises *daily* market price index and trading volume series for the three largest stock exchanges: New York, Tokyo and London. For the New York Stock Exchange, we use the NYSE composite index. The data cover the period of January 2, 1970 - December 30, 1995, and consist of 6,568 observations for each series. For the Tokyo Stock Exchange, we use the Nikkei 225 Index, which is taken from the PACAP database of the University of Rhode Island, is using. The TSE data cover the period of January 4, 1975, to December 30, 1995, and consists of 5,696 observations. For London, we use the FT-SE 100 index. The index covers the period of January 4, 1984, December 30, 1995, and consists of 3,023 observations for each variable.

The NYSE composite index includes all common stocks traded on the NYSE and is weighted by its market value. The index is a measure of the changes in the aggregate market value of NYSE common stocks, adjusted to eliminate the effect of capitalization changes, new listings and delistings. The Nikkei 225 Index is a share-price weighted index like the Dow Jones average in the U.S. (as simple averages of the component stocks' prices adjusted by a divisor to account for non-market factors, rights, and changes to the constituent issues). First published in 1950, the Index comprises 225 of the largest capitalized stocks on the First Section of the Tokyo Stock Exchange and represents roughly 65 percent of the total market capitalization for the Tokyo Stock Exchange.[3] The FT-SE 100 index, was started on January 3, 1984, by the Stock Exchange (SE) and Financial Times (FT), incorporating the top 100 U.K. companies, accounting for about 70 percent of the total market value of all U.K. equities. It shows a very close historical correlation with most broad index of the market. FT-SE 100 is calculated as a weighted-average index. Base value is 1000 at the opening of business on January 3, 1984. The FT-SE100 data is obtained from the Datastream database.

In recent years there has been a proliferation of empirical studies documenting anomalous seasonal regularities in security returns. These include calendar effects related to the time of day [Harris [13]]; the day of the week [French [11], Jeffe and Westerfield [15], Keim and Stambaugh [18]]; the turn of month [Ariel [1]]; and the turn of the year [Lakonishok and Smidt [20]]. These patterns appear to conflict with the theoretical notions of efficiency and rational expectations in the market for securities.

We employ a three-step procedures developed by Gallant, Rossi, and Tauchen [23] to adjust for seasonal regularities. Then, we use these adjusted data to test for the robustness of the dynamic relations. In step one, the original stock return series on dummy variables for day of the week (one for each day from Tuesday through Friday), dummy variables for pre-holiday, dummy variables for turn-of-the year, and dummy variables for turn of the month. This is the location regression that adjusts for documented shifts in mean due to seasonal tendencies. If y is the series to be adjusted and x contains the adjustment regressors, the location regression is

$$y_t = x_t'\beta + u_t . \tag{1}$$

Denoting the residuals from the location regression by u_t, the second step involves performing the variance regression by regressing $log(u_t^2)$ on the same set of adjustment variables used in the location regression:

$$\log(u_t^2) = X_t'\gamma + \varepsilon_t. \tag{2}$$

This regression makes adjustments for seasonal regularities in the variance.

Denoting the predicted value from the variance equation by $\hat{\theta}_t$, the final adjustment we make to get the adjusted series is the linear transformation:

$$y_t^a = a + b[\mu_t / \exp(\hat{\theta}_t / 2)], \tag{3}$$

where a and b are chosen in such a way that y_t^a has the same mean and variance as y_t (the log of the original series). This transformation makes the units of measurement of adjusted and unadjusted data the same, making it easier to interpret the results.

The NYSE opens its trading at 9:30 a.m. and continues trading until 4:00 p.m.; London operates from 9:00 a.m. to 5:00 p.m. Trading on the TSE is divided into a morning session from 9:00 to 11:00 a.m.; followed by an afternoon session from 1:00 to 3:00 p.m. On April 29, 1991, the start of the afternoon session was moved forward 30 minutes to 12:30 p.m. This trading structure is unique to the TSE.[1]

There is no overlap between the operating hours of the Tokyo Exchange and London or New York exchanges, but there is a two-and-one-half hours overlap between the London and New York markets.

