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Do Bulls and Bears Move across Borders? International Transmission of Stock Returns and Volatility

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This article investigates empirically how returns and volatilities of stock indices are correlated between the Tokyo and New York markets. Using intradaily data that define daytime and overnight returns for both markets, we find that Tokyo (New York) daytime returns are correlated with New York (Tokyo) overnight returns. We interpret this result as evidence that information revealed during the trading hours of one market has a global impact on the returns of the other market. In order to extract the global factor from the daytime returns of one market, we propose and estimate a signal-extraction model with GARCH processes.

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When the New York stock market opens its business day, many things that happened overnight must be incorporated in stock prices. One relevant piece of information is how the Tokyo stock market did earlier in the day. Similarly, Tokyo stock brokers certainly take notice of how the New York market ended a few hours before the Tokyo market opens. There are several reasons why the returns and volatility of the two largest equity markets may be related. The two economies are related through trade and investment, so that any news about economic fundamentals in one country most likely has implications for the other country. An international asset-pricing model can incorporate correlations between stock returns in different countries.[1] Some suggest that growing financial market integration will increase the degree of correlation between the stock returns of different countries by making portfolio managers in the home market more responsive to changes in foreign markets.

Another possible reason for the international correlation of stock price changes is market contagion. That is, stock prices in one country may be affected by the changes in another country beyond what is conceivable by connections through economic fundamentals. For instance, the October 1987 crash (Black Monday) in New York, which set off worldwide stock price declines, is cited as evidence for international bear-market contagion [e.g., King and Wadhwani (1990)]. One survey [Shiller, Konya, and Tsutsui (1991)] has found that Tokyo participants are in general influenced by what happens in New York (but not vice versa). In particular, many traders in Tokyo recall that the day after Black Monday they sold stocks on information about the market crash in New York, probably without assessing exactly what fundamental links the New York price declines had to the Tokyo stock prices. Under this market-contagion scenario, speculative trading and noise trading [in the sense of Black (1986) or Delong et al. (1990)] may occur in the international context; price movements driven by fads and a herd instinct may be transmittable across borders.

The nature of the international transmission of stock returns and volatility has been a focus of extensive studies: Bennett and Kelleher (1988); von Furstenberg and Jeon (1989); Hamao, Masulis, and Ng (1990); King and Wadhwani (1990); Schwert (1990); Susmel and Engle (1990); Neumark, Tinsley, and Tosini (1991); Becker, Finnerty, and Tucker (1992); and Dravid, Richardson, and Craig (1993), to name a few. These articles report several empirical regularities: (i) the volatility of stock prices is time-varying; (ii) when volatility is high, the price changes in major markets tend to become highly correlated; (iii) correlations in volatility and prices appear to be causal

[1] See Solnik (1974a, 1974b), Adler and Dumas (1983), and Stulz (1981) for models of international asset pricing.

from the United States to other countries; and (iv) lagged spillovers of price changes and price volatility are found between major markets.[2] We will link these regularities in a rigorous model through which intraday stock price movements across markets can influence each other.

To understand the international transmission mechanism, it is important to recognize that the Tokyo and New York stock markets do not have any overlapping trading hours. We can decompose daily price changes (returns and volatility) into daytime (open-to-close) and overnight (close-to-open) returns, where the daytime segment in one market is a subset of the overnight segment of the other market in real time. This decomposition of daily price changes is crucial for clean tests of how information is transmitted from one market to the other.[3] Intuitively, traders in Tokyo will use any information revealed overnight which may be relevant to their pricing of stocks in Tokyo as soon as the opening bell rings. Major overnight news for Tokyo traders is how stock prices moved in New York. Some parts of the price movements in New York reflect only local news, while other parts reflect news which should affect a global economy—in particular, the Japanese economy.

Suppose, for example, that the dollar depreciates unexpectedly and substantially against the yen and European currencies during the New York daytime hours. This depreciation most likely affects stock returns in New York, since exporters will benefit from either price competitiveness or a higher profit margin, and domestic manufacturing firms competing with imports will enjoy similar benefits. The news of dollar depreciation (or yen appreciation) will be taken into account in an investment strategy at the opening of Tokyo trading, since it will adversely affect Japanese exporters but will favorably affect Japanese importers. This is an example of a global factor. Suppose, on the other hand, a financial scandal in Japan lowers stock returns in Japan, while essentially it does not affect stock returns in the United States (as was the case in 1991). This is an example of a local factor. Of course, these are merely examples. With so many news items, it is difficult to differentiate global and local factors one by one. Hence, at the beginning of the day, investors in the other country have to infer how much movement is due to the global factor.

Our econometric framework is designed to separate the global factor that affects stock returns globally from a local factor that affects

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2 Lagged spillovers are defined as correlations between the foreign daytime return (volatility) and the subsequent domestic daytime return (volatility), without any overlapping trading hours.

3 Many studies have used daily returns in studying international transmissions of stock returns. Among them are King and Wadhwani (1990), von Furstenberg and Jeon (1989), and Eun and Shim (1989). Hamao, Masulis, and Ng (1990) and the current article adopted a finer frequency, but we define the opening price at 10 AM or 9:15 AM in order to avoid a nonsynchronous trading problem which, as we will show, seems to bias their results in favor of the volatility spillovers.

stock returns locally. King and Wadhwani (1990) modeled such a phenomenon as a signal-extraction problem. Investors are assumed to extract the global factor from observed price changes in the foreign market by taking a fraction of the foreign price change. The fraction is the best estimate of the portion of total variance of returns which is due to the global factor. Although King and Wadhwani's approach was seminal in a study of international equity returns correlations, they used close-to-close returns, so that all returns in one country have overlapping hours with returns in the other country. We have improved upon the approach of King and Wadhwani (1990) by decomposing close-to-close returns into daytime and overnight returns and by allowing time-varying volatility in performing the signal extraction.

There are several reasons why we also focus on time-varying stock return volatility. First, it is well known that the volatility of stock prices (or foreign exchange rates) is "clustered," in that a market tends to be volatile for a week or two, and then relatively calm for the following several weeks [see Bollerslev, Chou, and Kroner (1992) for a survey article]. Second, volatility is related to the rate of information flow [Ross (1989)]. The predictability of volatility can be due to the fact that the arrival rate of information is correlated over time. Third, correlations in absolute price changes are associated with the dispersion of beliefs [e.g., see Shalen (1993) for a two-period noisy rational expectations model of a futures market]. When the new information arrives, different prior beliefs about news give incentive to trade and lead to price changes. As traders observe the new price, they may revise their prior beliefs, which leads to continued trading and future price changes. If it takes time for the market to resolve these heterogenous beliefs when traders revise their prior beliefs in response to new information, this process of groping for the equilibrium price may contribute to volatility clustering. Whether the volatility is correlated across markets is important in examining the speed of the market adjustment to new information. We devise such a test of lagged volatility spillovers across markets—as applied in Engle, Ito, and Lin (1990), and Ito, Engle, and Lin (1992) for the foreign exchange markets—for the stock market. Using tests for lagged returns and volatility spillovers, we can examine how promptly domestic stock prices react to overnight foreign news as the domestic market reopens.

In performing this analysis, we carefully select an appropriate proxy for opening quotes. The reason for doing so is the finding by Stoll and Whaley (1990a) that it takes an average of 5 minutes for large stocks and 67.4 minutes for small stocks on the New York Stock Exchange (NYSE) for the first transaction to occur after the market opens. Because of the delay in trading, the measured opening price index does not accurately reflect the true underlying price value. This "nonsynchronous trading problem," or "stale quote problem," may induce spurious lagged spillovers. To address this question, we report a wide range of correlations between daytime and overnight returns using different proxies for opening time. As suggested by our correlation analysis and by Stoll and Whaley (1990a), we avoid a nonsynchronous trading problem by choosing the opening quotes as a price index quoted 30 (or 15) minutes after the NYSE [or the Tokyo Stock Exchange (TSE)] officially opens.

The specification of the signal extraction model is more complicated than that of the GARCH-in-mean model used by Hamao, Masulis, and Ng (1990), which allows the nonlinear dependence of stock return correlations through the conditional variances. Given this, we will test whether the signal-extraction model improves upon the GARCH-in-mean approach in modeling the international transmission of stock returns and volatility. In particular, we will compare the performance of these models to determine which one better characterizes investors' behavior.

The rest of the article is organized as follows. Section 1 sets out the theoretical and empirical framework. Section 2 presents correlation analyses using different definitions for opening prices. Section 3 reports model estimation and comparisons. Lagged spillovers are examined in Section 4. Section 5 summarizes our main findings.

1. Model and Econometric Specifications

1.1 General framework and notation

In this article, we adopt the Nikkei 225 (NK 225) and the Standard and Poor's 500 (S&P 500) as the stock price indices for our analysis.[4] We measure the stock return as the change in the logarithm of the stock price index, which excludes the dividend payments. For both Tokyo and New York, we divide daily (close-to-close) returns into daytime (open-to-close) returns and overnight (previous close-to-open) returns:

$$NK_t = NKN_{t-1} + NKD_t$$

$$SP_t = SPN_t + SPD_t$$

where NK and SP denote returns of the NK 225 and on the S&P 500,

[4] The Standard and Poor 500's price index (S&P 500) is the equity-value weighted average of 500 stock prices selected by Standard and Poor, Inc. The hourly data for the S&P 500 are kindly provided to us by Dr. J. Harold Muherlin at the Dartmouth College. The Nikkei 225 price index (NK 225) is a price-weighted average of 225 stock prices selected by Nihon Keizai Shimbun Sha (Japanese Economic Newspaper, Inc.)

