Correlations in Price Changes and Volatility across International Stock Markets

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The short-run interdependence of prices and price volatility across three major international stock markets is studied. Daily opening and closing prices of major stock indexes for the Tokyo, London, and New York stock markets are examined. The analysis utilizes the autoregressive conditionally heteroskedastic (ARCH) family of statistical models to explore these pricing relationships. Evidence of price volatility spillovers from New York to Tokyo, London to Tokyo, and New York to London is observed, but no price volatility spillover effects in other directions are found for the pre-October 1987 period.

The extent of international financial integration has received much attention in recent years. However, its empirical implications for the functioning of individ-

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ual capital markets has received far less attention. In this study, we consider the short-term relations among security prices across three major stock markets: Tokyo, London, and New York. We are interested in (1) the extent to which security price changes in one market influence the opening prices in the next market to trade and (2) whether changes in price volatility in one market are positively related to changes in price volatility observed in the next market to trade. The financial press strongly suggests that such a relation exists.[1]

Earlier research has examined the correlation of asset prices across international markets. Hilliard (1979) studied the contemporaneous and lagged correlation in daily closing price changes across 10 major stock markets. Jaffe and Westerfield (1985a, 1985b) examined daily closing prices in the Australian, British, Canadian, Japanese, and U.S. stock markets. Eun and Shim (1989) studied daily stock returns across nine national stock markets, while Barclay, Litzenberger, and Warner (1990) examined daily price volatility and volume for common stocks dually listed on the New York and Tokyo stock exchanges. They all report evidence of positive correlations in daily close-to-close returns across individual stock exchanges.

We examine the transmission mechanisms of the conditional first and second moments in common stock prices across international stock markets and allow for changing conditional variances as well as conditional mean returns.[2] As Engle (1982) notes, it is reasonable for stock return variances to be conditional on current information given that their means are conditional on this data set.

Unlike earlier studies, we divide daily close-to-close returns into their close-to-open and open-to-close components. This enables us to analyze separately the spillover effects of price volatility in foreign markets on the opening price in the domestic market and on prices after the opening of trading. This separation is relevant since spillover effects from foreign markets on the conditional means of the close-to-open return (which reflect effects on opening prices in the domestic market) are predicted by international asset pricing models, while spillover effects on conditional means of the open-to-close return (which reflect effects on prices in the domestic market after the opening of trading) are predicted not to occur.[3] In addition, volatility

[1] This point is exemplified by the following quote: "A sharp downward movement in the New York stock market last week triggered fear here in Japan and the Tokyo market experienced the largest drop this year." [*Nihon Keizai Shimbun (Japan Economic Journal)*, May 22, 1988].

[2] In related research, Engle, Ito, and Lin (1990) apply the generalized autoregressive conditional heteroskedastic (GARCH) model to test for spillovers in daily exchange rate volatility across Japanese and American foreign exchange markets. They find that changes in volatility in the foreign exchange market previously open are positively correlated with changes in volatility in the next market to open trading based on close-to-close price data.

[3] See Stulz (1981), Solnik (1983), Errunza and Losq (1985), and Cho, Eun, and Senbet (1986) for examples of international asset pricing models.

spillovers onto the conditional variances of the close-to-open and open-to-close returns of the domestic market can occur, a question on which little theoretical work exists. Such volatility spillovers could represent a causal phenomenon across markets that trade sequentially; alternatively, they could reflect global economic changes that concurrently alter stock-return volatility across international stock markets.

Prior statistical analysis of common stock daily returns has documented mild serial correlation over very short periods of time.[4] Previous analyses of daily and monthly U.S. common stock returns have found that "large price changes tend to be followed by large changes—of either sign—and small changes tend to be followed by small changes . . ." [see Mandelbrot (1963, p. 418); also see Fama (1965, pp. 85–87)]. There is also evidence that percentage changes in stock prices and indices exhibit fatter tails than that predicted by a stationary normal distribution [e.g., see Westerfield (1977) and Kon (1984)].

The autoregressive conditional heteroskedastic (ARCH) model recognizes the temporal dependence in the second moment of stock returns and exhibits a leptokurtic distribution for the unconditional errors from the stock returns generating process. This model was introduced by Engle (1982) and generalized by Bollerslev (1986, 1987) and Engle, Lilien, and Robins (1987). Examining the descriptive validity of these models, French, Schwert, and Stambaugh (1987) find that the generalized autoregressive conditional heteroskedastic-in-mean (GARCH-M) model is an attractive representation of daily stock-return behavior in the United States, successfully capturing the effects of time-varying volatility on a stock's expected return.

1. Data

In this article, we examine daily and intraday stock-price activity over the three-year period, April 1, 1985, to March 31, 1988. We study daily open and close data from three stock markets: Tokyo, London, and New York.[5] In each market, we chose the most comprehensive and diversified stock index that met the previously mentioned data requirements. For the Tokyo Stock Exchange, we used the Nikkei 225 Stock Index. This index of "first section" stocks includes the largest 225 firms in Japan and represents 52.2 percent of the total equity

[4] See, in particular, the evidence of serial correlation in daily stock returns of U.S. stocks found by Fama (1965) and studied by Scholes and Williams (1977). For evidence on the statistical properties of the Nikkei daily return series, see Tse (1989).

[5] A description of the basic institutional features of these stock exchanges can be found in Cohen et al. (1986, chap. 2).

capitalization of the Tokyo Stock Exchange at the end of 1987.[6] The Nikkei 225 is a share price weighted index (similar to the Dow Jones stock index, which has no dividend reinvestment). However, cash dividends paid on most Japanese stocks are relatively small, so this dividend omission is of little consequence.[7] The price data were obtained from Nihon Keizai Shimbun Sha. Opening price data were recorded at 9:15 A.M. until December 18, 1987, and at 9:01 A.M. thereafter, while closing prices are recorded at 3:00 P.M. Tokyo time.

In the London stock market, we used the Financial Times–Stock Exchange 100 Share (FTSE) Index, which represents 70 percent of the equity capitalization of all United Kingdom equities at the end of 1987. This is an equity value weighted arithmetic index. The opening price data were recorded at 9:00 A.M., while the closing price data (legal closing) were recorded at 3:30 P.M. London time. The data sources were the London International Stock Exchange and the *Financial Times*.

In the New York stock market, we used the Standard & Poors 500 Composite Index. This represented 76 percent of the equity capitalization of the NYSE as of midyear 1989, though it currently includes a small number of AMEX and OTC stocks. The S&P 500 is an equity value weighted arithmetic index. The primary data source was S&P's monthly "500 Information Bulletin." The opening stock price was measured at 10:01 A.M. until September 30, 1985, and at 9:31 A.M. thereafter and the close is at 4:00 P.M. EST. From these daily opening and closing prices, we compute daily close-to-close, close-to-open, and open-to-close returns for our three stock indices.[8]

Figure 1 shows trading hours of the three exchanges in Eastern Standard Time. With the exception of the morning trading in New York, which represents late afternoon trading in London, the trading activity in these markets is not concurrent. To minimize the trading overlap between the London and New York stock markets to one hour, we measured the London closing price at the 3:30 legal close rather than the 5:00 official close of the exchange.[9] A technical prob-

[6] While an equity value weighted index for the Tokyo Stock Exchange (TOPIX) exists, data on opening prices of this index were not available.

[7] Campbell and Hamao (1989) document the dividend–price ratio for the Tokyo market.

[8] These three indices are each composed of only common stocks of companies headquartered in the nation where the stock market is based.

[9] However, differences in daylight savings time in the United Kingdom and the United States can cause some minor variability in concurrent trading periods. In 1985–1986, daylight savings time began on the last Sunday in April in the United States and the last Sunday in March in the United Kingdom. Since 1987, daylight savings time has begun on the first Sunday in April in the United States. Daylight savings time ends the last Sunday in October in both countries. This difference in conventions caused the trading overlap between the two markets to decrease by an hour for the month of March in 1985–1986 and for the last week of March in 1987–1989.

