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DO BULLS AND BEARS MOVE ACROSS BORDERS? INTERNATIONAL TRANSMISSION OF STOCK RETURNS AND VOLATILITY AS THE WORLD TURNS

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ABSTRACT

This paper investigates empirically how returns and volatilities of stock indices are correlated between Tokyo and New York. Intradaily data are used, so that daytime and overnight returns are defined for both markets. Tokyo daytime hours overlap with New York overnight hours, while New York daytime hours overlap with Tokyo overnight hours. We find that in general Tokyo (New York) daytime returns are significantly correlated with New York (Tokyo) overnight returns. This suggests that information revealed during the trading hours of one market has a global impact on the returns of the other market. One exception is that after the October 1987 Crash, the Tokyo overnight returns were not significantly affected by New York daytime returns. We propose and estimate a signal extraction model with GARCH processes to determine the global factor from daytime returns. This is the problem of setting the opening price of a domestic market conditional on the foreign daytime returns. We also investigate lagged return and volatility spillovers. Except for a lagged return spillover from New York to Tokyo for the period after the Crash, there are no significant lagged spillovers in returns or in volatilities.

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1. Introduction

When the New York stock market opens its business day, many things that have happened overnight have to be incorporated in its pricing. One relevant piece of information is how the Tokyo stock market did earlier in the day. Similarly, Tokyo stock brokers take notice how the New York market ended a few hours before the Tokyo market opens. There are many 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 fundamentals in one country most likely has implications for the other country. According to this view, stock returns priced by international factors imply international correlations in an international asset pricing model.[1] Growing financial market integration implies that, according to this type of model, changes in stock prices in one market quickly affect those of another market (often in the same direction).

Another reason for international correlations of stock price changes is "market psychology." The October 1987 Crash (Black Monday) in New York setting off worldwide stock price declines is often cited as evidence for international contagion of bear psychology. Speculations (or fads, noises, or even a herd instinct) may be transmittable across borders. One survey (Shiller, Konya, and Tsutsui (1991)) has found that Tokyo participants are influenced by what happens in New York (and not vice versa). An excellent paper by King and Wadhwani (1990) proposes to model such a phenomenon as a signal extraction problem.

Since Tokyo and New York do not have any overlapping trading hours, clean tests of how information is transmitted from one market to the other can be formulated. Decomposition of daily movement (returns and conditional volatility) into daytime (open-to-close) movement and overnight (close-to-open) movement is crucial for meaningful analyses.[2] For example, the following efficient market hypothesis can be tested: any predictable returns and conditional volatility of one market because of the movement of the other market should be incorporated in the opening price (that is, overnight movement). In order to carry out this inference, a global factor and a local factor have to be separated. For this, the paper proposes a signal-extraction method similar to King and Wadhwani (1990). In particular, a test of "heat waves" (market-specific volatility clustering) and "meteor showers" (worldwide volatility clustering), as proposed in Engle, Ito and Lin (1990) and Ito, Engle, and Lin (1991), can be implemented in the stock market.

The purpose of this paper is three-fold: First, we will carefully decompose daytime and overnight stock movements in Tokyo and in New York and pay attention to the nonsynchronous trading problem; second, we will estimate "contemporaneous" correlation between the (daytime) returns and volatility in one market and the overnight returns and volatility of the other; and third, we will test whether (daytime) returns and volatility of one market would predict those of the other market.

1.1. Related Literature

The worldwide scope of the October 1987 Crash stimulated many studies on the international transmission of returns and volatility: Bennett and Kelleher (1988), Hamao, Masulis, and Ng (1990), Neumark, Tinsley, and Tosini (1991), Schwert (1990), Susmel and Engle (1990), and Von Furstenberg and Joen (1989), to name a few. In these papers several features were claimed to be found:[3] (i) Volatility of stock prices is time-varying. It rose considerably around October 1987, but quickly decreased afterwards, even to a level lower than that before the Crash. (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 asymmetric in causality between the United States and other countries. The US movement affects other markets, but not vice versa. (iv) Spillovers of price changes and volatility are found between major markets even with non-overlapping time zones. These features are often presented without a logical link between them. In this paper, we will present a general framework, in which a link between these features comes out naturally.[4]

In summary, our framework is based on a contagion model proposed by King and Wandhwani (1990), but with finer frequency so that daytime returns and overnight returns are separated. In particular, we provide a direct test of the contagion model, identify the proportions of global and local factors (information contents) in the variances of prices, and examine how promptly market prices would react to news revealed in the other market. Our approach also yields an insight into a often-made claim that correlations in international equity prices are positively related to volatility.