The following figure illustrates the relationship of business hours among these three markets:

London Time	20:01	24:00	04:00	08:00	12:00	16:00	20:00
Tokyo time	06:01	10:00	14:00	18:00	22:00	02:00	06:00
New York Time	16:01	20:00	24:00	04:00	08:00	12:00	16:00
London Market				←	1		→

Tokyo Market	← 2 →	← 2 →					
New York Market					←	3	→

where 1, 2, and 3 denote London stock market business hours, Tokyo stock market business hours, and New York stock market business hours, respectively. The London and New York overlap of hours consists of the last two-and one-half hours of the LSE's operating hours and the first two-and one-half hours of the NYSE's operating hours.

III. METHODOLOGY

It has long been recognized that the volatility of stock prices is time-varying and clustered. GARCH models are capable of capturing the three most empirical features observed in stock return data: leptokurtosis, skewness, and volatility clustering.

To examine the cross-market dependence on return, trading volume, and volatility, we extend the specification of the GARCH process to account for possible variations in the effect of volatility spillover across markets

This multivariate setting takes into account the cross-sectional correlations in residual as well as the conditional heteroskedasticity; i.e., the multivariate GARCH model uses information from the history of more than one market. Hence, if the system of equations is estimated simultaneously, then full efficiency can be attained. According to Conrad, Gultekin, and Kaul [5], multivariate models provide a greater precision in the estimates of the parameters because such models utilize information in the entire variance-covariance matrix of the errors. Further, the generated regressor problem associated with univariate models is avoided in multivariate models because it estimates all parameters jointly. Modeling the returns of the three markets simultaneously has several advantages over the univariate approach that has been used so far. First of all, such modeling eliminates the two-step procedure found with the univariate approach, 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 following multivariate GARCH model is posited for the joint processes governing the daily rates of return for the Japan, U.S. and U.K. markets:

$$r_t = a + \sum \Phi_p r_{t-p} + e_t \tag{4}$$

$$e_t \mid \Omega_{t-1} \sim N(0, H_t) \tag{5}$$

$$vech(H_t) = a + bvech(\varepsilon_{t-1}\varepsilon_{t-1}') + cvech(H_{t-1}) \tag{6}$$

or

$$H_t = \Gamma'\Gamma + \sum_{k=1}^{K} F_k^{'} H_{1-k} F_k + \sum_{l=1}^{L} G_l^{'} e_{t-l} e_{t-l}^{'} G_l \tag{7}$$

where the returns vector is denoted by r'_t. The residual vector is given by $e_t^{'}$, with its corresponding conditional covariance matrix $\{H_t\}_{ij} = h_{ij,t}$. e_t is represented by a column vector of forecast errors of the best linear predictor of r_t conditional on past information, denoted by Ω_{t-1}, and including the P lagged values of r_t and trading volume. Where vech(.) denotes the column-stack operator of the lower portion of a sysmmetric matix, ε_t is an $n \times 1$ vector of innovation, a is $(1/2N(N+1) \times 1)$ parameter vector, and b and c are $(1/2N(N+1) \times (1/2N(N+1)$ matrices of constant parameters. The multivariate GARCH(1,1) specification has $(1/2N^2(N+1)^2 + (1/2N(N+1))$ parameters in the conditional variance and covariances. Thus, for tractability, reasonable restrictions on the parameters are necessary. According to Engle and Kroner [8], various restrictions may be imposed in this parametriztion to make estimation easier. A more parsimouioun representation can be obtained by imposing a diagonal restriction on the multivariate GARCH parameters' matrices so that each variance and covariance element depends only on its own past values and prediction errors (Bollerslev, Engle, and Wooldridge [3]).