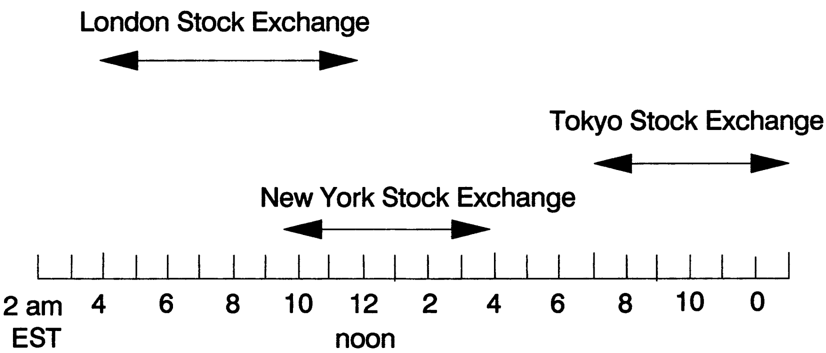

Figure 1
Exchange trading hours

lem in studying pricing relations across markets was the existence of nonsynchronous holidays and twice monthly Saturday trading on the Tokyo Exchange. When measuring spillover effects from foreign markets in periods where one or both foreign markets were closed, we substitute the most recent "volatility surprise" (defined below) available for the foreign exchange that was closed.[10]

In the case of the S&P and the Nikkei, the use of index prices near the open of trading can present some difficulties. When individual stocks of the index have not yet opened trading, the previous day's closing price quotes are substituted into the index. For the S&P 500 index, Stoll and Whaley (1988) report that stocks on average begin trading 5 to 7 minutes after the exchange open. For Nikkei, we have been unable to determine the exact extent of the problem, though for most of the time series we are using prices 15 minutes after the official open, which should minimize the effects of stale prices. In the case of the FTSE index, firm quotes rather than transaction prices are used, and these quotes must be available while the exchange is open. The result of this substitution procedure for the S&P and the Nikkei is to induce higher serial correlation between close-to-open and open-to-close returns in adjacent days. It can also artificially induce positive serial correlation in the open-to-close return data. For New York, we also studied the use of noon-to-close returns in place of open-to-close returns. This has the added benefit of eliminating overlapping trading between London and New York.

Our sample period includes October 1987 when all major stock exchanges experienced large declines in prices. Since the "crash" took place in the three markets we are analyzing sequentially across a 24-hour period, it may seriously influence the estimation of the first

[10] We also estimated our model dropping out domestic returns for any days where at least one of the two foreign markets was closed. Qualitatively similar spillover effects were observed.

and second moment spillover effects.[11] To separate out any "crash" effect, we have also estimated our models over the subperiod prior to the stock market crash (i.e., from April 1, 1985, to September 30, 1987).

2. Methodology

We being with a brief review of the ARCH family of statistical models. To capture the effect of changing volatility in a time series, Engle (1982) developed the ARCH model where the conditional variance h is a linear function of past squared errors, ϵ's, as well as possible exogenous variables X. The simplest representation of this model is an ARCH(1) which has the form

$$R_t = \alpha + \epsilon_t \qquad \text{where } \epsilon_t \mid \mathscr{F}_{t-1} \sim \mathscr{N}(0, h_t)$$

and

$$h_t = a + c\epsilon_{t-1}^2 + fX_t \qquad \text{where } a > 0 \text{ and } c, f \geq 0$$

The conditional variance at time t is a positive function of the square of last period's error. While the ARCH models do not allow the conditional variance at time t to have a stochastic component, the models can incorporate additional squared error terms from prior periods. For example, in an ARCH(2) model the conditional variance is a linear function of the squared errors from the most recent prior two periods.

Bollerslev (1986) generalized this model by allowing the conditional variance h to be a function not only of last period's error squared but also of its conditional variance. The GARCH(1, 1) model defines the conditional variance of R at time t to be of the form

$$h_t = a + bh_{t-1} + c\epsilon_{t-1}^2 + fX_t$$

The GARCH formulation can also be extended to include squared errors from prior periods, for example, a GARCH(1, 2) model includes squared errors from the prior two periods in the conditional variance equation. For stability of the volatility process, the coefficients of the lagged errors and lagged conditional variances must sum to less than 1. Engle, Lilien, and Robins (1987) extend the GARCH model to allow the conditional mean to be a function of the conditional variance at time t. This GARCH(1, 1)-M model takes the form

$$R_t = \alpha + \beta h_t + \epsilon_t$$

[11] Roll (1988) discusses the international transmission of the crash in detail.

where the conditional variance is defined in the same way as the GARCH(1, 1) model.

Several characteristics of stock price indices need to be addressed. Scholes and Williams (1977) and Cohen et al. (1980) examine how nonsynchronous trading in individual stocks, bid–ask spreads, and minimum-size price changes can cause serial correlation in stock and index returns. Because the above institutional factors can induce a small, short-lived serial correlation in these returns, while the ARCH models assume that the conditional error is serially uncorrelated, it is necesssary to extract this serial correlation from the stock return's first moment. Bollerslev (1987) and French, Schwert, and Stambaugh (1987) adjust the conditional mean return for a first-order moving average, MA(1), so that the equation for R is altered in the following way:

$$R_t = \alpha + \beta h_t - \gamma\epsilon_{t-1} + \epsilon_t$$

French (1980) and Gibbons and Hess (1981) document negative mean returns for U.S. stocks on Mondays, while Fama (1965) and Godfrey, Granger, and Morgenstern (1964) document higher return variances for U.S. stocks on Mondays. Because of holidays and the high variability of daily stock returns, these Monday effects will not be clearly captured by an MA(5). To take these potential Monday effects directly into account in the three markets being studied, we include a dummy variable for the day following a weekend or holiday in both the conditional mean and variance equations.

Nonlinear optimization techniques are used to calculate the maximum-likelihood estimates based on the Berndt–Hall–Hall–Hausman algorithm.[12] The primary specification tests for the model involve the Ljung-Box statistic, which is used to test for a lack of serial correlation in the model residuals and in the residuals squared. This statistic has been shown by McLeod and Li (1983) to be asymptotically chi-square distributed. Skewness and kurtosis coefficients for the normalized residuals are also reviewed. The descriptive validity of the estimated model can be evaluated with a likelihood ratio (LR) statistic that is chi-square distributed.

We use daily open and closing price data (last market's open-to-close return to predict the next market's close-to-open and open-to-close conditional mean returns and conditional variances). Finally,

[12] Initial values must be chosen in using this estimation method. For this purpose, for example, the first-order autocorrelation coefficient of the returns squared is used as the initial value for the ARCH(1) coefficient in the variance equation. When an exogenous variable is added to the equation, we start with some small number for the coefficients of the new variable, while scaling down the existing coefficients. The R-squared convergence criterion used in our estimation was 0.001 in almost all cases.

we test for spillovers in conditional mean and volatility across countries using correlation analysis and the inclusion of lagged returns and estimated squared residuals from the other stock markets in the ARCH models.[13]

To address formally the issue of spillover effects from one stock exchange to another, we divide the daily close-to-close return into its close-to-open and open-to-close components. This allows us to analyze separately the effects of foreign stock trading on both the market's opening price (from its close-to-open return) and the market's subsequent pricing behavior until its daily close (from its open-to-close return). We focus primarily on the open-to-close returns and the question of price volatility spillover effects, though we do document that the close-to-open return is positively correlated with prior open-to-close returns in foreign markets measured over periods when the domestic market is closed.

We estimate the Nikkei, FTSE, and S&P indexes' close-to-open and open-to-close daily return processes with a GARCH-M model. The primary purpose of this initial estimation is to evaluate the descriptive validity of the GARCH-M model and to determine the appropriate specifications for the three-stock-return time series. The GARCH-M specification that best fits the data is employed when we examine the empirical significance of cross-country return and volatility spillovers. Nested specification tests using likelihood ratio (LR) statistics are undertaken to determine the most parsimonious and descriptively accurate GARCH-M model.

3. Data Analysis of Daily and Intraday Stock Return Series

We begin with an examination of the serial correlation of the close-to-close, close-to-open, and open-to-close returns on the three stock exchange indices for the full sample period and the pre-October 1987 subperiod. Table 1, Panel A shows the estimated serial correlations for the full sample period. Table 1, Panel B shows estimates for the precrash subperiod.