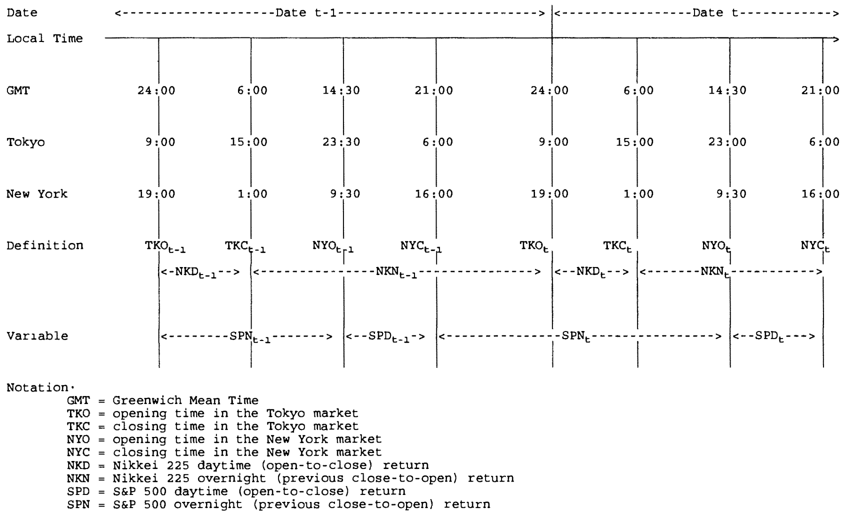

Figure 1
Timing and notation

respectively, and the suffixes D and N denote daytime or overnight, respectively. Note that NKD and SPD do not overlap in real time.

During the trading hours of each market, information or trading noise will be incorporated into stock prices (see Figure 1 for the timing of the New York and the Tokyo markets). We denote as e_t that part of the return that cannot be predicted based upon public information when the market opens. Let HR be the domestic stock return and FR be the foreign return. Allowing for a possible correlation with the preceding overnight return and for Monday or post-holiday effects through a dummy variable DM, we can write the foreign daytime return as follows[5]

$$FRD_t = c_d + a_d FRN_t + b_d DM_t + e_t \tag{1}$$

where $(FRD_t, FRN_t) \in \{(NKD_t, NKN_{t-1}), (SPD_t, SPN_t)\}$. We denote (x_t, y_t) as an element containing any pair of intradaily returns x_t and y_t on the NYSE and the TSE, $\{\ \}$ as a set of such elements, and $\in$ as the mathematical symbol for belonging to. Similar notations are used throughout the article.

When the domestic market opens in the morning, the information

[5] The Monday dummy for SPN is equal to one for the returns from Friday close to Monday open or the returns during holidays, and is equal to zero otherwise. The Monday dummy for NKN is equal to one for the returns from Friday close to Monday open in the absence of Saturday trading, the returns from Saturday close to Monday open in the presence of Saturday trading, or the returns during a single or multiple holidays, and is equal to zero otherwise.

about the foreign daytime market movement has become available to domestic investors.[6] If the market is efficient, foreign news should be fully reflected in the opening price of the domestic market. Two approaches to modeling how domestic investors process this foreign information, the aggregate-shock model (AS) and the signal-extraction model (SE), are described in the following two subsections.

1.2 Aggregate-shock model

The first approach is to use the unexpected return of the foreign market. We call this the aggregate-shock model, in which the domestic overnight return is specified as a function of the preceding domestic daytime return, the Monday or post-holiday dummy, and influences from abroad:[7]

$$HRN_t = c_n + a_n HRD_t + \phi e_t + b_n DM_t + v_t, \tag{2}$$

where $(HRN_t, HRD_t) \in \{(SPN_t, SPD_{t-1}), (NKN_t, NKD_t)\}$, the effect of unexpected returns from the foreign market is ϕe_t, and effects revealed after the close of the foreign market but before the opening of the domestic market are denoted as v_t.

It is instructive to summarize timing and notation as shown in Figure 1, where TKO, TKC, NYO, and NYC, are the times of Tokyo opening, Tokyo closing, New York opening, and New York closing. The daytime returns and overnight returns are defined as changes in the logarithm of the stock price index between those times, respectively. The information set containing domestic and foreign stock returns up to the point of time j (j = TKO, TKC, SPO, SPC) is denoted by $\Omega(j)$. Shocks e_t and v_t are assumed to be serially uncorrelated and mutually independent and follow a GARCH process:

$$e_t \mid \Omega(j) \sim N(0, q_t) \qquad j \in \{TKO_t, NYO_t\}, \tag{3a}$$

$$v_t \mid \Omega(j) \sim N(0, k_t) \qquad j \in \{TKC_t, NYC_t\}, \tag{4a}$$

where $N(\cdot,\cdot)$ denotes a normal distribution with the first element

[6] Price movements in foreign markets most likely reflect news on fundamentals of foreign economies and noise caused by foreign traders. However, there are exceptions. News-conference and economic-statistic announcements are made at times when the stock market is closed. For example, the U.S. money supply is reflected in the Tokyo overnight changes first. Investors in the United States may also place orders in Tokyo, causing "spillovers." In the following analysis, the only information on foreign markets that we use is returns and volatility.

[7] Kato (1990) found that daily returns for the Tokyo Stock Exchange Index were significantly lower on Monday and Tuesday than on the other days of the week. He examined whether Saturday trading could explain these systematic differences. Kato found that negative returns were observed on Monday when there was no trading on Saturday in the previous week, while the Tuesday effect almost disappeared when there was no trading on Saturday. In light of these results, we added a Tuesday dummy into the mean equation of the NK 225 overnight returns, but we did not find a significant Tuesday effect for most cases that we studied. Exclusion of Tuesday dummies did not affect our conclusions.

being the mean, and the second element being the variance conditional on $\Omega(j)$.

The GARCH approach to capturing the phenomenon of volatility clustering is very popular in modeling the second moments of financial data [see a recent survey by Bollerslev, Chou, and Kroner (1992)]. We assume that q_t and k_t follow a GARCH process:

$$q_t = \omega_q + \alpha_q(e_{t-1})^2 + \beta_q q_{t-1} + \gamma_q DM_t \tag{3b}$$

$$k_t = \omega_k + \alpha_k(v_{t-1})^2 + \beta_k k_{t-1} + \gamma_k DM_t. \tag{4b}$$

The aggregate shock model can be formulated as Equations (1)–(4). Since multivariate estimation of Equations (1)–(4) is very costly, we employ a two-stage GARCH estimation method. For example, in the first stage, we apply the GARCH method to estimate the *NKD* return in Equations (1) and (3). Obtaining the fitted value of the unexpected return e_t in the first stage and substituting it into the mean equation of the *SPN* return, we can estimate Equations (2) and (4) by the GARCH method again. A similar procedure can be applied to *SPD* returns and *NKN* returns. This two-stage approach is asymptotically equivalent to a multivariate procedure if the conditional mean equations are correctly specified and if domestic daytime and overnight returns shocks are mutually uncorrelated.[8]

1.3 Signal-extraction model

The second approach is to decompose the unexpected return in the foreign market into two uncorrelated shocks, global and local. Specifically, we assume that

$$e_t = w_t + u_t, \tag{5}$$

where w_t is a global factor and u_t is a local factor. The global factor influences stock returns in the home and foreign markets, and the local factor contains only shocks and noise idiosyncratic to the home market. A global factor may be a shock to international fundamentals or internationally contagious psychology, and a local factor may be a shock to local fundamentals or local market moods. The distributions of the global and the local factors are

$$w_t \mid \Omega(j) \sim N(0, g_t) \qquad j \in \{TKO_t, NYO_t\} \tag{6}$$

and

$$u_t \mid \Omega(j) \sim N(0, h_t) \qquad j \in \{TKO_t, NYO_t\}. \tag{7}$$

[8] From the correlation analysis reported in Tables 1 and 2, we found significant contemporaneous correlations between the domestic daytime and the foreign overnight returns, but insignificant correlations between the domestic daytime and (lagged) foreign daytime returns. This may assure our specification of the mean equation.

In an efficient market, information that is revealed in Tokyo (New York) and that is relevant for New York (Tokyo)—in short, the global factor—will be fully reflected in the opening price in New York (Tokyo). The key assumption here is that investors and econometricians cannot identify global and local shocks, but will try to infer them. Investors are assumed to know the parameters of the return-generating processes. From Equation (5), the unexpected part of the foreign daytime return, that is, e_t, has two components: w_t and u_t. However, domestic investors are assumed to observe only the combined shock, not the individual components. This is a classic problem of signal extraction. Investors can extract an unobserved global factor using a Kalman-filtering procedure which minimizes the mean squared errors of the estimated global factor. The following Kalman-filtering procedure for New York investors to estimate the global factor w_t from the unexpected Tokyo price changes is based on related work by King and Wadhwani (1990), Diebold and Nerlove (1990), and extensions by Harvey, Ruiz, and Sentana (1991). The estimate of the global factor w_t is

$$w_t^* = [g_t/(g_t + h_t)]e_t, \tag{8}$$

where the superscript * denotes the expected value of $\Omega(j)$ based on public information at the close of foreign market, with $j \in \{TKC_t, NYC_t\}$. This notation is used throughout this article. The estimate of the foreign global factor is proportional to the unexpected foreign daytime return, that is, equal to the ratio of the variance of the global factor to that of the unexpected returns. As the global information becomes more important in the total variances, the proportion of the extracted global factor in the unexpected returns increases.

The variance of estimate global information, g_t^*, conditional on the information available at the close of the foreign market becomes

$$g_t^* = g_t - [g_t^2/(g_t + h_t)]. \tag{9}$$

Because part of foreign closing prices reflects the global factor, using the foreign closing prices to estimate the global factor can reduce the uncertainty of the estimated global factor. This information (or Kalman filter) gain decreases the variance of the estimated global factor as shown in the second term of Equation (9). As the prices contain more global information (or the noise-to-information variance ratio is lowered), the information gain from observing foreign closing prices increases and the variance in the estimated global information decreases.