The most generally used multivariate GARCH is the so-called diagonal-vec model of order p,q, where the conditional covariance matrix is given by

$$H_t = A + \sum_{i=1}^{p} A_i \otimes (\varepsilon_{t-i}\varepsilon_{t-i}^T) + \sum_{i=1}^{q} B_i \otimes H_{t-i} \tag{8}$$

where the symbol ⊗ stands for the Hadamard product, that is, element-by-element multiplication. All quantities in the above equation are d×d matrices, except for ε_t, which is a d×1 column vector. The matrices A, A_i and B_i of a diagonal-vec model are restricted to being symmetric to ensure that the conditional covariance matrix H_t is symmetric.

In the bivariate case, the diagonal model is simply as follows:

The mean equation matrix is

$$\begin{pmatrix} x_{1t} \\ y_{1t} \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + \begin{pmatrix} d & e & f & g \\ h & i & j & k \end{pmatrix} \begin{pmatrix} x_{1t-1} \\ x_{2t-1} \\ y_{1t-1} \\ y_{2t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \tag{9}$$

where x_{1t} = returns on stock exchange one, x_{2t} = trading volumes on stock exchange one, y_{1t} = returns on stock exchange two and y_{2t} = trading volumes on stock exchange two.

The conditional covariance matrix is

$$\begin{pmatrix} h_{11,t} \\ h_{12,t} \\ h_{22,t} \end{pmatrix} = \begin{pmatrix} c_{01} \\ c_{02} \\ c_{03} \end{pmatrix} + \begin{pmatrix} a_{11} & 0 & 0 \\ 0 & a_{22} & 0 \\ 0 & 0 & a_{33} \end{pmatrix} \begin{pmatrix} \varepsilon^2_{1,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon^2_{2,t-1} \end{pmatrix} + \begin{pmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & 0 \\ 0 & 0 & b_{33} \end{pmatrix} \begin{pmatrix} h_{11,t-1} \\ h_{12,t-1} \\ h_{22,t-1} \end{pmatrix} \tag{10}$$

In other words, this presentation is obtained by assuming that matrices are diagonal.

The diagonal-vec model introduced by Bollerslev, Engle and Wooldridge [3] appears to provide good model fits in a number of applications. However, other models may be highly desirable in specific application for the following two reasons: (1) the diagonal-vec model does not ensure positive definiteness of the conditional covariance matrices V_t, and (2) the diagonal-vec model requires a large number of parameters, and whereas a more parsimonious model might be desired.

The BEKK model, introduced by Engle and Kroner [8], has the following conditional covariance matrix structure:

$$V_t = AA^T + A_1(\varepsilon_{t-1}\varepsilon^T_{t-1})A_1^T + B_1V_{t-1}B_1^T \tag{11}$$

Because of the presence of a paired transposed matrix factor for each of the d×d matrices A, A_1, B_1, symmetry and non-negative-definiteness of the conditional covariance matrix V_t is assured. Note that A, A_1, B_1 need not be symmetric.

In the bivariate case, the BEKK model is as follows:

The mean equation matrix is

$$\begin{pmatrix} x_{1t} \\ y_{1t} \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + \begin{pmatrix} d & e & f & g \\ h & i & j & k \end{pmatrix} \begin{pmatrix} x_{1t-1} \\ x_{2t-1} \\ y_{1t-1} \\ y_{2t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \tag{12}$$

where x_{1t} = returns on stock exchange one, x_{2t} = trading volumes on stock exchange one, y_{1t} = returns on stock exchange two and y_{2t} = trading volumes on stock exchange two.

The conditional covariance matrix is

$$H_t = C_0{}'C_0 + \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}' \begin{pmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{21t-1}^2 \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} + \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}' H_{t-1} \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \tag{13}$$

Given a sample of T observations of the returns vector, r_t, the parameters of the multivariate systems are estimated by computing the conditional log-likelihood function for each time period as

$$L_t(\Theta) = -\log 2\pi - \frac{1}{2}\log|H_t| - \frac{1}{2}e_t'(\Theta)H_t^{-1}(\Theta)e_t(\Theta) \tag{15}$$

$$L(\Theta) = \sum_{t=1}^{T} L_t(\Theta) \tag{16}$$

where Θ is the vector of all parameters. Numerical maximization of the log-likelihood function yields the maximum likelihood estimates and associated asymptotic standard errors.