1.2. Tokyo Stock Exchange and New York Stock Exchange

The Tokyo Stock Exchange (TSE) and the New York Stock Exchange (NYSE) are the world largest equity markets. We adopt the Nikkei 225 and S&P 500 as the stock price indices for our analysis.[5] 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. and trades until 11:00 a.m., then breaks for lunch until 1:00 p.m.[6] The afternoon session continues until 3:00 p.m. Since Tokyo is ahead of New York by 14 hours (in the winter) or 13 hours (in the summer), these trading hours do not overlap in real time.

At the beginning of the day, overnight orders for each stock have to be matched at some price. In the NYSE, trading is done through specialists who can directly participate in trading and take inventory positions. In the TSE, a particular type of securities firms, <u>saitori</u> members, specializes in matching orders without taking positions.[7] Not all stocks are traded as soon as the market opens. It often takes from several minutes to an hour before most of the "major" stocks have transactions.[8] Whenever a stock price index is used, the "opening" price of the index has to be carefully dealt with, since many of the individual stock prices included in the index are not transaction prices of that day. In the usual case, "stale quotes" such as the preceding day's closing price are used if an initial transaction of the day is yet to come.[9] It may be the case that the market is groping for a price level to balance demand and supply of the moment, which may be quite different from the preceding day's closing price. If so, the measured index does not accurately reflect the true underlying price index. This is a problem of nonsynchronous trading. In order to minimize this problem, we take 10:00 a.m. quotes as the opening of the day for both Tokyo and New York. By 10 a.m., most of the stocks in both the Nikkei225 and S&P 500 have had their initial trade of the day.

2. Model and Econometric Specifications

2.1. General Framework and Notation

For both Tokyo and New York, daily (close-to-close) returns are divided into daytime (open-to-close) returns and overnight (close(t-1)-to-open) returns:

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

$$SP_t = SPN_t + SPD_t$$

where NK and SP denote returns in Nikkei 225 and S&P 500, respectively, and suffix D or N defines daytime or overnight, respectively.

During the trading hours of each of the two markets, information or trading noises will be incorporated into stock prices. We denote as en_t or es_t that part of returns which can not be predicted based upon public information when the market opens. Suffix n or s denotes Nikkei 225 or S&P 500, respectively. Allowing for possible autocorrelations from overnight returns, and for post-holiday effects through a dummy variable, DM, and Friday effects through a dummy variable, DF, we can write the daytime returns as follows:[10]

$$NKD_t = c_{nd} + a_{nd}NKN_{t-1} + b_{nd}DM_t + d_{nd}DF_t + en_t \qquad (1)$$

$$SPD_t = c_{sd} + a_{sd}SPN_t + b_{sd}DM_t + d_{sd}DF_t + es_t \qquad (2)$$

Note that NKD and SPD do not overlap in real time.

The following analysis is an exercise for investors who plan to place orders and price stocks at the opening. While the domestic market is closed, the information from the foreign market is available to domestic investors. This information is valuable for pricing domestic stock returns when the market re-opens. If the market is efficient, it should be reflected in the opening price of the domestic market. The question is how to use the foreign market information.

The first avenue is to use the unexpected returns of the foreign market. We call this the aggregate shock model. In this model, the S&P 500 overnight returns are modeled as a function of the preceding S&P 500 daytime returns, the Monday dummy, and influences from abroad:

$$SPN_t = c_{so} + a_{so}SPD_{t-1} + \mu_{so}en_t + b_{so}DM_t + vn_t \qquad (3)$$

where the effect of unexpected returns from Tokyo is $\mu_{so}en_t$, and effects revealed after the close of the Tokyo market but before the opening of the New York market are denoted by vn. Similarly, the Nikkei 225 overnight returns of calendar date t exploit information revealed during the New York market hours of calendar date t-1:

$$NKN_t = c_{no} + a_{no}NKD_{t-1} + \mu_{no}es_t + b_{no}DM_t + vs_t \qquad (4)$$

Again, vs is information revealed after the New York close but before the Tokyo open. The Friday dummy is not used in equations (3) and (4) because, for overnight returns, the Monday dummy covers the weekend (Friday close to Monday open).