For the full sample period, we find evidence in the close-to-close return series of the Tokyo and New York markets of negative correlation at lag 2 and positive correlation at lags 5, 9, and 10 (which potentially reflects the documented "day of the week" effect). For

[13] Since these residuals are proxies for the true unobservable innovations, an estimated regressor problem exists. Thus, the t-statistics for the associated parameter estimates will not be strictly t-distributed though these estimates remain consistent and likelihood ratios can also be used to measure the importance of these effects.

the open-to-close returns, we also find evidence of negative correlation at lag 2 and positive correlation at lag 5. When the stock crash and subsequent period are excluded, the serial correlations of the returns for the various stock indices tend to exhibit large positive correlations at lag 1 and much diminished correlations at lag 2. Large positive correlations at lags 5, 9, and 10 continue to be observed.

For the close-to-open returns, we find positive correlation at lags 1 and 9 for Tokyo, and negative correlation at lags 3 and 8 for New York. However, over the precrash period these higher-order lagged correlations are much less important. This serial correlation is likely to reflect the effects of late opening and early closing of trading in individual stocks comprising the indices especially in the case of the New York and Tokyo exchanges, as well as the effects of bid–ask spreads on all three exchanges. Estimating the GARCH-M model with higher-order MA processes specified produced no evidence supporting the significance of moving-average parameters of a higher order than an MA(1). This suggests that at least part of the observed serial correlation is induced by the GARCH in mean effect. Given the lack of consistent evidence of significant higher-order serial correlation beyond a possible "day of the week" effect, we follow the approach of Bollerslev (1987) and French, Schwert, and Stambaugh (1987) by specifying an MA(1) process in conjunction with a GARCH-M model, which we apply to all three stock return series. We also include a dummy variable for the trading day following a weekend or holiday in both the conditional mean and variance equations to capture potential "day of the week" effects.

Table 1 also presents estimated contemporaneous and first-order lagged correlations of open-to-close returns across our three major stock markets. Since an international dateline separates the New York and Tokyo stock markets, lagged correlations of the returns of the S&P and the FTSE indices are also reported. We find large positive correlations between "contemporaneous" Tokyo and London returns, London and New York returns, and lagged New York and Tokyo returns, while a large negative correlation is observed between lagged New York and London returns and a smaller positive correlation between "contemporaneous" New York and Tokyo returns. In the precrash subperiod, the cross correlations of contemporaneous and lagged index returns tend to be predictably weaker in size and statistical significance. Comparing the mean returns and standard deviations in the two tables also yields the not surprising conclusion that mean returns are higher and standard deviations smaller if the stock crash and subsequent period are excluded. The evidence in Table 1 suggests the need to estimate our GARCH models for both time intervals to ensure the robustness of our conclusions.

Table 1
Data summary, close-to-close, open-to-close, and close-to-open returns

Panel A: Sample period: April 1, 1985–March 31, 1988

	Number of obs.	Mean	Standard deviation	Autocorrelations Lag 1	2	3	4	5	6	7	8	9	10
NK C-C[1]	836	.0936	1.1237	.0188	−.1136	−.0023	−.0676	.1185	−.0643	−.0544	.0101	.0112	.0057
				(.0346)	(.0346)	(.0350)	(.0350)	(.0352)	(.0357)	(.0358)	(.0359)	(.0359)	(.0359)
NK O-C	837	.0201	1.0790	−.0265	−.1028	.0200	−.0717	.1277	−.0447	−.0390	.0264	.0160	.0031
				(.0346)	(.0346)	(.0350)	(.0350)	(.0351)	(.0357)	(.0358)	(.0358)	(.0358)	(.0358)
NK C-O	836	.0739	0.2243	.1634	.0060	.0713	.0829	.0860	.0587	−.0544	.0379	.1152	.0765
				(.0346)	(.0355)	(.0355)	(.0357)	(.0359)	(.0362)	(.0363)	(.0364)	(.0364)	(.0368)
FTSE C-C	760	.0488	1.2607	−.0120	.0930	.0229	.0380	.0595	−.1037	.0962	.0529	.1214	.0005
				(.0363)	(.0363)	(.0366)	(.0366)	(.0367)	(.0368)	(.0372)	(.0375)	(.0376)	(.0381)
FTSE O-C	760	−.0102	0.8619	−.0192	−.0540	.1015	.0631	−.0201	−.0589	.0890	.1585	.0854	−.0314
				(.0363)	(.0363)	(.0364)	(.0368)	(.0369)	(.0369)	(.0370)	(.0373)	(.0382)	(.0385)
FTSE C-O	760	.0581	0.8282	−.1114	.0940	−.0091	−.0435	.0769	−.0664	.0313	−.0570	.0755	−.0141
				(.0363)	(.0367)	(.0370)	(.0370)	(.0371)	(.0373)	(.0375)	(.0375)	(.0376)	(.0378)
S&P C-C	760	.0574	1.3823	.0427	−.1169	−.0547	−.0666	.0924	.0353	.0307	.0012	−.0124	−.0414
				(.0363)	(.0363)	(.0368)	(.0369)	(.0371)	(.0374)	(.0374)	(.0375)	(.0375)	(.0375)
S&P O-C	760	.0586	1.3609	.0387	−.1088	−.0494	−.0591	.0918	.0422	.0274	−.0059	−.0094	−.0435
				(.0363)	(.0363)	(.0368)	(.0368)	(.0370)	(.0373)	(.0373)	(.0374)	(.0374)	(.0374)
S&P C-O	760	−.0012	0.1528	−.0059	−.0045	−.1199	.0162	.0816	−.0320	.0271	−.1515	.0130	.0726
				(.0363)	(.0363)	(.0363)	(.0368)	(.0368)	(.0370)	(.0371)	(.0371)	(.0379)	(.0379)

Correlation coefficients[2]

	NK O-C		FTSE O-C		S&P O-C
S&P O-C (−1)	.48583	NK O-C	−.00561	FTSE O-C	.41200
FTSE O-C (−1)	.36397	SP O-C (−1)	−.24117	NK O-C	.11673

Table 1
Continued

Panel B: Sample period: April 1, 1985–September 30, 1987

	Number of obs.	Mean	Standard deviation	Autocorrelations Lag 1	2	3	4	5	6	7	8	9	10
NK C-C[1]	701	.1062	0.8470	.1965	−.0526	−.0828	.0025	.0520	−.0347	−.0591	−.0668	.0167	.0626
				(.0378)	(.0392)	(.0393)	(.0396)	(.0396)	(.0397)	(.0397)	(.0398)	(.0400)	(.0400)
NK O-C	702	.0191	0.7883	.1328	−.0255	−.0487	−.0002	.0654	.0182	−.0278	−.0405	.0277	.0598
				(.0377)	(.0384)	(.0384)	(.0385)	(.0385)	(.0387)	(.0387)	(.0387)	(.0388)	(.0388)
NK C-O	702	.0875	0.2392	.1475	−.0152	.0568	.0702	.0654	.0433	−.0756	.0238	.1069	.0600
				(.0377)	(.0386)	(.0386)	(.0387)	(.0389)	(.0390)	(.0391)	(.0393)	(.0393)	(.0397)
FTSE C-C	632	.1014	0.8782	.0451	.0500	−.0501	−.0328	.0055	−.0562	.0403	.0421	.1614	.0564
				(.0398)	(.0399)	(.0400)	(.0401)	(.0401)	(.0401)	(.0402)	(.0403)	(.0404)	(.0414)
FTSE O-C	632	.0089	0.6547	−.0113	.0304	−.0283	−.0281	−.0258	−.0446	.0633	.0117	.0950	.1035
				(.0398)	(.0398)	(.0398)	(.0399)	(.0399)	(.0399)	(.0400)	(.0402)	(.0402)	(.0405)
FTSE C-O	632	.0923	0.5614	−.0917	−.0158	−.0119	−.0322	.0270	−.0040	.0689	.0106	.0995	.0454
				(.0398)	(.0401)	(.0401)	(.0401)	(.0402)	(.0402)	(.0402)	(.0404)	(.0404)	(.0408)
S&P C-C	633	.0950	0.8657	.0915	−.0345	.0177	−.0492	−.0697	−.0183	−.0069	.0307	.0182	.0634
				(.0398)	(.0401)	(.0401)	(.0401)	(.0402)	(.0404)	(.0404)	(.0404)	(.0405)	(.0405)
S&P O-C	633	.0920	0.8460	.0800	−.0077	.0265	−.0276	−.0802	−.0111	−.0210	.0346	.0232	.0616
				(.0398)	(.0400)	(.0400)	(.0400)	(.0401)	(.0403)	(.0403)	(.0403)	(.0404)	(.0404)
S&P C-O	633	.0033	0.1566	−.0090	−.0004	−.1422	.0268	.0977	−.0275	.0335	−.1875	.0110	.0740
				(.0398)	(.0398)	(.0398)	(.0406)	(.0406)	(.0409)	(.0410)	(.0410)	(.0424)	(.0424)