IV. EMPIRICAL EVIDENCES

Table 1 reports statistics for the returns and trading volumes of the three stock markets as well as statistics testing for normality, autocorrelation and stationarity. The measures for skewness in the three stock markets show that all return series are negatively skewed and that all trading volumes are positively skewed with respect to the normal distribution. The measures for excess kurtosis show that all return and trading volume series are highly leptokurtic with respect to the normal distribution. The Wald and the Kolmogorov-Smirnov statistics reject normality for each of the return and trading volume series of all three stock markets. The test results indicate that the null hypothesis that return series are nonstationary series is rejected in all three stock exchanges, but the null hypothesis that trading volume series are nonstationary is rejected in the London and Tokyo stock exchanges, not in the New York stock exchange. The Ljung-Box statistic for up to 12 lags, calculated for the return, the squared return and trading volumes series, indicate the presence of significant linear and non-linear dependencies, respectively, in the returns of all three markets.

Table 1

Preliminary statistics of returns on New York, Tokyo and London Stock Exchanges

	Returns of New York			Returns of Tokyo			Returns of London		
	Total	Before Crash	After Crash	Total	Before Crash	After Crash	Total	Before Crash	After Crash
Observations	6578	4502	2085	5199	3377	1822	3386	1352	2034
sample mean	0.0120	0.0094	0.0177	0.0516	0.0682	0.0208	0.0201	0.0272	0.0159
Standard Devidation	0.3779	0.4023	0.3189	0.8973	0.5760	1.2968	0.4287	0.4826	0.3913
Skewness	-2.234	-2.532	-0.733	-0.244	-0.186	-0.144	-1.071	-2.050	0.0985
Kurtosis	57.878	64.415	7.1749	25.393	5.8292	14.958	13.801	20.064	3.2044
Wald-statistics	803612	702687	1560	95566	1121	9191	14672	17181	613
Kolmogorov-Smirnov	0.065	0.035	0.053	0.103	0.054	0.093	0.039	0.035	0.043
LB(12)	181.26	178.30	29.701	164.05	186.45	56.452	53.900	35.685	33.670
$LB^2(12)$	478.95	324.75	179.81	990.46	938.73	262.63	1507.7	669.22	345.67
Minimum	-9.244	-9.244	-2.720	-14.38	-4.408	-14.38	-5.385	-5.385	-1.945
Maximum	3.7445	3.7445	1.4758	10.007	4.0373	10.007	2.5803	2.5803	2.5796
1st qunatile	-0.166	-0.191	-0.117	-0.309	-0.218	-0.551	-0.224	-0.229	-0.218
Median	0.0067	0.0000	0.0154	0.0619	0.0776	-0.003	0.0320	0.0608	0.0171
3rd quantile	0.1957	0.2092	0.1734	0.4207	0.3666	0.5788	0.2805	0.3224	0.2533

Table 1 (continued)

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 21.0126 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 contemporaneous correlation matrix of return and trading volume among New York, London and Tokyo stock exchanges is presented on Table 2. The correlations of returns range from a high of 0.3477 between New York and London, to a low of 0.1253 between New York and Tokyo. The correlations of trading volume range from a high of 0.7276 between New York and London, to low of 0.2175 between London and Tokyo.

The maximum likelihood estimates of the multivariate diagonal GARCH model are reported in Panel 1 of Table 3. The full model considers price, trading volume and volatility spillovers among the New York, London, and Tokyo stock exchanges. In terms of return interdependencies, there are significant return spillovers from New York and Tokyo to London; there are also significant return spillovers from New York, London to Tokyo and significant return spillovers from Tokyo to New York. In terms of return and trading volume interdependencies, there are significant return spillovers from New York to returns of Tokyo. The BEKK GARCH model finds similar results.