Through this signal-extraction procedure, we denote the estimate of the foreign global factor as w_t^*. In an efficient market, the foreign global factor, w_t^*, will influence the domestic overnight return, *HRN,* but not its daytime return, *HRD*. Hence, the domestic overnight return can be written as

$$HRN_t = c_n + a_n HRD_t + \mu w_t^* + b_n DM_t + v_t, \tag{10}$$

where the effect of the foreign global factor on the domestic return is determined by μ.

Substituting Equation (8) into Equation (10), we can write the domestic overnight return, HRN_t, as

$$HRN_t = c_n + a_n HRD_t + \mu[g_t/(g_t + h_t)]e_t + b_n DM_t + v_t. \tag{11}$$

Equation (11) points out two main themes in the international transmission of stock returns and volatility. First, if the shocks have time-varying conditional variances, the signal-extraction model predicts that the correlation coefficient between the foreign daytime and the domestic overnight returns, $\mu[g_t/(g_t + h_t)]$, is time varying and is dependent on volatility measures. If the shocks do not have time-varying variances, then the correlation coefficient is time invariant and the domestic overnight return process becomes Equation (2) with ϕ equal to $\mu[g/(g + h)]$. The assumption of GARCH processes can reconcile two stylized facts in the literature: (i) time-varying volatility and (ii) the time-varying correlations in international stock returns.

Second, if the foreign global factor is fully observed, then the local factor will not affect the domestic overnight return. However, if domestic investors only observe the price movements, any local moods will transmit to the domestic market via the extraction procedure. This is the case even if the domestic market rationally and efficiently incorporates the foreign information into prices.

We assume that g_t and h_t follow (pseudo) GARCH processes:

$$g_t = \omega_g + \alpha_g[(w_{t-1}^*)^2 + g_{t-1}^*] + \beta_g g_{t-1} + \gamma_g DM_t \tag{12}$$

$$h_t = \omega_h + \alpha_h[(u_{t-1}^*)^2 + h_{t-1}^*] + \beta_h h_{t-1} + \gamma_h DM_t \tag{13}$$

where u_t^* is the estimate of u_t conditional on the information available at the close of the foreign market ($u_t^* = e_t - w_t^*$), and h_t^* is the estimate of the conditional variance of u_t^*.[9] The process is analogous to the ARCH models employed by Diebold and Nerlove (1990) and King, Sentana, and Wadhwani (1990) with latent factor structures, as well as to one by Harvey, Ruiz, and Sentana (1991). Specifically, if news w_t or u_t follows a GARCH process with a normal density, then without directly observing w_t or u_t, the best estimator of w_{t-1}^2 conditional on public information $\Omega(j)$, for $j = TKC_{t-1}$ or NYC_{t-1}, is

[9] Because from Equation (5), the aggregate shock, $u_{t-1}^* + w_{t-1}^*$, is known after e_{t-1} is observed, the conditional variance of w_{t-1}^*, h_{t-1}^*, is equal to the conditional variance of u_{t-1}^*, g_{t-1}^*.

$$\mathrm{E}(w_{t-1}^2 \mid \Omega(j)) = (w_{t-1}^*)^2 + g_{t-1}^*.$$

Hence g_{t-1}^* and h_{t-1}^* enter into the variance process of Equations (12) and (13), respectively. The density function of w_t or u_t conditional on the information set is no longer normal. As a result, the Kalman-filtering process still produces minimizing mean squared errors (MMSE) estimators but is not optimal. Diebold and Nerlove (1990), and King, Sentana, and Wadhwani (1990) estimate the conditional variance process similar to Equations (12) to (13), but without the g_{t-1}^* term in Equations (12) and (13). However, Monte Carlo experiments by Harvey, Ruiz, and Sentana (1991) show that a correction of g_{t-1}^* is needed to obtain a better estimator with smaller mean squared errors. Hence, their correction of the conditional variance is adopted in Equations (12) and (13).

Since the New York and Tokyo markets open and close sequentially, we can write the log likelihood function for *NKD, NKN, SPD,* and *SPN* jointly as *L,* the sum of the log likelihood function for each individual return conditional on a recursive information set. We can simplify this joint likelihood function using the assumptions that the domestic daytime and overnight returns shocks are uncorrelated and that there is no spillover from the foreign market returns shock to the domestic market returns. Then the joint log likelihood function can be written as the sum of log likelihood functions for foreign daytime and domestic overnight returns:

$$\begin{aligned}\log L &= \sum_{t=1}^{T} [f(FRD_t \mid \Omega(i)) + f(HRN_t \mid \Omega(j))] \\ &= T\log(2\pi) - (1/2)\sum_{t=1}^{T} \{\log(g_t + h_t) + [e_t^2/(g_t + h_t)] \\ &\quad + \log(k_t) + (v_t^2/k_t)\}\end{aligned} \tag{14}$$

where $f(X \mid \Omega(i))$ is a normal distribution of variable X conditional on the information set $\Omega(i)$, and $(i, j) \in \{(\mathrm{TKO}_t, \mathrm{TKC}_t), (\mathrm{NYO}_t, \mathrm{NYC}_t)\}$.

The scoring algorithm described in Pagan (1980) and Watson and Engle (1983) is employed to estimate the whole system for the Tokyo daytime and the New York overnight returns and for the New York daytime and the Tokyo overnight returns. This algorithm is used to calculate the values of v_t, e_t, g_t, and h_t according to the signal-extraction process described in Equations (5)–(14) and to seek the estimates that maximize the log likelihood function. The standard errors that we construct are robust to the density function, which minimizes the problem of the non-normality of shocks.[10]

2. Correlation Analysis

2.1 Tokyo Stock Exchange and New York Stock Exchange

The TSE and the NYSE are the two largest equity markets in the world. The NYSE opens its trading at 9:30 A.M. and continues trading until 4:00 P.M. The TSE opens at 9:00 A.M., trades until 11:00 AM, and then breaks for lunch until 1:00 P.M.[11] The afternoon session continues until 3:00 P.M. Since Tokyo is ahead of New York by either 14 hours (in the winter) or 13 hours (in the summer), these trading hours do not overlap in real time.

Following an overnight trading halt of 18 or 17-and-a-half hours, a special clearing procedure is used at the open to clear overnight orders for each stock submitted prior to the opening. In the NYSE, opening trades are carried out through specialists who can directly participate in trading and take inventory positions. When orders are imbalanced, specialists can take positions for their own profit. After the NYSE opens, a continuous trading mechanism is employed. In the TSE, an agent of the exchange, known as *Saitori,* specializes in matching orders without taking positions.[12] A batched trading system, *Itayose,* is used to match overnight selling and buying orders at a single price. If there are large discrepancies between demand and supply at any price within the price limits, the *Saitori* member calls, and periodically revises, the bid (or ask) prices, *Kehai,* until transactions can be matched. Following the *Itayose* opening procedure, a continuous and regular trading process, called *Zaraba,* is used.

At the open, traders cannot observe a sequence of recent transaction prices to infer the value of stocks nor be informed about imbalances in overnight orders. Therefore, opening prices contain more noise and tend to produce autocorrelated returns. Stoll and Whaley (1990a) and Amihud and Mendelson (1991) report such empirical evidence. Furthermore, Stoll and Whaley (1990a) report that the average time to open a NYSE stock was 15 minutes during the period 1982–1988. Consequently, the opening index measured only a minute after trad-

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[10] Robust standard errors are obtained from the matrix $\mathbf{H}^{-1}(\mathbf{S}'\mathbf{S})\mathbf{H}^{-1}$ where $\mathbf{H}$ is the Hessian matrix and $\mathbf{S}$ is the score matrix. See Bollerslev and Wooldridge (1989) for details. Specifically, letting θ be the parameter of interest, we can estimate the Hessian matrix $\mathbf{H}$ with the following formula: $T^{-1}\sum_{t=1}^{T}\{(\nabla_\theta e_t)^2(g_t + h_t)^{-1} + \frac{1}{2}(\nabla_\theta h_t + \nabla_\theta g_t)^2(h_t + g_t)^{-2} + (\nabla_\theta v_t)^2 k_t^{-1} + \frac{1}{2}(\nabla_\theta k_t)^2(k_t)^{-2}\}$, where ∇ is a derivative operator.

[11] A change took place in the spring of 1991, so that the afternoon session starts at 12:30 PM. However, the sample period of this paper does not extend to the time of the change.

[12] See Macey and Kanda (1990) for a good survey comparing the institutions of the NYSE and TSE, including legal perspectives on specialists and saitori members.

ing begins may not reflect all of the relevant information. To examine this issue, we present a wide range of correlation analyses between S&P 500 and NK 225 daytime and overnight returns in Tables 1 and 2.

2.2 Autocorrlation of domestic returns

Table 1 presents the variances of overnight returns, the first 15-minute or 30-minute returns, and subsequent daytime returns, and correlations between these returns and their lagged returns for four subperiods. Since the 9:01 quotes for NK 225, obtained from Nikkei NEEDS, are available after October 23, 1986, we break the sample periods at that point. The rest of the break points correspond to the Crash regime.

Panel A of Table 1 shows that the 9:30-to-10:00 returns on the NYSE are approximately 8 to 24 times more volatile than the overnight returns and that the variance of the 10:00-close returns, spanning 6 hours, is approximately 3 to 4 times that of the 9:30-to-10:00 returns. Panel B of Table 1 shows a similar phenomenon on the TSE, indicating that the variance of the 9:01-to-9:15 returns is approximately 20 to 40 times larger than that of the overnight returns. It is also larger than the variance of the 9:15-to-10:00 returns.