The second avenue is to decompose the unexpected returns in the foreign market into two types of shocks, uncorrelated with each other, global and local. Specifically, we assume that

$$en_t = wn_t + un_t$$

and

$$es_t = ws_t + us_t$$

where wn_t and ws_t are the global factors, and un_t and us_t are the local factors. The global factor influences stock returns in home and foreign markets, and the local factor contains only shocks and noises 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.

In an efficient market, information that is revealed in Tokyo and that is relevant for New York -- in short, the global factor -- will be fully reflected in the opening price in New York. The key assumption here is that investors and econometricians cannot identify global and local shocks, but would try to infer them. Investors are assumed to know the parameters of returns generating processes and to estimate, through the signal extraction process, relevant information about the global factor from observed daytime returns.[11] Through this signal extraction procedure, we denote the estimate of the global factor as wn^*_t and ws^*_t. Hence, in an efficient market, the global factor in Tokyo, wn_t, will influence the S&P 500 overnight returns, SPN, but not its daytime returns, SPD. Hence, the New York overnight return could be written as

$$SPN_t = c_{sn} + a_{sn}SPD_{t-1} + \mu_{sn}wn^*_t + b_{sn}DM_t + vn_t \qquad (5)$$

where * indicates the estimate conditional upon information after the close of the Tokyo market and the effect of the global factor from Tokyo is μ_{sn}. Similarly, the Nikkei overnight returns of t exploit global information revealed during the New York trading hours of calendar date t-1.

$$NKN_t = c_{nn} + a_{nn}NKD_{t-1} + \mu_{nn}ws^*_t + b_{nn}DM_t + vs_t \qquad (6)$$

At this point, it is instructive to summarize timing and notation as shown in Figure 1, where TKO, TKC, NYO, and NYC, are the time of Tokyo opening, Tokyo closing, New York opening, and New York closing in real time. The daytime returns and overnight returns are defined as the changes between those timings, respectively.

The information set containing returns and other stock price related public information up to the point of time j (j = TKO, TKC, SPO, SPC) is denoted by $\Omega(j)$. In the aggregate shock model, shocks em and vm, for m=n or s, are assumed

```
Location                     Date and local time

            ..  ---------------------------------------------------------  ..
GMT        t-1,1200am  6am    2:30pm     9pm   t,12am    6am  2:30pm      9pm
Tokyo        t-1,9am   3pm   11:30pm   t,6am    9am      3pm 11:30pm  t+1,6am
New York       |         | t-1,9:30am    4pm     |        |    t,9:30am   4pm
               |         |      |         |      |        |      |         |
Definition    TKO       TKC    NYO       NYC    TKO      TKC    NYO       NYC

               ---------------------------------------------------------
Variable       |NKD(t-1)|      NKN(t-1)          | NKD(t)|      NKN(t) ...
               ---------------------------------------------------------
            ... SPN(t-1)      | SPD(t-1) |          SPN(t)       | SPD(t)  |
               ---------------------------------------------------------
Shocks         |   en    | vn |    es     | vs |   en    | vn |    es     |
               |en=wn+un|     | es=ws+us |      |en=wn+un|     | es=ws+us |
```

Notation:

TKO - Tokyo market, opening time
TKC - Tokyo market, closing time
NYO - New York market, opening time
NYC - New York market, closing time

NKD - Nikkei 225 daytime (open-to-close) return
NKN - Nikkei 225 overnight (close-to-open) return, with close of date t-1
SPD - S&P 500 daytime (open-to-close) return
SPN - S&P 500 overnight (close-to-open) return, with close of date t-1

en - aggregate shock to Nikkei daytime return
es - aggregate shock to S&P daytime return
vn - shock to Nikkei overnight return
vs - shock to S&P overnight return
wn - global factor contained in Nikkei daytime return, part of en
un - local factor contained in Nikkei daytime return, part of en
ws - global factor contained in S&P daytime return, part of es
us - local factor contained in S&P daytime return, part of es