Table 2
The contemporaneous correlation matrix of returns and trading volumes among New York, London and Tokyo Stock Exchanges

	Returns of New York	Volumes of New York	Returns of Tokyo	Volumes of Tokyo	Returns of London	Volumes of London
Total sample						
Returns of New York	1					
Volumes of New York	-0.0004	1				
Returns of Tokyo	0.1253	-0.0193	1			
Volumes of Tokyo	-0.015	0.3461	0.1401	1		
Returns of London	0.3477	-0.0264	0.2662	0.0169	1	
Volumes of London	-0.0098	0.7276	-0.0003	0.2175	0.0228	1
Before Crash						
Returns of New York	1					
Volumes of New York	-0.0177	1				
Returns of Tokyo	0.105	0.0114	1			
Volumes of Tokyo	-0.0201	0.6235	0.1482	1		
Returns of London	0.3423	-0.1236	0.2992	0.0111	1	
Volumes of London	-0.332	0.7309	-0.0326	0.5437	-0.037	1
After Crash						
Returns of New York	1					
Volumes of New York	0.0662	1				
Returns of Tokyo	0.1689	0.0026	1			
Volumes of Tokyo	-0.0051	-0.2965	0.157	1		
Returns of London	0.3625	0.0248	0.2536	0.022	1	
Volumes of London	0.0278	0.6021	0.0797	-0.0961	0.1207	1

Table 3
Mean, trading volume and volatility spillovers estimated from a diagonal multivariate GARCH model.

The model to be estimated is given by the following equations. Mean equation matrix:

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + \begin{pmatrix} d & e & f & g \\ h & i & j & k \end{pmatrix} \begin{pmatrix} x_{1t-1} \\ x_{2t-1} \\ y_{1t-1} \\ y_{2t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$$

where x_{1t} and y_{1t} are trading volumes and returns on domestic stock exchange, respectively; x_{2t} and y_{2t} are trading volumes and returns on foreign stock exchange.

Conditional covariance matrix:

$$\begin{pmatrix} h_{11,t} \\ h_{12,t} \\ h_{22,t} \end{pmatrix} = \begin{pmatrix} c_{01} \\ c_{02} \\ c_{03} \end{pmatrix} + \begin{pmatrix} a_{11} & 0 & 0 \\ 0 & a_{22} & 0 \\ 0 & 0 & a_{33} \end{pmatrix} \begin{pmatrix} \varepsilon^2_{1,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon^2_{2,t-1} \end{pmatrix} + \begin{pmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & 0 \\ 0 & 0 & b_{33} \end{pmatrix} \begin{pmatrix} h_{11,t-1} \\ h_{12,t-1} \\ h_{22,t-1} \end{pmatrix}$$

	Total Coefficient	T-ratio	Before Crash Coefficient	T-ratio	After Crash Coefficient	T-ratio
	Spillover between New York (domestic) to Tokyo (foreign)					
c_1	0.03684	(3.7994)	0.02664	(2.3953)	0.0937	(2.3458)
d	-0.00004	(-0.6071)	0.00011	(0.7111)	-0.00022	(-1.367)
e	6.402E-6	(0.3797)	5.487E-5	(0.182)	-0.00002	(-1.070)
f	0.13682	(8.0575)	0.17869	(8.8446)	0.04203	(1.4757)
g	-0.01316	(-2.2053)	-0.01209	(-1.1699)	-0.0091	(-1.273)
c_2	0.04263	(2.9768)	0.04377	(2.8721)	-0.04327	(-0.459)
h	0.00052	(6.1969)	0.00104	(4.816)	0.00031	(0.7738)
i	-0.00005	(-2.5119)	-0.00012	(-3.1242)	0.00004	(0.8576)
j	0.2508	(12.6657)	0.21154	(10.2325)	0.53989	(8.7809)
k	0.1937	(12.588)	0.22447	(10.9556)	0.12497	(5.0792)
c_{01}	0.00361	(8.6583)	0.00286	(3.9623)	0.00058	(3.0112)
c_{02}	0.00096	(1.4122)	0.00685	(1.2837)	0.00658	(1.8072)