The second part of Table 2 shows autocorrelation coefficients for S&P 500 (NK 225) returns between different time spans. Four empirical results are revealed: (i) the correlation of one segment with the subsequent segment is higher than that between segments distant in time; (ii) the largest correlations generally appear between the close-to-9:01 (close-to-9:30) and 9:01-to-9:15 (9:30-to-10:00) returns in Tokyo (New York); (iii) the return correlations of segments between overnight and the first 15 minutes in Tokyo (30 minutes in New York) are positive; (iv) price reversals tend to occur one hour (30 minutes) after the official opening of the TSE (NYSE), respectively, although this appears to be a weak effect. Stoll and Whaley (1990a) and Amihud and Mendelson (1991) report price reversals for individual stock returns around the opening; for stock portfolios, however, we find positive autocorrelations around the opening and price reversals afterwards. The bid-ask spread, combined with temporary shocks to individual stock returns, may cause negative autocorrelations in individual stock returns and stock portfolio returns, but nonsynchronous trading leads to positive correlations in stock portfolio returns [e.g., Stoll and Whaley (1990b)]. Accordingly, the sign of the autocorrelations in portfolio returns depends on the combined effects of bid-ask spreads and nonsynchronous trading. As a whole, our findings suggest that the stock price index at 9:01 on the TSE (9:30 on the NYSE) contains stale quotes and that the index at the official opening

Table 1
Variances and autocorrelations of domestic returns

A: S&P 500

	10/1/85–10/22/86			10/23/86–9/30/87			10/1/87–12/31/87			1/1/88–12/29/89		
	C–930	930–10	10–C	C–930	930–10	10–C	C–930	930–10	10–C	C–930	930–10	10–C
Variance	0.009	0.143	0.561	0.010	0.240	0.717	0.402	3.218	8.341	0.012	0.169	0.683
Autocorrelations												
$(10\text{–C})_{t-1}$	0.070	0.273*	−0.048	−0.056	0.277*	−0.063	−0.009	−0.320*	0.173	−0.052	0.137*	−0.184*
C–930	0.209*	−0.027	0.235*	−0.020	−0.118	0.012	0.191*	0.112*				
930–10			0.130*		−0.075		0.304*		0.041			

B: NK 225

	10/1/85–10/22/86			10/23/86–9/30/87				10/1/87–12/31/87				1/1/88–12/29/89			
	C–915	915–10	10–C	C–901	901–915	915–10	10–C	C–901	901–915	915–10	10–C	C–901	901–915	930–10	10–C
Variance	0.105	0.105	0.337	0.005	0.167	0.123	0.554	0.011	0.432	0.612	4.127	0.005	0.112	0.048	0.198
Autocorrelations															
$(10\text{–C})_{t-1}$	0.268*	0.239*	0.004	0.143*	0.352*	0.201*	−0.123*	0.046	−0.016	−0.216	−0.313	0.112*	0.133*	0.076	−0.094*
C–901	n.a.	0.374*	−0.024		0.390*	0.054	−0.068		0.691*	0.153	0.022		0.620*	−0.175*	−0.008
901–915		n.a.	n.a.			0.305*	−0.133*			0.512*	0.071			−0.056	0.093*
915–10			0.109				0.134*				0.507*				0.046

Autocorrelations between S&P 500_i and S&P 500_j returns and between NK 225_i and NK 225_j returns, where i denotes the time span in the ith row and j denotes the time span in the jth column. Various time spans are listed in the second row and the first column. For example, C–915 denotes close-to-9:15, 930–10 denotes 9:30-to-10:00, and $(10\text{–C})_{t-1}$ denotes the previous day's 10:00-to-close. The other notions for time spans can be inferred from these examples. Bartlett's standard errors can be approximated by the square root of the number of observations. The number of observations in Panel A is 269, 237, 64, and 504, and the corresponding standard errors for Panel A are 0.061, 0.065, 0.125, and 0.0445 for four subperiods, respectively. The number of observations in Panel B is 298, 257, 68, and 522, and the corresponding standard errors are 0.058, 0.062, 0.122, and 0.044 for four subperiods, respectively. The 9:01 quotes are not available in the Nikkei NEEDS before October 22, 1986, so the C–915 returns are used for the period from October 1, 1985, to October 22, 1986.

* indicates that the null of zero correlation can be rejected at a 5-percent significance level.

n.a., not available.

time may not be suitable for measuring the "opening quotes" of the day.

2.3 Cross-market correlations

Since the objective of this paper is an examination of the nature of stock returns transmission using intradaily data, as shown in Figure 1 for the timing of the NYSE and TSE, much of our emphasis is placed on investigating two types of correlations in stock returns across these two markets: contemporaneous correlation, which measures the correlation between foreign daytime returns and foreign overnight returns: and lagged spillover, which measures the correlation between foreign daytime returns and subsequent domestic daytime returns. Table 2 shows cross-market correlations using different proxies for the "opening quotes"—9:01, 9:15, and 10:00 quotes for the TSE, and 9:30 and 10:00 quotes for the NYSE. Panel A reports contemporanceous correlations between SPN_t and NKD_t, and between NKN_t and SPD_t. Contemporaneous correlations between SPD_t and NKN_t are generally larger than those between NKD_t and SPN_t. Moreover, SPD_t (NKD_t) returns are more highly correlated with NK 225 close-to-9:15 (S&P 500 close-to-10:00) returns than NK 225 close-to-9:01 (S&P 500 close-to-9:30) returns. Using the hourly data of S&P 500 and NK 225 indices, Becker, Finnerty, and Tucker (1992) also report that the first-hour correlations between lagged NK 225 (S&P 500) returns and subsequent S&P 500 (NK 225) returns are substantial. From our results and theirs, we can conclude that the existence of nonsynchronous trading in opening quotes may delay the incorporation of lagged NK 225 (S&P 500) daytime returns into S&P 500 (NK 225) opening indices. To avoid a nonsynchronous trading problem, we use the 10:00 quotes on the NYSE or the 9:15 quotes on the TSE for our study.

We present correlations between foreign daytime returns and subsequent domestic daytime returns (i.e., lagged spillovers) in Panel B of Table 2. We find that the correlations in Panel B are much smaller than the counterpart in Panel A, and that they are higher when quotes at the official opening time are used. These reinforce our results in Panel A that much of the foreign news is reflected in prices 30 or 15 minutes after the markets open. It is worth noting that contemporaneous correlations between foreign daytime and domestic overnight returns are much smaller around the Crash, but correlations between foreign daytime returns and subsequent domestic daytime returns (i.e., lagged spillovers) rise around the Crash. One might conjecture a scenario in which traders take more time to figure out the implications of a sharp decline in prices or follow other traders' behaviors in the same market (a herd instinct).

We report correlations between the overnight returns of the two

Table 2
Cross-market correlations

A: Correlations between SPN_t and NKD_t, and between NKN_t and SPD_t

	10/1/85–10/22/86		10/23/86–9/30/87		10/1/87–12/31/87		1/1/88–12/29/89	
SPN_t:	C–930	C–10	C–930	C–10	C–930	C–10	C–930	C–10
NKD_t:								
901–C	0.057	0.094	0.053	0.252*	0.016	0.053	0.064	0.157*
915–C	n.a.	n.a.	0.044	0.213*	−0.049	0.010	0.093*	0.114*
10–C	0.100	0.109	0.066	0.160*	−0.145	−0.062	0.068	0.152*

	10/1/85–10/22/86		10/23/86–9/30/87			10/1/87–12/31/87			1/1/88–12/29/89		
NKN_t:	C–915	C–10	C–901	C–915	C–10	C–901	C–915	C–10	C–901	C–915	C–10
SPD_t:											
930–C	0.539*	0.393*	0.217*	0.504*	0.404*	0.310*	0.536*	0.644*	0.392*	0.582*	0.479*
10–C	0.454*	0.327*	0.154*	0.362*	0.286*	0.180*	0.321*	0.423*	0.312*	0.469*	0.360*

B: Correlations between SPD_t and NKD_t, and between SPD_{t-1} and NKD_t

	10/1/85–10/22/86		10/23/86–9/30/87		10/1/87–12/31/87		1/1/88–12/29/89	
SPD_t:	930–C	10–C	930–C	10–C	930–C	10–C	930–C	10–C
NKD_t:								
901–C			0.124*	−0.010	0.126	0.137	0.033	−0.038
915–C	0.039	0.021	0.137*	0.028	0.095	0.109	0.066	0.026
10–C	0.010	−0.035	0.119	0.042	0.023	0.039	0.064	−0.001

	10/1/85–10/22/86		10/23/86–9/30/87			10/1/87–12/31/87			1/1/88–12/29/89		
NKD_t:	915–C	10–C	901–C	915–C	10–C	901–C	915–C	10–C	901–C	915–C	10–C
SPD_{t-1}:											
930–C	0.064	0.015	0.187*	−0.033	−0.085	0.729*	0.649*	0.586*	0.259*	−0.066	−0.032
10–C	0.030	−0.014	0.100	−0.061	−0.101	0.634*	0.604*	0.593*	0.197*	−0.070	−0.019

Table 2
Continued

C: Correlations between SPN_t and NKN_{t-1}, and between SPN_t and NKN_t

	10/1/85–10/22/86		10/23/86–9/30/87		10/1/87–12/31/87		1/1/88–12/29/89	
SPN_t:	C–930	C–10	C–930	C–10	C–930	C–10	C–930	C–10
NKN_{t-1}:								
C–901	n.a.	n.a.	0.086	0.136*	0.081	0.126	−0.021	0.088*
C–915	0.049	0.169*	0.044	0.158*	0.236	0.174	−0.024	0.120*
C–10	−0.006	0.098	0.014	0.204*	0.263*	0.209	0.018	0.084

	10/1/85–10/22/86		10/23/86–9/30/87			10/1/87–12/31/87			1/1/88–12/29/89		
NKN_t:	C–915	C–10	C–901	C–915	C–10	C–901	C–915	C–10	C–901	C–915	C–10
SPN_t:											
C–930	0.096	0.057	0.076	0.110	0.103	0.249*	0.372*	0.307*	0.170*	0.239*	0.225*
C–10	0.346*	0.254*	0.157*	0.346*	0.288*	0.370*	0.623*	0.684*	0.289*	0.411*	0.393*

Cross-market correlations using different proxies for the opening price index of the NK 225 and S&P 500. Various proxies are listed in the second row and the first column of each panel. For example, C–915 denotes the previous day's close-to-9:15, and C–10 denotes close-to-10:00. The other notations for time spans in Table 2 can be inferred from these examples. Readers can also refer to Figure 1 for the timing of S&P 500 and NK 225 daytime and overnight returns. Bartlett's standard errors can be approximated by the square root of the number of observations. The number of observations in Panel A is 269, 237, 64, and 504, and the corresponding standard errors for Panel A are 0.061, 0.065, 0.125, and 0.0445 for four subperiods, respectively. The number of observations in Panel B is 298, 257, 68, and 522, and the corresponding standard errors are 0.058, 0.062, 0.122, and 0.044 for four subperiods, respectively.