Correlation coefficients[2]

NK O-C		FTSE O-C		S&P O-C	
S&P O-C (−1)	.11604	NK O-C	.05259	FTSE O-C	.11989
FTSE O-C (−1)	.00597	SP O-C (−1)	−.10882	NK O-C	.09540

[1] C-C, O-C, and C-O stand for close-to-close, open-to-close, and close-to-open, respectively. To minimize the trading overlap between London and New York, FTSE close is measured at 3:30 P.M. legal close. Returns are measured in percent. Numbers in parentheses are standard errors.

[2] (−1) denotes one-period lag. For example, corr(NK, S&P(−1)) gives a correlation coefficient between Nikkei and S&P on the prior trading day (when the New York market closes several hours prior to the Tokyo market).

4. Spillover Effects in Open-to-Close Stock Returns

To assess the appropriateness of the GARCH-M specification for open-to-close daily stock returns, we employ an MA(1)–GARCH(1, 1)-M model, as discussed in Section 2, which has the following form:

$$R_t = \alpha + \beta h_t + \delta D_t + \gamma \epsilon_{t-1} + \epsilon_t$$
$$h_t = a + b h_{t-1} + c \epsilon_{t-1}^2 + d D_t \qquad (1)$$

where h represents the conditional variance of the stock index return, R, at time t, and D represents a dummy variable that takes a value of 1 on days following weekends and holidays and is 0 otherwise. This formulation more clearly tests the spillover effect often asserted to exist when ovelapping close-to-close returns of several stock exchanges are studied. By using open-to-close returns for stock markets without concurrent trading, stock returns across markets are measured in such a way that their trading periods do not overlap in time, thus eliminating the spillover effect in opening prices predicted by international capital asset pricing models.

Table 2 shows the results of our initial estimation of the GARCH-M model for the open-to-close returns series in the U.S., U.K., and Japanese markets.[14] The likelihood ratio [LR(4)] statistics, which allow us to test the null hypothesis that the returns are normally distributed against the alternative that they are generated by an MA(1)–GARCH(1, 1)-M model, are significant at the 1 percent level in all three markets. No indications of serious model misspecification are observed; for example, none of the Ljung-Box values for the first 12 normalized residuals or residuals squared are significant at conventional levels. Of somewhat greater concern are the coefficients of kurtosis for the normalized residuals that take on values of 7.66 for the Nikkei, 22.78 for the FTSE, and 7.74 for the S&P, relative to a predicted value of 3.0.[15] These coefficients, however, are much smaller for the subperiod prior to the October 1987 stock market crash as seen in Panel B of Table 2.[16] Finally, it is noteworthy that the conditional variance has a significant effect only on the conditional mean in the precrash subperiod and then only in the Tokyo and London markets.

We next introduce an exogenous variable into the conditional variance that captures the potential volatility spillover effect from the

[14] We also estimated more complicated GARCH-M specifications that consistently indicated that the simpler specification was more strongly supported by the data.

[15] The higher kurtosis in London may be in part a manifestation of the smaller number of stocks in this index which a more diversified index would lessen.

[16] We explored a volatility spillover model that included lagged high–low spread squared in the conditional variance. This alternative formulation fit the data rather poorly.

Table 2
Estimation of a GARCH model using open-to-close stock returns

$$R_t = \alpha + \beta h_t + \delta D_t + \gamma \epsilon_{t-1} + \epsilon_t$$
$$h_t = a + b h_{t-1} + c\epsilon_{t-1}^2 + dD_t$$

where R_t = open-to-close return, h_t = conditional variance of R_t, and D_t = weekend dummy variable that equals 1 on a day following a weekend or holiday or 0 otherwise.

	Japan stock market Nikkei 225 Stock Index		U.K. stock market FTSE 100 Stock Index		U.S. stock market S&P 500 Stock Index	
Panel A: Sample period: April 1, 1985–March 31, 1988						
Number of obs.	837		760		760	
Log-likelihood	−969.32		−874.84		−1072.07	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
α	.0623	2.01	.1175	2.60	.1214	2.46
β	.0377	0.95	−.1465	−1.89	.0124	0.28
γ	.1227	2.57	−.0368	−0.87	.0544	1.08
δ	−.0580	−1.50	−.1299	−2.10	−.0327	−0.47
a	.1237	5.98	.0316	2.10	.0091	0.47
b	.2720	6.77	.8551	42.88	.7937	45.72
c	.8403	16.41	.0847	4.95	.2056	16.77
d	.0284	0.86	−.0059	−0.13	.1519	2.18
LR(6) for H_0: $\beta = \gamma = \delta = b = c = d = 0$[1]	562.97		180.26		480.01	
Coefficient of skewness for normalized residuals	−0.87		−2.05		−0.91	
Coefficient of kurtosis for normalized residuals	7.66		22.78		7.74	
Ljung-Box(12) for normalized residuals[2]	8.99		14.68		5.41	
Ljung-Box(12) for normalized squared residuals[2]	4.13		5.09		3.78	
Panel B: Sample period: April 1, 1985–September 30, 1987						
Number of obs.	702		632		633	
Log-likelihood	−733.18		−618.05		−772.44	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
α	−.0447	−1.01	.2805	2.35	.1464	1.53
β	.2208	2.42	−.5596	−1.89	−.0483	−0.32
γ	.1228	2.80	−.0335	−0.76	.0685	1.62
δ	−.1247	−2.31	−.1513	−2.36	−.0376	−0.50
a	.0268	3.10	.0295	1.33	−.0180	−1.14
b	.7782	34.55	.8789	16.64	.9192	38.95
c	.1825	7.35	.0610	2.37	.0552	3.92
d	.0031	0.08	−.0223	−0.39	.1671	2.63
LR(6) for H_0: $\beta = \gamma = \delta = b = c = d = 0$[1]	190.80		20.97		38.79	
Coefficient of skewness for normalized residuals	−0.66		−0.36		−0.41	
Coefficient of kurtosis for normalized residuals	5.42		3.70		5.03	
Ljung-Box(12) for normalized residuals[2]	8.39		19.11		8.39	
Ljung-Box(12) for normalized squared residuals[2]	13.68		20.10		5.55	

[1] $\chi^2(6)$ critical values: 10.64 (10%), 12.59 (5%), 16.81 (1%).
[2] $\chi^2(12)$ critical values: 18.55 (10%), 21.03 (5%), 26.22 (1%).

Table 3
Volatility spillovers estimated from a GARCH model using open-to-close stock returns of the domestic market and one foreign market

$$R_t = \alpha + \beta h_t + \delta D_t + \gamma \epsilon_{t-1} + \epsilon_t$$
$$h_t = a + bh_{t-1} + c\epsilon_{t-1}^2 + dD_t + fX_t$$

where R_t = the domestic open-to-close return, h_t = conditional variance of R_t, D_t = weekend/holiday dummy variable which equals 1 on a day following a weekend or holiday and 0 otherwise, and X_t = most recent squared residual derived from an MA(1)–GARCH(1,1)-M model applied to the open-to-close return of the previously open foreign market.