Note: The horizontal line shows the timing in real time. For example, when it is 9:30 a.m.(EST) in New York on date t-1, it is 11:30 p.m. (same day) in Tokyo. Various vertical lines show the correspondence of the timings, with the following exceptions: the opening time in actual market hours are 9:00 a.m. in Tokyo and 9:30 a.m. in New York, but it is 10:00 a.m. in the definitions of returns of price indices of both markets. This adjustment is done to correct for the non-synchronous trading problem at opening.

Figure 1: Timing and Notation

to be serially uncorrelated and mutually independent. Moreover, those shocks are assumed to follow a GARCH process:

$$em|\Omega(j) \sim N(0,\ qm_t) \qquad \{(m,j)\} = \{(n,TKO)\ (s,\ NYO)\} \quad (7)$$

$$vm|\Omega(j) \sim N(0,\ km_t) \qquad \{(m,j)\} = \{(n,TKC)\ (s,\ NYC)\} \quad (8)$$

The same assumptions are held for the distribution of the global and the local factors in the signal extraction model. That is

$$wm|\Omega(j) \sim N(0,\ gm_t) \qquad \{(m,j)\} = \{(n,TKO)\ (s,\ NYO)\} \quad (9)$$

$$um|\Omega(j) \sim N(0,\ hm_t) \qquad \{(m,j)\} = \{(n,TKO)\ (s,\ NYO)\} \quad (10)$$

where N(.,.) denotes a normal distribution with the first element being the mean, and the second element being the variance conditional on $\Omega(j)$.

2.2 Aggregate Shock Model

The aggregate shock model can be formulated as equations (1) to (4), and (7) to (8). Since the shocks em and vm, for m = n and s, are mutually uncorrelated, we can apply a two-stage GARCH estimation method to estimate the model. In the first stage, we employ the GARCH method to the Nikkei 225 daytime returns in equations (1) and (7). Obtaining the fitted value of unexpected return en_t in the first stage and substituting it into the mean equation of the S&P 500 overnight returns, we can estimate equations (4) and (8) by the GARCH method again. A similar procedure can be applied to S&P 500 daytime returns and Nikkei overnight returns. Note that this two-stage procedure will yield consistent estimators if the model is correctly specified.

The aggregate shock model and the estimation method are similar to those used in Hamao et al. (1990). However, there is a technical difference between Hamao et al. and this paper in the specification of daytime (or overnight) returns: we have included a term for the preceding domestic overnight (or daytime) returns and they have a GARCH in mean. We choose our specification for intra-daily stock returns for two reasons. First, the intra-daily stock returns exhibit some significant serial dependence that will be discussed in section 3. Second, the GARCH-in-Mean model does not perform well in short high frequency samples.

2.3 Signal Extraction Model

From equation (1), the unexpected part of daytime returns of the Tokyo market, that is, en_t, has two components: wn_t and un_t. However, New York investors are assumed to observe only the combined shock, not the individual components. This is a classic problem of signal extraction. To minimize the mean squared errors of the estimators, New York investors can estimate the global factor wn_t from the unexpected Tokyo price changes as

$$wn^*_t = [\ gn_t \ / \ (gn_t + hn_t)]\ en_t \tag{11}$$

where * is the expectation based on public information $\Omega(TKC)$. The estimate of the Tokyo global factor is proportional to the unexpected foreign daytime returns, with the proportion equal to the variance ratio of the global factor to 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 estimated global information, gn^*_t, conditional on the information available after the close of the Tokyo market becomes

$$gn^*_t = gn_t\ \{1 - [gn_t \ / \ (gn_t + hn_t)]\} \tag{12}$$

Because part of Tokyo closing prices reflects the global factor, using the Tokyo 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 (12). As the prices contain more global information (or the noise-to-information variance ratio is lower), information gain from observing Tokyo closing prices becomes larger, and then the variance of the estimated global information will be smaller.