* indicates that the null of zero correlation can be rejected at a 5-percent significance level.

n.a., not available.

Table 3
Aggregate shock model for stock returns—NKD and SPN

	9/29/85–12/29/89		9/29/85–9/30/87		1/1/88–12/29/89	
	Coeff.	St. error	Coeff.	St. error	Coeff.	St. error
Stage 1:						
c_d	−0.010	(0.031)	−0.013	(0.031)	−0.019	(0.025)
a_d	0.018	(0.547)	0.098	(0.085)	0.020	(0.079)
b_d	−0.080†	(0.389)	−0.073	(0.061)	−0.070	(0.049)
ω_q	0.011†	(0.109)	0.011	(0.013)	0.006	(0.032)
α_q	0.130†	(0.318)	0.141**	(0.040)	0.023	(0.021)
β_q	0.839**	(0.244)	0.859**	(0.032)	0.872**	(0.149)
γ_q	0.014	(0.111)	−0.019	(0.049)	0.080†	(0.042)
Skewness	−7.704**		−0.518**		0.629**	
Kurtosis	157.457**		4.511**		8.625**	
LB(12)	3.518		4.458		17.187	
LBS(12)	0.198		22.640**		0.870	
Stage 2:						
c_n	0.058**	(0.014)	0.065**	(0.019)	0.057**	(0.020)
a_n	0.107*	(0.058)	0.148**	(0.026)	0.088**	(0.038)
b_n	−0.206**	(0.038)	−0.238**	(0.053)	−0.174**	(0.046)
ϕ	0.086†	(0.054)	0.074**	(0.029)	0.091**	(0.043)
ω_k	0.006†	(0.014)	−0.006	(0.011)	0.028†	(0.019)
β_k	0.104†	(0.114)	0.110**	(0.045)	0.082**	(0.048)
α_k	0.827**	(0.125)	0.754**	(0.104)	0.773†	(0.117)
γ_k	0.039†	(0.046)	0.145**	(0.054)	−0.023†	(0.057)
Skewness	−0.189**		−0.414**		−0.364**	
Kurtosis	10.575**		5.176**		7.631**	
LB(12)	19.201*		10.939		10.233	
LBS(12)	12.703		13.182		2.306	

The model is Stage 1: $NKD_t = c_d + a_d NKN_{t-1} + b_d DM_t + e_t$, $e_t \mid \Omega(\mathrm{TKO}_t) \sim N(0, q_t)$, $q_t = \omega_q + \beta_q q_{t-1} + \alpha_q e_{t-1}^2 + \gamma_q DM_t$; Stage 2: $SPN_t = c_n + a_n SPD_{t-1} + b_n DM_t + \phi e_t + v_t$, $v_t \mid \Omega(TKC_t) \sim N(0, k_t)$, $k_t = \omega_k + \beta_k k_{t-1} + \alpha_k v_{t-1}^2 + \gamma_k DM_t$.

A two-stage univariate GARCH method is applied to estimate NKD_t first and SPN_t second. Robust standard errors are in parentheses. LB(12) and LBS(12) are the Ljung-Box statistics for the standardized residual and its square, respectively.

† indicates the significance at a 5-percent level when the usual standard errors are used.

** and * indicate the significance at 5-percent and 10-percent levels, respectively, when robust standard errors are used. The statistics of skewness and kurtosis are for the standardized residuals $e_t/(q_t)^{1/2}$ or $v_t/(k_t)^{1/2}$.

markets in Panel C. We find that the correlations between SPN_t and NKN_t are higher than those between NKN_{t-1} and SPN_t. This evidence is not surprising in itself. NKN_{t-1} and SPN_t have overlapping hours from the New York close to the Tokyo open, and none of major world stock exchanges are open to trade during that particular time of the day. NKN_t and SPN_t overlap with a part of the business hours of European stock markets (especially the London Stock Exchange) as shown in Figure 1. Much of the third-country information revealed during that period leads in turn to a higher correlation between NKN_t and SPN_t. Another possible reason that the correlation between NKN_{t-1} and SPN_t is weaker than that between SPN_t and NKN_t is that 8 hours overlap in the latter, but only 3 hours in the former.

Table 4
Aggregate shock model for stock returns—SPD and NKN

	9/29/85–12/29/89		9/29/85–9/30/87		1/1/88–12/29/89	
	Coeff.	St. error	Coeff.	St. error	Coeff.	St. error
Stage 1:						
c_d	0.058†	(0.034)	0.076*	(0.040)	−0.009	(0.039)
a_d	0.214**	(0.090)	0.058	(0.099)	0.294**	(0.108)
b_d	0.094	(0.070)	0.101	(0.092)	0.142*	(0.078)
ω_q	0.110†	(0.193)	0.005	(0.051)	0.202**	(0.090)
β_q	0.259†	(0.196)	0.043†	(0.033)	0.085†	(0.113)
α_q	0.583**	(0.192)	0.870**	(0.096)	0.749**	(0.153)
γ_q	0.132†	(0.329)	0.220*	(0.132)	−0.376**	(0.134)
Skewness	−1.779**		−0.346**		−1.326**	
Kurtosis	17.851**		4.759**		13.679**	
LB(12)	8.623		6.716		16.901	
LBS(12)	5.397		5.497		3.781	
Stage 2:						
c_n	0.153**	(0.011)	0.145**	(0.014)	0.152**	(0.016)
a_n	0.129*	(0.024)	0.174**	(0.025)	0.133**	(0.038)
b_n	−0.004†	(0.024)	0.012	(0.034)	−0.041	(0.034)
ϕ	0.145**	(0.032)	0.189**	(0.019)	0.189**	(0.020)
ω_k	−0.001	(0.002)	−0.005**	(0.002)	0.009	(0.013)
α_k	0.093**	(0.027)	0.068†	(0.075)	0.075†	(0.049)
β_k	0.888**	(0.029)	0.931**	(0.024)	0.782**	(0.127)
γ_k	0.022**	(0.010)	0.026**	(0.011)	0.032†	(0.022)
Skewness	−0.379**		−0.429**		−0.425**	
Kurtosis	4.729**		4.323**		4.499**	
LB(12)	33.111**		25.471**		20.826**	
LBS(12)	10.128		9.365		4.925	

The model is Stage 1: $SPD_t = c_d + a_d SPN_t + b_d DM_t + e_t$, $e_t \mid \Omega(\text{NYO}_t) \sim N(0, q_t)$, $q_t = \omega_q + \beta_q q_{t-1} + \alpha_q e_{t-1}^2 + \gamma_q DM_t$; Stage 2: $NKN_t = c_n + a_n NKD_t + b_n DM_t + \phi e_t + v_t$, $v_t \mid \Omega(NYC_t) \sim N(0, k_t)$, $k_t = \omega_k + \beta_k k_{t-1} + \alpha_k v_{t-1}^2 + \gamma_k DM_t$.

A two-stage univariate GARCH method is applied to estimate SPD_t first and then NKN_t. The statistics of skewness and kurtosis are for the standardized residuals $e_t/(q_t)^{1/2}$ or $v_t/(k_t)^{1/2}$. LB(12) and LBS(12) are the Ljung-Box statistics for the standardized residual and its square, respectively.

† indicates the significance at a 5-percent level when the usual standard errors are used.

** and * indicate the significance at 5-percent and 10-percent levels, respectively, when robust standard errors are used. Robust standard errors are in parentheses.

3. Model Estimation

3.1 Aggregate-shock model

In this section, we employ an aggregate-shock model without decomposing the unexpected daytime return into global and local factors. We investigate whether the unexpected daytime returns in Tokyo have any impact on the overnight return in New York. This impact itself does not violate the efficient market hypothesis but indicates that the unexpected returns in Tokyo contain some global information. The sensitivity coefficient which measures the effect of the foreign daytime return on the domestic overnight return is ϕ in Equation (2).