Panel A: Sample period: April 1, 1985–March 31, 1988

	From U.S. to Japan		From Japan to U.K.		From U.K. to U.S.	
Number of obs.	837		760		760	
Log-likelihood	−927.48		−848.89		−1062.73	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
α	.0355	0.97	.0774	1.76	.1223	2.35
β	.0634	1.27	−.0831	−1.11	−.0093	−0.19
γ	.1357	3.17	−.0330	−0.82	.0603	1.32
δ	−.1216	−2.40	−.1203	−1.97	−.0330	−0.43
a	.0389	3.57	.0376	2.13	.0058	0.30
b	.6104	15.24	.8390	30.00	.7790	34.40
c	.2685	6.69	.0447	2.03	.1349	5.81
d	.0442	1.27	−.0120	−0.20	.1135	1.89
f	.0464	5.24	.0312	5.36	.1459	6.54
LR(1) for H_0: $f = 0$[1]	83.68		51.89		18.68	
LR(7) for H_0: $\beta = \gamma = \delta = b = c = d = f = 0$[2]	646.66		232.15		498.69	
Coefficient of skewness for normalized residuals	−0.55		−1.41		−0.82	
Coefficient of kurtosis for normalized residuals	5.65		13.90		6.62	
Ljung-Box(12) for normalized residuals[3]	9.01		15.75		6.17	
Ljung-Box(12) for normalized squared residuals[3]	6.51		4.98		4.69	

previously open foreign stock market into the domestic stock market. Interpreting the squared residual from the above model as a "volatility surprise," we take the most recent squared residual derived from model (1), denoted by X, using open-to-close returns in the foreign market that trades most recently (i.e., Tokyo for London, London for New York, and New York for Tokyo), and append it to the domestic market's conditional variance specification:[17]

$$R_t = \alpha + \beta h_t + \delta D_t + \gamma \epsilon_{t-1} + \epsilon_t$$
$$h_t = a + bh_{t-1} + c\epsilon_{t-1}^2 + dD_t + fX_t \tag{2}$$

In this GARCH specification, X_t can be interpreted as the most recent volatility surprise observed in the foreign markets.

[17] We also used the most recent h_t from the previously open foreign market as X_t. The results were essentially unchanged.

Table 3
Continued

Panel B: Sample period: April 1, 1985–September 30, 1987

	From U.S. to Japan		From Japan to U.K.		From U.K. to U.S.	
Number of obs.	702		632		633	
Log-likelihood	−728.40		−616.99		−772.43	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
α	−.0383	−0.85	.2757	2.23	.1474	1.56
β	.2145	2.31	−.5573	−1.80	−.0457	−0.31
γ	.1208	2.63	−.0296	−0.68	.0657	1.58
δ	−.1177	−2.21	−.1397	−2.14	−.0413	−0.55
a	.0174	2.28	.0248	1.12	−.0202	−1.26
b	.7271	25.84	.8754	17.06	.9197	39.53
c	.1988	6.87	.0558	2.21	.0527	3.85
d	.0193	0.57	.0015	0.02	.1576	2.63
f	.0347	3.90	.0043	0.99	.0123	0.82
LR(1) for H_0: $f = 0$[1]	9.54		2.12		0.03	
LR(7) for H_0: $\beta = \gamma = \delta = b = c = d = f = 0$[2]	200.34		23.09		38.82	
Coefficient of skewness for normalized residuals	−0.69		−0.35		−0.43	
Coefficient of kurtosis for normalized residuals	5.94		3.58		5.10	
Ljung-Box(12) for normalized residuals[3]	7.77		19.38		8.31	
Ljung-Box(12) for normalized squared residuals[3]	10.28		17.79		5.18	

[1] $\chi^2(1)$ critical values: 2.71 (10%), 3.84 (5%), 6.64 (1%).

[2] $\chi^2(7)$ critical values: 12.02 (10%), 14.07 (5%), 18.48 (1%).

[3] $\chi^2(12)$ critical values: 18.55 (10%), 21.03 (5%), 26.22 (1%).

The results of estimating this model for both the full sample period and the precrash subperiod are shown in Table 3. For the full sample period, the effect of a volatility surprise in the most recent foreign market to trade on the return volatility in the domestic market is statistically significant for all three stock exchanges. More precisely, the parameter estimate on the foreign volatility surprise is positive and statistically significant for all three markets, and the LR statistics for inclusion of this spillover effect variable are 83.68 for the Nikkei, 51.89 for the FTSE, and 18.68 for the S&P, which are all significant at the 1 percent level. On the other hand, when the post-October 1987 period is removed from the sample, the effect becomes less pervasive, as seen in Panel B. Only in one of the three markets is a statistically significant volatility spillover effect observed, namely, from the United States to Japan.[18]

[18] We also converted the Japanese stock returns into U.S. dollars using the open (9:00 A.M.) and close (3:00 P.M.) spot interbank exchange rate quotations (yen/dollar), S_o and S_c, from the Tokyo foreign exchange market:

Table 4
Volatility spillovers estimated from a GARCH model using open-to-close stock returns of the domestic market and two foreign markets

$$R_t = \alpha + \beta h_t + \delta D_t + \gamma \epsilon_{t-1} + \epsilon_t$$
$$h_t = a + bh_{t-1} + c\epsilon_{t-1}^2 + dD_t + f_1 X_{1t} + f_2 X_{2t}$$

where R_t = the domestic open-to-close return, h_t = conditional variance of R_t, D_t = weekend/holiday dummy variable that equals 1 on a day following a weekend or holiday and 0 otherwise, and X_{it} = squared residuals derived from an MA(1)–GARCH(1,1)-M model applied to the open-to-close return of the two foreign markets.

Panel A: Sample period: April 1, 1985–March 31, 1988

	From U.S. (f_1) & U.K (f_2) to Japan		From Japan (f_1) & U.S. (f_2) to U.K.		From U.K. (f_1) & Japan (f_2) to U.S.	
Number of obs.	837		760		760	
Log-likelihood	−923.28		−820.37		−1062.47	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
α	.0429	1.29	.0731	1.69	.1310	2.54
β	.0620	1.35	−.0728	−0.99	−.0226	−0.47
γ	.1191	2.70	−.0276	−0.69	.0617	1.34
δ	−.1080	−2.14	−.1186	−1.99	−.0291	−0.37
a	.0262	1.90	.0422	2.23	.0020	0.10
b	.5211	11.71	.8273	22.16	.7776	29.82
c	.3055	6.27	.0389	1.52	.1328	5.70
d	.0258	0.84	−.0317	−0.47	.1370	2.05
f_1	.0519	4.76	.0185	2.51	.1418	6.53
f_2	.0995	3.59	.0159	8.88	.0078	0.76
LR(1) for H_0: $f_2 = 0$[1]	8.40		57.03		0.53	
LR(2) for H_0: $f_1 = f_2 = 0$[2]	92.08		103.93		19.21	
LR(8) for H_0: $\beta = \gamma = \delta = b = c = d = f_1 = f_2 = 0$[3]	655.05		289.19		499.22	
Coefficient of skewness for normalized residuals	−0.54		−0.70		−0.82	
Coefficient of kurtosis for normalized residuals	5.85		6.00		6.59	
Ljung-Box(12) for normalized residuals[4]	8.50		16.78		6.23	
Ljung-Box(12) for normalized squared residuals[4]	6.40		8.48		5.17	

Next, we expand the exogenous variables in the conditional variance equation by including the squared residuals from the GARCH-M model of the open-to-close returns for both foreign markets that complete their trading cycles while the domestic market is closed. This yields the following modification of the model:

$$\text{Return in dollars} = (S_o/S_c)_t (1 + \text{return in yen}) - 1$$

Although the Japanese foreign currency market is closed on Saturdays, the Tokyo Stock Exchange is open on the first and fourth Saturday of the month for two hours. In order to align Japanese returns consistently with the U.S. returns, Saturday trading is ignored. This conversion allows us to assess whether our findings are mitigated or exacerbated by the conversion into a single currency. We reestimated models (1) and (2) for the dollar-denominated Nikkei index. The outcomes were very similar to the local-currency case, demonstrating the robustness of our results. (The exchange rate data were provided by Nihon Keizai Shimbun Sha.)