Table 3 (continued)

c_{03}	0.01386	(9.4938)	0.02229	(9.0534)	0.04312	(5.7897)
a_{11}	0.07295	(27.6467)	0.08424	(19.0842)	0.0217	(7.3204)
a_{12}	0.02315	(2.5652)	-0.01153	(-0.6178)	0.05075	(2.861)
a_{22}	0.24131	(23.7656)	0.29101	(23.2972)	0.18233	(9.7705)
b_{11}	0.9013	(156.153)	0.89998	(105.883)	0.9721	(254.13)
b_{12}	0.85189	(11.320)	-0.78957	(-1.9747)	0.75022	(6.3047)
b_{22}	0.77024	(91.394)	0.68772	(47.392)	0.79681	(44.110)

	Total		Before Crash		After Crash	
	Coefficient	T-ratio	Coefficient	T-ratio	Coefficient	T-ratio
	Spillover between New York (domestic) to London (foreign)					
c_1	0.03677	(2.6563)	0.02001	(0.4999)	0.01728	(0.7206)
d	-0.00015	(-1.6407)	0.00015	(0.3625)	2.24E-6	(0.0243)
e	0.00006	(1.6166)	0.00000	(0.0100)	0.00002	(0.3795)
f	0.10796	(5.0633)	0.13054	(3.7435)	0.08229	(3.5473)
g	-0.01409	(-0.9753)	0.02144	(0.8318)	-0.02498	(-1.392)
c_2	0.04082	(2.4267)	0.07114	(1.6094)	0.01807	(0.5924)
h	-0.00018	(-1.5974)	-0.00041	(-0.8980)	9.36E-6	(0.0749)
i	0.00002	(0.4573)	0.000009	(0.0526)	-0.00003	(-0.413)
j	0.24522	(12.8295)	0.20989	(5.4536)	0.26094	(10.607)
k	-0.00335	(-0.1741)	-0.00792	(-0.2376)	-0.02122	(-0.878)
c_{01}	0.00353	(8.8325)	0.00119	(1.8896)	0.00046	(4.2272)
c_{02}	0.00199	(4.102)	0.00062	(0.9955)	0.00014	(1.6855)
c_{03}	0.00773	(5.9504)	0.00745	(1.9179)	0.00637	(4.2227)
a_{11}	0.07734	(18.9641)	0.02089	(3.3871)	0.01726	(8.9709)
a_{12}	0.04356	(8.005)	0.01646	(1.5493)	0.00621	(2.6319)
a_{22}	0.08669	(10.553)	0.06050	(3.4513)	0.06285	(8.3881)
b_{11}	0.89826	(135.050)	0.96806	(94.9003)	0.97701	(384.36)
b_{12}	0.90743	(58.468)	0.95628	(28.4873)	0.98879	(247.23)
b_{22}	0.8661	(63.997)	0.89403	(25.1211)	0.88964	(53.013)

Table 3 (continued)

	Total Coefficient	T-ratio	Before Crash Coefficient	T-ratio	After Crash Coefficient	T-ratio
Spillover between Tokyo (domestic) to London(foreign)						
c_1	0.09618	(2.7606)	0.0759	(2.2231)	0.11057	(1.0058)
d	-0.00004	(-1.2527)	-0.00018	(-3.2281)	-2.87E-6	(-0.053)
e	0.00002	(0.3257)	0.00043	(3.4468)	-0.00011	(-0.56)
f	0.1586	(7.3699)	0.21893	(6.1688)	0.12273	(4.3501)
g	0.22188	(6.7378)	0.1613	(4.2209)	0.29408	(5.0673)
c_2	0.03342	(1.6511)	0.02928	(1.1468)	0.01417	(0.3142)
h	0.00001	(0.5866)	0.00002	(0.5417)	1.14E-6	(0.0425)
i	-0.00001	(-0.2858)	0.00001	(0.1246)	0.00002	(0.2817)
j	-0.03009	(-3.9546)	-0.02033	(-1.2777)	-0.03637	(4.219)
k	0.10502	(4.9307)	0.08706	(2.6787)	0.11795	(4.097)
c_{01}	0.03586	(7.6756)	0.04803	(5.9746)	0.03814	(5.2117)
c_{02}	0.00984	(2.5626)	0.03793	(2.6671)	0.00601	(2.0918)
c_{03}	0.00892	(4.7387)	0.01286	(2.4987)	0.00742	(3.3708)
a_{11}	0.27276	(27.531)	0.44318	(17.0313)	0.16747	(9.9053)
a_{12}	0.06754	(4.0103)	0.10174	(3.4445)	0.03659	(2.6419)
a_{22}	0.07147	(7.0081)	0.06867	(3.1877)	0.07627	(5.9135)
b_{11}	0.73343	(73.2816)	0.57734	(24.5129)	0.81448	(47.743)
b_{12}	0.7399	(9.4088)	-0.34323	(-1.0566)	0.88405	(19.893)
b_{22}	0.8762	(46.6593)	0.86635	(20.0402)	0.87484	(35.138)