Conditional variances of unexpected returns in the two markets are

Table 5
Signal-extraction model for stock returns—NKD and SPN

	9/28/85–12/31/89		9/28/85–7/31/87		1/1/88–12/31/89	
	Coeff.	St. error	Coeff.	St. error	Coeff.	St. error
NKD_t						
Mean equation						
c_d	0.004	(0.047)	−0.010	(0.030)	0.0002	(0.025)
a_d	−0.092	(0.337)	0.061	(0.086)	−0.064	(0.061)
b_d	−0.016†	(0.192)	−0.066	(0.063)	−0.097	(0.052)
Variance equation: g_t						
ω_g	0.006	(0.020)	0.018	(0.023)	0.002	(0.060)
α_g	0.399†	(0.472)	0.180**	(0.071)	0.074	(0.253)
β_g	0.617†	(0.489)	0.815**	(0.061)	0.745	(0.230)
γ_g	−0.019	(0.082)	−0.038	(0.094)	0.100	(0.093)
Variance equation: h_t						
ω_h	0.076*	(0.041)	0.003	(0.035)	0.053†	(0.287)
α_h	0.817†	(0.833)	0.929**	(0.402)	0.419	(1.758)
γ_h	0.085†	(0.211)	−0.008	(0.087)	−0.047	(0.097)
SPN_t						
Mean equation						
c_n	0.057**	(0.015)	0.065**	(0.019)	0.050**	(0.020)
a_n	0.106**	(0.051)	0.147**	(0.026)	0.067	(0.042)
b_n	−0.162**	(0.038)	−0.233**	(0.055)	−0.169**	(0.047)
μ	0.175†	(0.192)	0.106*	(0.063)	0.201†	(0.354)
Variance equation: k_t						
ω_k	0.006†	(0.012)	0.018	(0.018)	0.029**	(0.016)
α_k	0.113†	(0.085)	0.140**	(0.057)	0.080**	(0.044)
β_k	0.839**	(0.084)	0.600**	(0.140)	0.809**	(0.089)
γ_k	0.032†	(0.047)	0.144**	(0.056)	−0.044	(0.054)
GARCH(1)	0.097		1.363		0.023	

The model is NKD_t: Mean eq.: $NKD_t = c_d + a_d NKN_{t-1} + b_d DM_t + w_t + u_t$; Variance eq.: $w_t \mid \Omega(TKO_t) \sim N(0, g_t)$, $u_t \mid \Omega(TKO_t) \sim N(0, h_t)$, $g_t = \omega_g + \beta_g g_{t-1} + \alpha_g[(w^*_{t-1})^2 + g^*_{t-1}] + \gamma_g DM_t$, $h_t = \omega_h + \alpha_h[(u^*_{t-1})^2 + h^*_{t-1}] + \gamma_h DM_t$; SPN_t: Mean eq.: $SPN_t = c_n + a_n SPD_{t-1} + b_n DM_t + \mu w^*_t + v_t$; Variance eq.: $v_t \mid \Omega(TKC_t) \sim N(0, k_t)$, $k_t = \omega_k + \beta_k k_{t-1} + \alpha_k v^2_{t-1} + \gamma_k DM_t$, where $w^*_t = [g_t/(g_t + h_t)]e_t$ and $g^*_t = g_t[1 - g_t/(g_t + h_t)]$.

The 9:15-to-close returns and the previous day's close-to-10:00 returns are used for the NKD_t and SPN_t, respectively. The score algorithm is applied to estimate NKD_t and SPN_t simultaneously. The likelihood function is

$$\begin{aligned}\log L &= \sum_{t=1}^{T} [f(NKD_t \mid \Omega(TKO_t)) + f(SPN_t \mid \Omega(TKC_t))] \\ &= T\log(2\pi) - (1/2) \sum_{t=1}^{T} \{\log(g_t + h_t) + [e_t^2/(g_t + h_t)] + \log(k_t) + (v_t^2/k_t)\}.\end{aligned}$$

Robust standard errors are in parentheses. GARCH(1) is the robust Lagrange multiplier test for the null that $\beta_h = 0.0$.

† indicates the significance at a 5-percent level when the usual standard errors are used.

** and * indicate the significance at 5-percent and 10-percent levels, respectively, when robust standard errors are used.

modeled as GARCH processes. The two-stage GARCH estimation method is applied to the aggregate-shock model for Tokyo daytime returns and New York overnight returns as described in Section 1.2. These results are reported in Table 3. In Table 4, a parallel investi-

Table 6
Signal extraction model for stock returns—SPD and NKN

	9/28/85–12/31/89		9/28/85–7/31/87		1/1/88–12/31/89	
	Coeff.	St. error	Coeff.	St. error	Coeff.	St. error
SPD_t						
Mean equation						
c_d	0.020	(0.031)	0.073†	(0.039)	0.018	(0.040)
a_d	0.017	(0.067)	−0.154*	(0.087)	0.052**	(0.101)
b_d	0.177**	(0.058)	0.221**	(0.077)	0.154**	(0.074)
Variance equation: g_t						
ω_g	0.112	(0.155)	−0.007	(0.054)	0.078	(0.109)
α_g	0.150†	(0.171)	0.048†	(0.172)	0.043	(0.077)
β_g	0.639**	(0.310)	0.856**	(0.135)	0.852**	(0.147)
γ_g	0.019	(0.259)	0.124†	(0.173)	−0.167	(0.365)
Variance equation: h_t						
ω_h	−0.006	(0.017)	0.034	(0.065)	0.005	(0.050)
α_h	1.103**	(0.140)	0.759**	(0.372)	0.776	(0.906)
γ_h	0.020	(0.093)	0.002	(0.125)	0.067	(0.117)
NKN_t						
Mean equation						
c_n	0.139*	(0.012)	0.153**	(0.016)	0.159**	(0.017)
a_n	0.090**	(0.031)	0.167**	(0.024)	0.114**	(0.037)
b_n	0.002†	(0.024)	0.017	(0.034)	−0.047	(0.034)
μ	0.279	(0.261)	0.260**	(0.063)	0.262**	(0.061)
Variance equation: k_t						
ω_k	−0.009**	(0.002)	−0.004**	(0.002)	0.010	(0.014)
α_k	0.080**	(0.020)	0.068**	(0.024)	0.063	(0.045)
β_k	0.902**	(0.022)	0.926**	(0.025)	0.788**	(0.143)
γ_k	0.021**	(0.009)	0.028**	(0.011)	0.023	(0.021)
GARCH(1)	0.076		1.049		0.065	

The model is SPD_t: Mean eq.: $SPD_t = c_d + a_d SPN_t + b_d DM_t + w_t + u_t$; Variance eq.: $w_t \mid \Omega(NYO_t) \sim N(0, g_t)$, $u_t \mid \Omega(NYO_t) \sim N(0, h_t)$, $g_t = \omega_g + \beta_g g_{t-1} + \alpha_g[(w^*_{t-1})^2 + g^*_{t-1}] + \gamma_g DM_t$, $h_t = \omega_h + \alpha_h[(u^*_{t-1})^2 + h^*_{t-1}] + \gamma_h DM_t$; NKN_t: Mean eq.: $NKN_t = c_n + a_n NKD_t + b_n DM_t + \mu w^*_t + v_t$; Variance eq.: $v_t \mid \Omega(NYC_t) \sim N(0, k_t)$, $k_t = \omega_k + \beta_k k_{t-1} + \alpha_k v^2_{t-1} + \gamma_k DM_t$, where $w^*_t = [g_t/(g_t + h_t)]e_t$, and $g^*_t = g_t[1 - g_t/(g_t + h_t)]$.

The 10:30-to-close returns and the previous day's close-to-9:15 returns are used for the SPD_t and NKN_t, respectively. The score algorithm is applied to estimate SPD_t and NKD_t simultaneously. The likelihood function is

$$\log L = \sum_{t=1}^{T} [f(NKD_t \mid \Omega(TKO_t)) + f(SPN_t \mid \Omega(TKC_t))]$$

$$= T\log(2\pi) - (1/2)\ T\sum_{t=1}^{T} \{\log(g_t + h_t) + [e_t^2/(g_t + h_t)] + \log(k_t) + (v_t^2/k_t)\}.$$

Robust standard errors are in parentheses. GARCH(1) is the robust Lagrange multiplier test for the null that $\beta_h = 0.0$.

† indicates the significance at a 5-percent level when the usual standard errors are used.

** and * indicate the significance at 5-percent and 10-percent levels, respectively, when robust standard errors are used.

gation is done for New York daytime and Tokyo overnight returns. After fitting the GARCH model, we calculate the skewness and the kurtosis of standardized residuals. These statistics are still too large to accept the null hypothesis of a normal distribution. Therefore, we

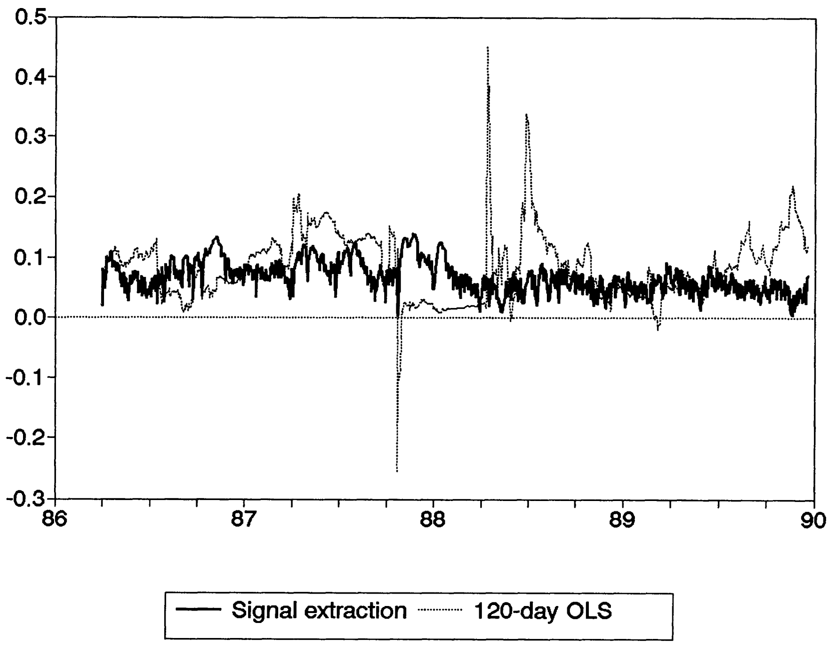

Figure 2
Comparison of signal extraction and 120-day OLS regression coefficients for the model of *NKD* and *SPN*
Comparison of signal extraction and 120-day OLS regression coefficients for the model of *NKD* and *SPN* from April 1986 to December 1989. The solid line plots the estimated signal extraction coefficients reported in Table 6, while the broken line plots the estimated coefficients for the 120-day rolling regression of *NKD* on *SPN*.

report the robust standard errors as calculated by Bollerslev and Wooldridge (1989).