Table 4
Continued

Panel B: Sample period: April 1, 1985–September 30, 1987

	From U.S. (f_1) & U.K (f_2) to Japan		From Japan (f_1) & U.S. (f_2) to U.K.		From U.K. (f_1) & Japan (f_2) to U.S.	
Number of obs.	702		632		633	
Log-likelihood	−726.73		−616.53		−771.86	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
α	−.0260	−0.62	.2489	2.29	.1363	1.39
β	.1918	2.12	−.4926	−1.79	−.0368	−0.24
γ	.1052	2.20	−.0299	−0.68	.0693	1.64
δ	−.1015	−1.80	−.1408	−2.21	−.0409	−0.53
a	.0017	0.17	.0221	0.98	−.0220	−1.37
b	.6701	20.18	.8615	15.17	.9297	40.15
c	.2228	6.15	.0607	2.08	.0484	3.57
d	.0355	1.04	−.0002	−0.003	.1575	2.45
f_1	.0353	3.82	.0027	0.58	.0127	0.88
f_2	.0743	3.36	.0111	1.72	−.0027	−0.64
LR(1) for H_0: $f_2 = 0$[1]	3.35		0.94		1.13	
LR(2) for H_0: $f_1 = f_2 = 0$[2]	12.89		3.06		1.15	
LR(8) for H_0: $\beta = \gamma = \delta = b = c = d = f_1 = f_2 = 0$[3]	203.69		24.03		39.95	
Coefficient of skewness for normalized residuals	−0.72		−0.36		−0.43	
Coefficient of kurtosis for normalized residuals	6.35		3.76		5.09	
Ljung-Box(12) for normalized residuals[4]	7.24		19.63		8.45	
Ljung-Box(12) for normalized squared residuals[4]	6.72		19.21		5.11	

[1] $\chi^2(1)$ critical values: 2.71 (10%), 3.84 (5%), 6.64 (1%).
[2] $\chi^2(2)$ critical values: 4.61 (10%), 5.99 (5%), 9.21 (1%).
[3] $\chi^2(8)$ critical values: 13.36 (10%), 15.51 (5%), 20.09 (1%).
[4] $\chi^2(12)$ critical values: 18.55 (10%), 21.03 (5%), 26.22 (1%).

$$R_t = \alpha + \beta h_t + \delta D_t + \gamma \epsilon_{t-1} + \epsilon_t$$
$$h_t = a + b h_{t-1} + c \epsilon_{t-1}^2 + d D_t + f_1 X_{1t} + f_2 X_{2t} \qquad (3)$$

This enables us to examine separate volatility spillover effects from both foreign markets. If the spillover effect reflects the influence of a common economic effect on the volatility of all three stock market indices, introducing the second foreign market is unlikely to add much incremental explanatory power. Table 4 shows estimates for the two sample periods. For the full sample period, all three markets are affected by the volatility surprises of the two previously open foreign markets, with the exception that Tokyo has no significant influence on New York. We also find that the New York market's spillover effect is larger than that of the other foreign market in its effect on either London or Tokyo stock market volatility. Overall, the inclusion of a second foreign market does not appear to diminish the volatility spillover effect of the first foreign market and for the most part both foreign markets appear to have equally important spillover effects. These observed relations appear unlikely to be the result of a common economic effect manifesting itself in all three markets.

The results for the precrash subperiod are consistent with the single foreign market spillover case and show a distinctive asymmetry, that is, there is no significant volatility spillover to the London and New York markets, but there is an equally significant spillover effect from both London and New York to the Tokyo stock market. While the inclusion of the post-October 1987 period does increase the measured spillover effect, the main finding is clear: the Japanese market is most sensitive to volatility spillover effects from foreign markets, while the other two major stock exchanges are at most moderately sensitive, if at all, to volatility spillovers from foreign stock markets.

This asymmetry in influences across national stock markets is consistent with evidence uncovered in a recent study by Eun and Shim (1989). They employ a vector autoregression model to investigate the international transmission mechanism of stock market movements across nine major stock markets. Eun and Shim report that "innovations in the United States are rapidly transmitted to other markets in a clearly recognizable fashion, whereas no single foreign market can significantly explain the U.S. market movements." The underlying economic explanation for this result is far from resolved.[19]

5. Spillover Effects on the Conditional Means of Stock Returns

We next consider the possibility of a spillover effect in the stock returns of one market on the conditional *mean* as well as conditional variance in the next market to trade, again using open-to-close returns data. We modify the specification in model (2) by expanding the definition of the conditional mean to include the current open-to-close return of the most recent foreign market to trade, Y, and define the exogenous variable X in the conditional variance equation to be the most recent squared residual from model (1) for the open-to-close return of the same foreign market. The form of the model is

$$\begin{aligned} R_t &= \alpha + \beta h_t + \delta D_t + \phi Y_t + \gamma \epsilon_{t-1} + \epsilon_t \\ h_t &= a + b h_{t-1} + c \epsilon_{t-1}^2 + d D_t + f X_t \end{aligned} \tag{4}$$

[19] We also explored the effect of estimating this model using close-to-close returns. The qualitative results especially with regard to spillover effects turned out to be very similar.

The results of this estimation for the full sample period are shown in Table 5, Panel A. In all three markets, the parameter estimates did not change significantly from those obtained for model (4). However, statistically significant mean spillover effects, associated with Y_t, are observed in both the New York and Tokyo markets. In other words, the conditional mean return exhibits a positive spillover effect from the prior market; a high return in the New York (London) market is followed by a high return in the Tokyo (New York) market, but such a relation is not found between Tokyo and London. This contrasts with the conditional variance that exhibits a spillover effect in all three markets for the entire sample period. For the New York market, where the mean spillover effect is largest and most significant, the likely explanation is the one-hour overlap in trading with London. For the Tokyo market, the positive mean spillover effect is more difficult to explain, though it may reflect the use of stale quotes for stocks in the Nikkei index experiencing a delayed opening of trading.

Turning to the pre-stock crash estimates shown in Panel B of Table 5, we find some interesting differences in spillover effects for the open-to-close returns. The spillover in conditional mean in this subperiod is diminished in all three markets and becomes marginally insignificant for the Tokyo market. Since over this subperiod the Nikkei open was recorded 15 minutes after the start of trading, the effects of stale quotes on the opening price and the open-to-close return are minimized. The use of these more accurate opening prices for the Nikkei should also lower the S&P spillover into the Nikkei conditional mean, which is consistent with the observed marginally insignificant mean spillover effect. More interesting, the spillover in conditional variances is lowered in all three markets, though it remains relatively large and significant for Tokyo.

The spillover effects observed in New York for open-to-close returns are likely to be influenced by the fact that the London market does not close until after the open of trading in New York. One approach to eliminating the effects of this overlapping trading across markets and the effects of stale quotes being used at the S&P's open is to replace open-to-close returns with noon-to-close returns for the S&P index. By reestimating model (4) for the New York market using noon-to-close returns, we can then compare these results to those in Table 5. This comparison allows us to assess the influence on conditional means and variances in the New York market. The basic model (1) is also reestimated to determine whether or not the GARCH-M model is an appropriate specification for the S&P noon-to-close return series.

Table 6 shows the results of these two estimations for the full period and the precrash subperiod. For the basic MA(1)–GARCH(1, 1)-M

Table 5
Mean and volatility spillovers estimated from a GARCH model using open-to-close returns

$$R_t = \alpha + \beta h_t + \delta D_t + \phi Y_t + \gamma \epsilon_{t-1} + \epsilon_t$$
$$h_t = a + bh_{t-1} + c\epsilon^2_{t-1} + dD_t + fX_t$$

where R_t = the domestic open-to-close return, h_t = conditional variance of R_t, D_t = weekend/holiday dummy variable that equals 1 on a day following a weekend or holiday and 0 otherwise, X_t = most recent squared residual derived from an MA(1)–GARCH(1,1)-M model applied to the open-to-close return of the previously open foreign market, and Y_t = open-to-close return of the previouly open foreign market.