Table 4

Mean, trading volume, and volatility spillovers estimated from a BEKK multivariate GARCH model.

The model to be estimated is given by the following equations. Mean equation matrix:

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + \begin{pmatrix} d & e & f & g \\ h & i & j & k \end{pmatrix} \begin{pmatrix} x_{1t-1} \\ x_{2t-1} \\ y_{1t-1} \\ y_{2t-1} \end{pmatrix} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$$

where x_{1t} and y_{1t} are trading volumes and returns on domestic stock exchange, respectively; x_{2t} and y_{2t} are trading volumes and returns on foreign stock exchange.

Conditional covariance matrix:

$$H_t = C_0'C_0 + \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}' \begin{pmatrix} \varepsilon^2_{1,t-1} & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon^2_{21,t-1} \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} + \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}' H_{t-1} \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}$$

	Total Coefficient	T-ratio	Before Crash Coefficient	T-ratio	After Crash Coefficient	T-ratio
Spillover between New York (domestic) to Tokyo (foreign)						
c_1	0.02977	(2.880)	0.0233	(1.9556)	0.1139	(2.5954)
d	6.78E-6	(0.0783)	0.0003	(2.5386)	-0.0002	(-1.4726)
e	-4.18E-6	(-0.2327)	-2.88E-5	(-1.132)	-3.50E-5	(-1.2521)
f	0.11293	(7.5166)	0.1848	(11.079)	0.0486	(1.5546)
g	-0.01207	(-2.3832)	-0.0021	(-0.2265)	-0.0068	(-0.8716)
c_2	0.03461	(2.116)	0.0737	(3.5801)	-0.0166	(-0.1434)
h	-0.00018	(-1.797)	0.0009	(3.9554)	0.0004	(0.9452)
i	0.00002	(1.0553)	-0.0002	(-5.7787)	3.61E-6	(0.0529)
j	0.40714	(20.2624)	0.2946	(7.7377)	0.5779	(6.9995)
k	0.18974	(13.2328)	0.1973	(12.392)	0.1618	(5.6978)
c_{01}	0.30859	(82.2504)	0.0676	(1.2475)	0.0498	(1.0073)
c_{02}	0.05641	(4.5903)	-0.4874	(-1.5991)	-0.2488	(-0.1894)
c_{03}	0.00001	(0.2730)	0.003	(0.842)	0.0035	(0.0001)
a_{11}	0.35509	(18.1281)	0.8387	(26.9619)	-0.979	(-44.896)
a_{12}	-0.33775	(-5.5618)	0.1167	(2.2981)	-0.2495	(-0.5411)
a_{21}	-0.00466	(-0.698)	0.296	(13.6345)	0.0809	(3.4347)

Table 4 (continued)

b_{22}	0.91564	(153.462)	0.2899	(6.2772)	0.8979	(35.9615)
b_{11}	0.36612	(37.3236)	0.0604	(3.514)	0.1896	(9.4282)
b_{12}	-0.00469	(-0.1800)	-0.8335	(-25.174)	0.1497	(2.1328)
b_{21}	0.0501	(7.9457)	-0.045	(-3.6812)	0.0183	(2.9696)
B_{22}	0.41484	(33.0726)	0.3434	(21.4266)	0.4496	(15.9155)