The first salient result in Tables 3 and 4 is the existence of contemporaneous dependence in stock returns between the Tokyo and New York markets suggested by the significant t statistics of ϕ, the effect of the foreign unexpected daytime returns on the domestic overnight returns, after and before the Crash. The second salient result in Table 3 is an increase in the impact of Tokyo news on the New York stock returns. Hamao, Masulis, and Ng (1990) and King and Wadhwani (1990) found that the stock returns of the U.S.A. can significantly influence other stock markets, but not vice versa. In contrast, we found bidirectional correlations between the Tokyo and New York stock returns, although the magnitude of the coefficient for Tokyo's influence on New York is about half that of New York's on Tokyo.

3.2 Signal-extraction model

It is an implicit assumption in the aggregate-shock model that all of the news revealed during the trading hours of one market has a global

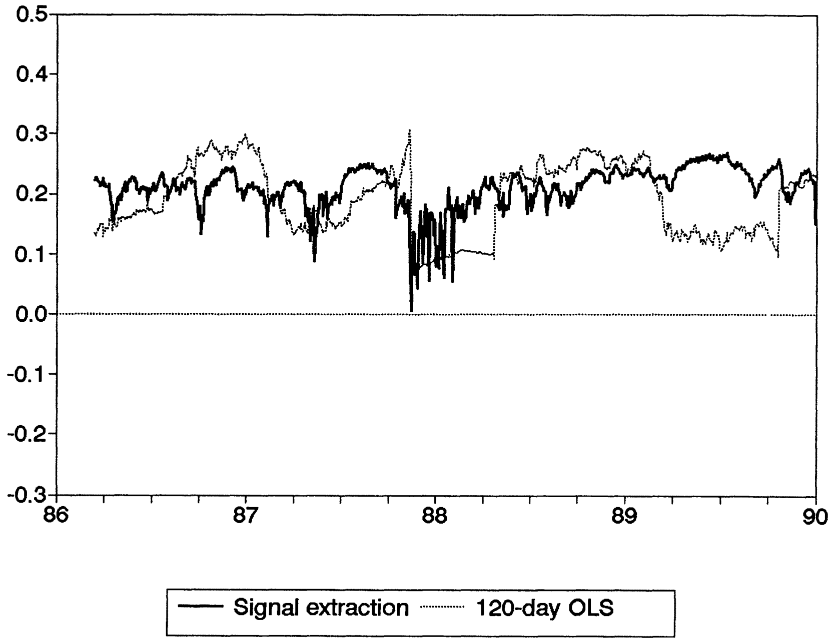

Figure 3
Comparison of signal extraction and 120-day OLS regression coefficients for the model of *SPD* and *NKN*
Comparison of signal extraction and 120-day OLS regression coefficients for the model of *SPD* and *NKN* from April 1986 to December 1989. The solid line plots the estimated signal extraction coefficients reported in Table 6, while the broken line plots the estimated coefficients for the 120-day rolling regression of *SPD* on *NKN*.

impact on stock returns in the other market. Realistically, some part of the information revealed through trading may only affect the returns locally. In the signal-extraction model, domestic investors are assumed to extract the global information optimally from the observed price changes.

In Table 5 (and similarly in Table 6), the equations for Tokyo daytime returns and New York overnight returns are simultaneously estimated via a state-space model with GARCH errors as described in Section 1.3. After estimation, we test whether the coefficient for lagged conditional variance, h_{t-1}, is significant in the conditional variance of the local factor, u_t. By evaluating the robust LM test statistics [see Bollerslev and Wooldridge (1989)], we find that the null hypothesis of no effect of the lagged conditional variance, h_{t-1}, on the conditional variance of the local factor (i.e., $\beta_b = 0$) cannot be rejected at least at a 10 percent level. From Tables 5 and 6, we find that the impact of the Tokyo global factor on the New York overnight return becomes insignificant when the robust standard error is used, whereas the impact of the New York global factor on the Tokyo daytime return remains significant at a 5 percent level. This result may suggest that the signal extraction model can provide some implications for how Tokyo traders extract the information from New York.

To compare the signal-extraction model in the context of time-varying correlations, we employ simple rolling ordinary least squares (OLS) regressions of domestic overnight returns on foreign daytime returns by fixing the number of observations at 120. The signal-extraction coefficient, $\mu[g_t/(g_t + h_t)]$, indicates the proportion of the unexpected return revealed in the foreign market that can be attributed to a global factor influencing the domestic market. The coefficient depends on the time-varying volatility of a global factor. We plot the signal-extraction coefficient and 120-day OLS regression coefficients in Figures 2 and 3. Both series exhibit time variation. King and Wadhwani (1990) also observed that the volatility related increase in the contagion effects (the signal-extraction coefficient) is a feature of the international transmission mechanism. From Equations (1) and (11), we see that the signal-extraction coefficient is related to the covariance of unexpected foreign daytime and domestic overnight returns; hence, the signal-extraction coefficients move quite closely to the 120-day rolling regression coefficients except during the second half of 1989. It is also worth pointing out that around the Crash period, the 120-day OLS regression coefficient for the foreign daytime return on the domestic overnight return decreases. This result suggests that the increase in daily correlations found by King and Wadhwani (1990) and Bennett and Kelleher (1988) around the Crash is likely caused by lagged spillovers from New York to Tokyo, and vice versa. We further investigate this possibility in Section 4.

3.3 Model comparison

To compare several competing models of international transmission of stock returns and volatility, we employ the Schwarz (1978) criterion that penalizes the log likelihood function by the number of parameters in the model. Since the Schwarz (1978) criterion is derived from a Bayesian procedure, the model with the lowest value can be interpreted as the one that, based on posterior probabilities, is the most likely to occur. The Schwarz (1978) criterion is $-2(\log L) + K(\log T)$, where K is the number of parameters, L is the likelihood function, and T is the sample size. Because we use either the two-stage estimation or the simultaneous estimation with sequential likelihood functions, we can write the Schwarz criterion as

$$-2[\log L(FRD) + \log L(HRN)] + \log(T_F)\cdot K_F + \log(T_H)\cdot K_H$$

where T_F and K_F (T_H and K_H) are the number of observations and

Table 7
Model comparison

A: NKD_t and SPN_t

	GARCH-in-Mean		AS model		SE model	
	NKD_t	SPN_t	NKD_t	SPN_t	NKD_t	SPN_t
10/1/85–12/29/89						
R^2	0.007	0.027	0.011	0.006	0.005	0.011
L.K.	−1471.611	−708.410	−1386.391	−704.988		−1897.501
S.C.		4479.241		4287.863		3921.232
10/1/85–9/30/87						
R^2	0.018	0.056	0.012	0.111	0.015	0.111
L.K.	−574.422	−289.990	−574.260	−272.667		−844.872
S.C.		1835.381		1787.875		1802.747
1/1/88–12/29/89						
R^2	0.004	0.032	0.007	0.049	0.002	0.052
L.K.	−382.771	−277.141	−379.400	−270.682		−650.148
S.C.		1425.892		1393.731		1412.645

B: SPD_t and NKN_t

	GARCH-in-Mean		AS model		SE model	
	SPD_t	NKN_t	SPD_t	NKN_t	SPD_t	NKN_t
10/1/85–12/29/89						
R^2	0.007	0.154	0.003	0.125	0.001	0.203
L.K.	−1383.121	−458.470	−1375.532	−451.712		−1778.133
S.C.		3802.402		3759.684		3682.396
10/1/85–9/30/87						
R^2	0.040	0.163	0.011	0.231	0.001	0.268
L.K.	−592.891	−205.541	−593.940	−176.230	−758.452	
S.C.		1702.644		1634.470		1629.714
1/1/88–12/29/89						
R^2	0.0001	0.242	0.028	0.198	0.012	0.246
L.K.	−592.300	−158.563	−589.880	−171.571		−751.731
S.C.		1607.826		1616.522		1615.742

The GARCH-in-Mean process is: $FRD_t = c_d + a_d q_t + b_d DM_t + d_d e_{t-1} + e_t$, with $e_t \mid \Omega(i) \sim N(0, q_t)$, $q_t = \omega_q + \beta_q q_{t-1} + \alpha_q e_{t-1}^2 + \gamma_q DM_t$; $HRN_t = c_n + a_n k_t + b_n DM_t + \phi FRD_t + d_n v_{t-1} + v_t$, with $v_t \mid \Omega(j) \sim N(0, k_t)$, $k_t = \omega_k + \beta_k k_{t-1} + \alpha_k v_{t-1}^2 + \gamma_k DM_t$; where $(FRD_t, HRN_t) \in \{(NKD_t, SPN_t), (SPD_t, NKN_t)\}$ and $(i, j) \in \{(TKO_t, TKC_t), (NYO_t, NYC_t)\}$.

The AS models are described in Tables 3 and 4. The SE models are described in Tables 5 and 6. L.K. is the log value of likelihood function. S.C. is the Schwarz criterion.

parameters in the process for foreign daytime (domestic overnight) returns, respectively.

Table 7 compares three models: GARCH-in-mean, Aggregate Shock (AS), and Signal Extraction (SE). The second and third models are described in Section 1. The GARCH-in-mean model applied by Hamao, Masulis, and NG (1990) is specified as follows:

$$FRD_t = c_d + a_d q_t + b_d DM_t + d_d e_{t-1} + e_t,$$

$$HRN_t = c_n + a_n k_t + \phi FRD_t + b_n DM_t + d_n v_{t-1} + v_t,$$

where e_t and v_t follow the process described in Equations (3) and (4).

Table 7 reveals some interesting results for the models' performance. In terms of the Schwarz criterion, the SE model is better than the other two models for Tokyo overnight returns except for the post-Crash period, whereas the AS model works better for New York overnight returns. We also report the regression determination coefficient (R^2) to measure the predictability of returns. The R^2 criterion is based on the quadratic loss function of realized data and their fitted values.[13] The predictability of the daytime returns measured by R^2 is much smaller than that of the overnight returns. This result is due to the inclusion of contemporaneous foreign market information in the mean equation of domestic overnight returns and lagged information in the mean equation of domestic daytime returns.