Panel A: Sample period: April 1, 1985–March 31, 1988

	From U.S. to Japan		From Japan to U.K.		From U.K. to U.S.	
Number of obs.	837		760		760	
Log-likelihood	−921.52		−847.68		−1051.83	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
α	.0272	0.67	.0753	1.71	.1008	1.71
β	.0595	1.09	−.0812	−1.10	−.0128	−0.24
γ	.1430	3.22	−.0341	−0.84	.0784	1.57
δ	−.1530	−2.58	−.1162	−1.86	−.0149	−0.17
ϕ	.1007	3.42	.0156	0.47	.2559	4.53
a	.0475	3.11	.0378	2.11	−.0007	−0.03
b	.5719	11.29	.8380	28.76	.7886	32.07
c	.2778	5.90	.0441	1.99	.1307	5.21
d	.1250	2.89	−.0110	−0.18	.1725	2.26
f	.0498	4.71	.0323	5.33	.1481	5.44
LR(1) for H_0: $\phi = 0$[1]	11.92		2.42		21.80	
Coefficient of skewness for normalized residuals	−0.46		−1.39		−0.81	
Coefficient of kurtosis for normalized residuals	5.45		13.49		6.58	
Ljung-Box(12) for normalized residuals[2]	6.99		16.02		8.76	
Ljung-Box(12) for normalized squared residuals[2]	7.68		5.15		4.22	

model defined by (1), we find that noon-to-close returns of the S&P index are well characterized by the GARCH model for both periods. This result supports our reestimation of the spillover effects using model (4) and these same noon-to-close returns. We find that the spillover effect in conditional mean is no longer significant, while the spillover effect in conditional variance is strengthened in both the full period and subperiod cases. The above evidence supports our earlier conclusions that significant spillovers in conditional variances occur across all three markets.

6. Spillover Effects in Close-to-Open Stock Returns

Prior studies of spillover effects have used close-to-close returns to estimate these effects. This tends to confuse several alternative causes of correlation in return processes across these markets since the time

Table 5
Continued

Panel B: Sample period: April 1, 1985–September 30, 1987

	From U.S. to Japan		From Japan to U.K.		From U.K. to U.S.	
Number of obs.	702		632		633	
Log-likelihood	−725.17		−616.59		−768.95	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
α	−.0746	−1.42	.1686	1.60	.1220	1.11
β	.2570	2.49	−.3058	−1.24	−.0335	−0.20
γ	.1256	2.69	−.0184	−0.40	.0886	1.99
δ	−.1505	−2.38	−.1148	−1.71	−.0119	−0.15
ϕ	.0632	1.98	.0114	0.33	.1038	2.05
a	.0166	.172	.0265	1.13	−.0148	−0.78
b	.7589	23.90	.8730	17.58	.9240	35.00
c	.1667	6.04	.0473	1.91	.0499	3.30
d	.0598	1.31	−.0091	−0.13	.1386	2.07
f	.0275	3.17	.0194	2.09	.0127	0.77
LR(1) for H_0: $\phi = 0$[1]	6.46		0.81		6.95	
Coefficient of skewness for normalized residuals	−0.63		−0.31		−0.42	
Coefficient of kurtosis for normalized residuals	5.46		3.21		5.20	
Ljung-Box(12) for normalized residuals[2]	7.30		19.39		9.33	
Ljung-Box(12) for normalized squared residuals[2]	12.80		13.71		5.65	

[1] $\chi^2(1)$ critical values: 2.71 (10%), 3.84 (5%), 6.64 (1%).
[2] $\chi^2(12)$ critical values: 18.55 (10%), 21.03 (5%), 26.22 (1%).

interval represented by these returns overlap. With a significant level of international financial integration, an overlap in the stock return time intervals across markets should induce positive correlation in the measured returns and possibly in return volatility. The extent to which previously documented positive correlations in returns across stock markets are due to overlapping time intervals can be evaluated by studying the spillover effects of concurrent open-to-close returns in the foreign market on close-to-open returns in the domestic market. This essentially accounts for the impact of "overnight" foreign trading on the opening price in the domestic market. The subsequent spillover effects in the domestic market after the opening of trading are captured in the open-to-close returns documented in the prior sections of this article. In estimating the spillover effects in both the conditional mean and conditional variance of the close-to-open returns in the domestic market, we use model (4) where the exogenous variables Y and X are defined as the most recent open-to-close return and its squared residual using model (1) in the two foreign markets that trade in this time interval.

Table 6
Mean and volatility spillovers estimated from a GARCH model using noon-to-close S&P returns

Base model:
$R_t = \alpha + \beta h_t + \delta D_t + \gamma\epsilon_{t-1} + \epsilon_t$
$h_t = a + bh_{t-1} + c\epsilon^2_{t-1} + dD_t$

Spillover model from U.K. to U.S.:
$R_t = \alpha + \beta h_t + \delta D_t + \phi Y_t + \gamma\epsilon_{t-1} + \epsilon_t$
$h_t = a + bh_{t-1} + c\epsilon^2_{t-1} + dD_t + fX_t$

where R_t = S&P noon-to-close return, h_t = conditional variance of R_t, D_t = weekend/holiday dummy variable that equals 1 on a day following a weekend or holiday and 0 otherwise, X_t = most recent squared residual derived from an MA(1)–GARCH(1,1)-M model applied to the FTSE open-to-close returns, and Y_t = most recent FTSE open-to-close return.

Panel A: Sample period: April 1, 1985–March 31, 1988

	Base model			Spillover model from U.K. to U.S.	
Number of obs.	760			760	
Log-likelihood	−813.48			−796.36	
	Coeff.	*t*-stat.		Coeff.	*t*-stat.
α	.0594	1.44	α	.0706	2.21
β	.0109	0.13	β	−.0126	−0.21
γ	−.0955	−2.06	γ	−.1057	−2.19
δ	.0820	1.46	δ	.0780	1.27
a	.0635	3.26	ϕ	.0475	1.28
b	.6218	15.47	a	.0456	2.11
c	.2635	18.63	b	.4962	10.64
d	.0814	1.83	c	.3188	7.55
			d	.1289	2.62
			f	.1471	5.88
LR(6) for H_0 $\beta = \gamma = \delta = b = c = d = 0$[1]	435.42		LR(2) for H_0 $\phi = f = 0$[2]	34.25	
Coefficient of skewness for normalized residuals	−1.11			−0.81	
Coefficient of kurtosis for normalized residuals	8.08			5.85	
Ljung-Box(12) for normalized residuals[3]	6.19			5.56	
Ljung-Box(12) for normalized squared residuals[3]	7.67			10.66	

The results of estimating the spillover effects on the close-to-open returns of the domestic market are shown in Table 7, Panel A for the April 1985–March 1988 period. For all three stock markets, we find clear evidence that the most recent open-to-close returns of the two foreign markets consistently have positive influences on the opening price in the next market to trade with at least one of these two foreign markets exhibiting statistical significance. We also find that, for at least one of the two foreign markets, the residual from the GARCH model in that market has a significant positive spillover effect on the conditional volatility of the close-to-open return in the next market to open trading. Comparing these results with those for spillover effects measured by the open-to-close returns in Table 5, Panel A, we find very similar spillover patterns with Tokyo's market return having little influence on the London opening price. Also, the influence of

Table 6
Continued

Panel B: Sample period: April 1, 1985–September 30, 1987

	Base model			Spillover model from U.K. to U.S.	
Number of obs.	633			633	
Log-likelihood	−572.45			−570.70	
	Coeff.	*t*-stat.		Coeff.	*t*-stat.
α	.1168	1.87	α	.0957	1.52
β	−.1552	−0.87	β	−.0982	−0.57
γ	−.0727	−1.68	γ	−.0775	−1.66
δ	.1134	1.93	δ	.1029	1.61
a	.0103	1.00	ϕ	.0022	0.06
b	.8353	21.94	a	.0041	0.32
c	.0823	4.36	b	.8063	15.58
d	.0921	3.22	c	.0914	3.92
			d	.1287	3.42
			f	.0229	1.38
LR(6) for H_0 $\beta = \gamma = \delta = b = c = d = 0$[1]	48.67		LR(2) for H_0 $\phi = f = 0$[2]	3.50	
Coefficient of skewness for normalized residuals	−0.69			−0.68	
Coefficient of kurtosis for normalized residuals	5.61			5.51	
Ljung-Box(12) for normalized residuals[3]	9.86			9.51	
Ljung-Box(12) for normalized squared residuals[3]	4.84			4.62	

[1] $\chi^2(6)$ critical values: 10.64 (10%), 12.59 (5%), 16.81 (1%).
[2] $\chi^2(2)$ critical values: 4.61 (10%), 5.99 (5%), 9.21 (1%).
[3] $\chi^2(12)$ critical values: 18.55 (10%), 21.03 (5%), 26.22 (1%).