	Total Coefficient	T-ratio	Before Crash Coefficient	T-ratio	After Crash Coefficient	T-ratio
	Spillover between New York (domestic) to London (foreign)					
c_1	0.0418	(2.4998)	0.03199	(0.6441)	0.01289	(0.5394)
d	-0.0001	(-1.3719)	0.00020	(0.3729)	0.00001	(0.125)
e	6.5E-59	(1.3027)	-0.00007	(-0.3580)	0.00002	(0.4238)
f	0.0637	(4.2136)	0.11338	(2.8567)	0.08051	(3.4922)
g	-0.0262	(-1.8652)	0.02964	(0.9620)	-0.01973	(-1.0767)
c_2	0.0466	(2.4890)	0.05209	(0.9454)	0.01063	(0.3494)
h	-0.0001	(-1.0901)	-0.00040	(-0.6775)	4.69E-6	(0.0377)
i	1.48E-5	(0.2693)	0.00006	(0.3261)	-0.00002	(-0.267)
j	0.1884	(8.1857)	0.21234	(4.5462)	0.27106	(10.8612)
k	-0.0084	(-0.4929)	-0.00814	(-0.2201)	-0.02682	(-1.1008)
c_{01}	0.0291	(0.1047)	0.14085	(0.5732)	0.0157	(4.0679)
c_{02}	0.3673	(0.1095)	-0.12960	(-0.1796)	0.0078	(0.2491)
c_{03}	0.0297	(0.00007)	0.00252	(0.00006)	0.08956	(9.0468)
a_{11}	-0.0352	(-0.4021)	0.21358	(0.7067)	0.98742	(420.982)
a_{12}	-0.0838	(-1.1508)	1.11832	(3.4152)	0.01729	(2.5746)
a_{21}	-0.8317	(-10.311)	-0.77776	(-3.2056)	0.00811	(1.4672)
b_{22}	-0.1527	(-1.9337)	-0.31575	(-1.1712)	0.92544	(75.2946)
b_{11}	0.2494	(9.6330)	0.16284	(2.2629)	0.12846	(15.8004)
b_{12}	0.4827	(16.9537)	0.17660	(2.2863)	0.00203	(0.0953)
b_{21}	0.0084	(0.3021)	0.07758	(1.3335)	-0.02151	(-1.7956)
B_{22}	0.117	(8.3991)	0.17700	(2.5613)	0.27327	(12.8581)

Turning to volatility spillover, it can seem far more extensive and reciprocal. In addition to its own past innovations, the conditional variance in each market is also affected by innovations coming from the others. 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.

A comparison of the results from the before and after October 1987 crash period reveals that national markets have grown more interdependent in the sense that information affecting asset prices has become more global in nature. Before the crash, there is significant trading volume spillover from New York to returns of Tokyo and from Tokyo to returns of London. After the crash, no return and trading volume interdependencies between any two markets was observed.

V. CONCLUSION

The above empirical results are consistent with the hypothesis that the cause of international transmission of stock returns and volatility is transmission of information from one stock market to another. Before the crash, the correlation between international stock returns might be caused by international contagion of liquidity traders' sentiments or by resolution of heterogeneous interpretations of foreign news. With the development of communication technology, the more efficient stock markets become, the less contagion effect among national stock markets.

NOTES

1. On the TSE, half-day Saturday trading (9:00 to 11:00 a.m.) has undergone various modifications over the past 30 years. These modifications include the following: (1) the third Saturday of each month was closed on a regular basis beginning January 1973; (2) in August 1983, the third Saturday closure was replaced by the second Saturday; (3) beginning August 1986, both the second and third Saturdays were closed; (4) for January 1989, all Saturdays except the last Saturday were closed; and (5) the current scheme of no Saturday trading became effective February 1989.

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