The above model comparison examines whether the signal-extraction process proposed in this paper can characterize investors' behavior better than the GARCH-in-mean process used in Hamao, Masulis, and Ng (1990). The comparison is based on the same data set but different model specifications. Hence, the analysis can help us to evaluate the performance of different specifications for investors' behaviour. We found weak evidence that the signal-extraction model performs better for Tokyo overnight returns than the GARCH-in-mean or the AS models.

4. Contemporaneous Correlations and Lagged Spillovers

In Table 8, we investigate correlations between daytime returns in one market and overnight returns in the other market with overlapping time spans (i.e., contemporaneous correlations). In addition, we report the results with different definitions of opening quotes so that they are comparable to the results of Hamao, Masulis, and Ng (1990).

The empirical results in Panel A show that when the S&P 500 9:30 opening quotes are used, then ϕ, the coefficient for measuring such a contemporaneous correlation between NKD and SPN, decreases and becomes statistically insignificant. This result also confirms the findings in our correlation analysis as well as those in Becker, Finnerty, and Tucker (1992). The bottom part of Panel A also shows that the estimated coefficients for volatility correlations between NKD and SPN (i.e., π) are generally insignificant when the robust standard

[13] If the distribution is Gaussian with constant variances, then the R^2 criterion is equivalent to the one based on the value of likelihood. The difference between Schwarz (1978) and R^2 in the Gaussian distribution is equal to the penalty that is related to the number of the variables and the parameters in the model.

Table 8
Contemporaneous return and volatility correlations

A: NKD_t and SPN_t

	9/28/85–12/31/89		9/28/85–7/31/87		1/1/88–12/31/89	
SPN:	SPC–930	SPC–10	SPC–930	SPC–10	SPC–930	SPC–10
Return correlations						
ϕ	0.075	0.070	0.0004	0.071	0.014	0.095
Tstat.	2.629	2.592	0.077	2.593	2.311	2.224
Volatility correlations						
π	0.021	0.034	0.0007	0.025	−0.001	−0.004
Tstat.	1.219†	1.862†	1.096†	1.290	−1.952	−0.194

B: SPD_t and NKN_t

	9/28/85–12/31/89			9/28/85–7/31/87			1/1/88–12/31/89		
NKN:	NKC–901	NKC–915	NKC–10	NKC–901	NKC–915	NKC–10	NKC–901	NK915–C	NK10–C
Return correlations									
ϕ	0.024	0.188	−0.027	0.030	0.184	−0.034	0.022	0.198	−0.019
Tstat.	4.538	12.940	−0.183	5.652	9.481	−1.190	14.715	9.624	−0.775
Volatility spillovers									
π	0.000	0.033	0.003	−0.003	0.004	0.020	−0.000	−0.001	0.025
Tstat.	0.377	1.096†	0.014†	−2.197	3.666	1.503†	−5.975	−0.988	1.268†

The model is: $FRD_t = c_d + a_d FRN_{t-1} + b_d DM_t + e_t$, with $e_t \mid \Omega(i) \sim N(0, q_t)$, $q_t = \omega_q + \beta_q q_{t-1} + \alpha_q e^2_{t-1} + \gamma_q DM_t$; $HRN_t = c_n + a_n HRD_{t-1} + b_n DM_t + \phi e_t + v_t$, with $v_t \mid \Omega(j) \sim N(0, k_t)$, $k_t = \omega_k + \beta_k k_{t-1} + \alpha_k v^2_{t-1} + \gamma_k DM_t + \pi FRD^2_t$; where $(FRD_t, HRN_t) \in \{(NKD_t, SPN_t), (SPD_t, NKN_t)\}$.

NK 225 9:15-to-close returns and S&P 500 10:00-to-close returns are used for *NKD* and *SPD*, respectively. The Nikkei's previous-day close-to-9:15 return and S&P 500's previous-day close-to-10:00 return are used for the *NKN* and the *SPN*, respectively. Tstat is the *t*-statistic.

† indicates the significance at a 5-percent level when the usual standard errors are used. Robust standard errors are larger than conventional standard errors. If the absolute values of (robust) *t*-statistics are greater than 1.96 in this table, then the absolute values of *t*-statistics using conventional standard errors are also greater than 1.96.

Table 9
Lagged spillovers

A: NKD_t and SPD_t

	9/28/85–12/31/89		9/28/85–7/31/87		1/1/88–12/31/89	
SPD:	SP930–C	SP10–C	SP930–C	SP10–C	SP930–C	SP10–C
Return spillovers						
σ	0.119	0.026	0.087	0.024	0.057	−0.012
Tstat.	2.434	0.599	1.628	0.574	0.812	−0.193
Volatility spillovers						
π	−0.012	0.041	−0.002	0.0004	0.041	0.109
Tstat.	−0.744	0.688†	−0.203	0.059	0.434†	0.878†

B: SPD_{t-1} and NKD_t

	9/28/85–12/31/89			9/28/85–7/31/87			1/1/88–12/31/89		
NKD:	NK901–C	NK915–C	NK10–C	NK901–C	NK915–C	NK10–C	NK901–C	NK915–C	NK10–C
Return spillovers									
σ	0.078	−0.029	−0.079	−0.004	−0.041	−0.044	0.080	−0.077	−0.025
Tstat.	2.333	−1.105	−6.171	−1.056	−1.522	−1.522	1.819†	−1.522	−1.056
Volatility spillovers									
π	0.024	0.042	0.006	0.023	0.026	0.019	0.005	0.024	−0.001
Tstat.	0.637†	1.767†	2.167	1.321†	1.546	1.509†	0.460†	0.559†	−0.159

The model is: $HRD_t = c_d + a_d HRN_{t-1} + b_d DM_t + \sigma FRD_t + e_t$, with $e_t \mid \Omega(i) \sim N(0, q_t)$, $q_t = \omega_q + \beta_q q_{t-1} + \alpha_q e^2_{t-1} + \gamma_q DM_t + \pi(FRD_t)^2$; where $(FRD_t, HRD_t) \in \{(NKD_t, SPD_t), (SPD_{t-1}, NKD_t)\}$.

The NK 225 9:15-to-close return and S&P 500 10:00-to-close return are used for the *NKD* and the *SPD*, respectively. Tstat is the *t*-statistic.

† indicates the significance at a 5-percent level when the usual standard errors are used. Robust standard errors are larger than conventional standard errors. If the absolute values of (robust) *t*-statistics are greater than 1.96 in this table, then the absolute values of *t*-statistics using conventional standard errors are also greater than 1.96.

errors are used, whereas they are significant when the usual standard errors are used. Panel B reports similar estimated coefficients for return and volatility correlations between SPD and NKN. The results show an interesting pattern between the return correlation coefficients in the regression for the NKN and the different proxies for opening quotes: the correlation coefficients peak at the regression of the close-to-9:15 returns.

Table 9 presents the estimated coefficient and *t*-statistics for the effects of the foreign daytime returns to the subsequent domestic daytime returns and volatility (i.e., lagged spillovers). Since there are no overlapping hours between the TSE and the NYSE, these t-statistics can be regarded as a causality test of whether New York daytime returns have any information additional to Tokyo overnight returns in predicting Tokyo daytime returns. In Panel A of Table 9, the student *t* statistics show that there is no such significant causality in volatility and returns for either direction between both markets before or after the Crash. The AS model employed here is related to the GARCH-in-mean model employed by Hamao, Masulis, and Ng (1990). The difference between these two models is the specification of expected returns in the mean equation. However, our results for contemporaneous correlations and lagged spillovers are consistent with the findings in Hamao, Masulis, and Ng (1990), Becker, Finnerty, and Tucker (1992), and our cross-market correlation analysis. The results suggest that spurious spillovers, caused by nonsynchronous trading problems at "open" with the 9:01 data in the TSE and the 9:30 data in the NYSE, are robust with respect to model specifications.

5. Conclusion

The global crash of stock markets in October 1987 increased research interest into how financial disturbances transmit from one market to another. In this article, we analyzed the international transmission mechanism by describing two ways investors can learn from information revealed in the foreign market overnight. One is an aggregate-shock model, in which investors use the return surprises from the other market to set opening prices. The other is a signal-extraction model in which return surprises are decomposed into two parts, global factors and local factors, and in which investors optimally extract the global factor from the observed price changes.

Using intradaily data to decompose daily returns into daytime and overnight returns, we estimated these two models and compared them with the GARCH-in-mean model of Hamao, Masulis, and Ng (1990). In carrying out our empirical analysis, we chose the opening price of a market as a price index 30 minutes (in New York) or 15 minutes (in Tokyo) after the market officially opens, in order to attenuate the problem of stale quotes or nonsynchronous trading. Our main results are as follows. First, the foreign daytime returns can significantly influence the domestic overnight returns. It has often been suggested in the literature that New York stock returns influence Tokyo, but not vice versa. Contrary to this belief, we find that cross-market interdependence in returns and volatilities is generally bi-directional between the New York and Tokyo markets. Second, we find weak evidence that the signal-extraction model characterizes Tokyo traders' behavior better than the other models in terms of the Schwarz criterion. While our empirical results are consistent with the contagion-effect hypothesis in King and Wadhwani (1990), we extend their model by incorporating the time-varying volatility to characterize volatility clustering and the time-varying extraction coefficient. Third, we find little evidence of the lagged return spillovers from New York daytime to Tokyo daytime or vice versa. In contrast to Hamao, Masulis, and Ng (1990), our results show little evidence against the hypothesis that the domestic market efficiently adjusts to foreign information. The differences between their results and ours may be attributed to nonsynchronous trading and stale quotes at open.

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