London on the opening price in New York is likely to be attenuated by the fact that the close in London occurs after the open in New York as a result of the overlap in trading periods. Further, the magnitude of the volatility spillover effect is much stronger in the conditional variance of the open-to-close returns.

The results of restricting the observations to the pre-October 1987 period are shown in Panel B of Table 7. In comparing these estimated spillover effects in the conditional mean and conditional variance of the close-to-open return with those of Panel A, we generally find similar results. However, one notable difference is observed for the spillovers in the conditional mean for the New York market; specifically, Japan has much greater influence than does London in the precrash period. Over this subperiod the Nikkei open was recorded 15 minutes after the start of trading; thus, the effects of using stale quotes on the open price and the close-to-open return of the Nikkei stock index are minimized. This should strengthen the spillover in conditional mean from Tokyo to London. It should also strengthen

Table 7
Mean and volatility spillovers estimated from a GARCH model using close-to-open stock returns of the domestic market and open-to-close stock returns of two foreign markets

$$R_t = \text{ga} + \beta h_t + \delta D_t + \phi_1 Y_{1t} + \phi_2 Y_{2t} + \gamma\epsilon_{t-1} + \epsilon_t$$
$$h_t = bh_{t-1} + c\epsilon_{t-1}^2 + dD_t + f_1 X_{1t} + f_2 X_{2t}$$

where R_t = the domestic close-to-open return, h_t = conditional variance of R_t, D_t = weekend/holiday dummy variable that equals 1 on a day following a weekend or holiday and 0 otherwise, Y_{it} = open-to-close returns in the two foreign markets, and X_{it} = squared residuals derived from an MA(1)–GARCH(1,1)-M model applied to the open-to-close returns of the two foreign markets.

Panel A: Sample period: April 1, 1985–March 31, 1988

	From U.S. (ϕ_1, f_1) & U.K. (ϕ_2, f_2) to Japan		From Japan (ϕ_1, f_1) & U.S. (ϕ_2, f_2) to U.K.		From U.K. (ϕ_1, f_1) & Japan (ϕ_2, f_2) to U.S.	
Number of obs.	837		760		760	
Log-likelihood	454.56		−597.06		648.71	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
α	.0132	3.41	.0297	1.29	.0043	2.03
β	.8021	4.71	−.0233	−0.41	−.1706	−1.94
γ	.1423	3.69	−.1666	−4.14	−.1064	−2.83
δ	.0084	1.19	.0639	1.42	−.0468	−8.63
ϕ_1	.0181	7.69	.0304	1.10	.0084	2.57
ϕ_2	.0017	0.47	.3200	13.92	.0027	1.10
a	.0001	0.51	.0126	1.96	.0002	1.45
b	.8827	110.44	.8529	47.52	.3182	9.58
c	.1284	9.65	.0253	1.72	1.1154	9.67
d	−.0002	−0.45	−.0358	−1.25	.0115	21.99
f_1	.00004	2.46	.0123	3.02	.0012	13.42
f_2	−.0001	−1.20	.0268	5.51	−.0002	−7.20
LR(10) for H_0: $\beta = \gamma = \delta = \phi_1 = \phi_2 = b = c = d = f_1 = f_2 = 0$[1]	780.38		675.06		597.59	
Coefficient of skewness for normalized residuals	0.21		−0.41		−0.93	
Coefficient of kurtosis for normalized residuals	5.23		4.57		28.38	
Ljung-Box(12) for normalized residuals[2]	15.00		11.24		9.95	
Ljung-Box(12) for normalized squared residuals[2]	26.95		4.66		1.33	

the spillover in conditional mean from New York to Tokyo, which may explain why this spillover effect is not noticeably weakened when estimated over the shorter precrash subperiod. With respect to spillovers in the conditional variance, we find that the spillovers from London and Tokyo to New York are significantly strengthened while the spillover from New York to Tokyo becomes small and statistically insignificant.

In comparing the parameter estimates for the weekend/holiday dummy variables in the conditional mean and variance equations for the open-to-close returns and the close-to-open returns, we uncover some interesting patterns. For the open-to-close returns, there are consistently significant negative parameter estimates for the week-

Table 7
Continued

Panel B: Sample period: April 1, 1985–September 30, 1987

	From U.S. (ϕ_1, f_1) & U.K. (ϕ_2, f_2) to Japan		From Japan ($\phi_1 f_1$) & U.S. (ϕ_2, f_2) to U.K.		From U.K. (ϕ_1, f_1) & Japan (ϕ_2, f_2) to U.S.	
Number of obs.	702		632		633	
Log-likelihood	305.16		−412.85		589.73	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
α	.0175	4.05	−.0400	−0.86	.0017	1.24
β	.7084	4.15	.2827	1.46	−.1597	−1.92
γ	.1477	3.33	−.1176	−2.58	−.1340	−3.26
δ	.0142	1.89	.1198	2.48	−.0285	−4.89
ϕ_1	.0236	8.00	.0206	0.72	.0012	0.35
ϕ_2	.0022	0.61	.3051	12.51	.0024	1.71
a	.0002	1.23	.0143	2.20	−.0000	−0.07
b	.8659	93.78	.8636	23.22	.3478	9.97
c	.1538	9.22	.0424	2.13	1.1279	8.94
d	.0000	0.00	−.0386	−1.54	.0061	19.64
f_1	−.0000	−0.86	.0106	2.24	.0015	18.45
f_2	−.0002	−2.88	.0155	2.95	−.0003	−5.37
LR(10) for H_0: $\beta = \gamma = \delta = \phi_1 = \phi_2 = b = c = d = f_1 = f_2 = 0$[1]	593.08		237.21		627.23	
Coefficient of skewness for normalized residuals	0.21		−0.24		0.45	
Coefficient of kurtosis for normalized residuals	5.59		4.17		27.53	
Ljung-Box(12) for normalized residuals[2]	11.44		15.76		10.37	
Ljung-Box(12) for normalized squared residuals[2]	22.30		10.04		1.50	

[1] $\chi^2(10)$ critical values: 15.99 (10%), 18.31 (5%), 23.21 (5%).

[2] $\chi^2(12)$ critical values: 18.55 (10%), 21.03 (5%), 26.22 (1%).

end/holiday dummy variable in the conditional mean of the Japanese and U.K. markets but not for the U.S. market. On the other hand, there is a significant positive parameter estimate in the conditional variance of the U.S. market but not for the Japanese and U.K. markets. In contrast, when we estimate the model with close-to-open returns, we observe a highly significant negative parameter estimate for the conditional mean and a significant positive parameter estimate for the conditional variance in the U.S. market and insignificant parameter estimates for the other two markets.[20] This concentration of the negative weekend effect on the opening price in the United States is consistent with the Smirlock and Starks (1986) finding that in the post-1974 period the negative weekend effect is concentrated near the opening for the U.S. market.

[20] It is noteworthy that our spillover estimates are very insensitive to the inclusion or exclusion of weekend/holiday dummy variables in the model specification.

7. Conclusions

This study documents the existence of price change and price volatility effects from one international stock market to the next. We find daily stock returns measured from close-to-open and open-to-close to be approximated by a GARCH(1, 1)-M model. For the conditional variance, we find spillover effects from the U.S. and the U.K. stock markets to the Japanese market. This effect shows an intriguing asymmetry: while the volatility spillover effect on the Japanese market is significant, the spillover effects on the other two markets are much weaker. This result is not affected by whether returns are converted into a single currency.

Unexpected changes in foreign market indices are associated with significant spillover effects on the conditional mean of the domestic market for both open-to-close and close-to-open returns. While the effect on the open-to-close returns suggests some informational inefficiencies in these markets, further examination of this evidence indicates that overlapping trading between London and New York and the inclusion of stale quotes in the calculation of the Nikkei and S&P opening prices are more likely explanations. For the close-to-open returns, this effect on the conditional mean is consistent with international financial integration, while the magnitude of volatility spillover is generally much less in this case.

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