Substituting equation (11) into equation (5), we can write the New York overnight returns, SPN_t, as

$$SPN_t = c_{sn} + a_{sn}SPD_{t-1} + \mu_{sn}[\ gn_t\ /\ (gn_t + hn_t)]en_t + b_{sn}DM_t + vn_t \quad (13)$$

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, $\mu_{sn}[gn_t/(gn_t+ hn_t)]en_t$, 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 New York overnight return process becomes equation (3) with ϕ equal to $\mu_{sn}[gn/(gn+ hn)]$. The assumption of GARCH processes can reconcile two stylized facts in the literature survey of section 1.1: (i) time-varying volatility and (ii) the time-varying correlations in international stock returns.

A similar signal extraction process can also be employed by Japanese investors to estimate the global factor revealed in the New York market. Hence, the Tokyo overnight returns are

$$NKN_t = c_{nn} + a_{nn}NKD_{t-1} + \mu_{sn}[\ gs_t\ /\ (gs_t + hs_t)]es_t + b_{nn}DM_t + vs_t \quad (14)$$

2.4. GARCH Model

The GARCH approach is very popular in modeling the second moments of financial data (see a recent survey by Bollerslev, Chou, and Kroner (1990)). It captures the phenomenon of volatility clustering by specifying that large price changes are likely to be followed by large price changes but of either sign. We assume that gm_t, qm_t, hm_t, and km_t follow (pseudo) GARCH processes:

$$gm_t = \omega_{gm} + \alpha_{gm}[(wm^*_{t-1})^2 + gm^*_{t-1}] + \beta_{gm}\ gm_{t-1} + \gamma_{gm}\ DM_t + \delta_{gm}\ DF_t \qquad (15)$$

$$hm_t = \omega_{hm} + \alpha_{hm}[(um^*_{t-1})^2 + hm^*_{t-1}] + \beta_{hm}\ hm_{t-1} + \gamma_{hm}\ DM_t + \delta_{hm}\ DF_t \qquad (16)$$

$$km_t = \omega_{km} + \alpha_{km}\ (vm_{t-1})^2 + \beta_{km}km_{t-1} + \gamma_{km}\ DM_t \qquad (17)$$

$$qm_t = \omega_{qm} + \alpha_{qm}\ (em_{t-1})^2 + \beta_{qm}\ qm_{t-1} + \gamma_{qm}\ DM_t + \delta_{qm}\ DF_t \qquad (18)$$

for suffix m = n or s.

The process is analogous to the ARCH models employed by Diebold and Nerlove (1989), and King, Sentana, and Wadhwani (1990) with latent factor structures, as well as one by Harvey and Ruiz (1990). Specifically, if news wm_t or um_t follows a GARCH process with a normal density, then without directly observing wm_t or um_t, the best estimators of wm^2_{t-1} conditional on public information $\Omega(j)$, for j = TKC or NYC, is

$$E(wm_{t-1}^2 \mid \Omega(j)) = (wm^*_{t-1})^2 + gm^*_{t-1}.$$

Hence, gm^*_{t-1} enters into the variance process of equation (15). Similarly, hm^*_{t-1} enters in equation (16).[12] The density function of wm_t or um_t conditional on the information set is no longer normal. As a result, the Kalman filtering process still produces MMSE (minimizing mean squared errors) estimators, but is not optimal. Diebold and Nerlove (1989), and King, Sentana, and Wadhwani (1990) estimate the conditional variance process similar to equations (15) to (16) without the term of gm^*_{t-1} in equations (15) and (16). However, Monte Carlo experiments by Harvey and Ruiz (1990) show that a correction of gm^*_{t-1} is needed, in order to obtain a better estimator with smaller mean squared errors. Hence, their correction of the conditional variance is adopted in equations (15) and (16).

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, or for the New York daytime and the Tokyo overnight returns. The log likelihood function is

$$\log L = -T\log(2\pi)-(1/2)\Sigma_{t=1,T}\{\log(gm_t+hm_t)+[em^2_t/(gm_t+hm_t)]+\log(km_t)+(vm^2_t/km_t)]\}$$

for suffix m = n or s.

The scoring algorithm is to calculate the values of vm_t, em_t, gm_t, and hm_t according to the signal extraction process described in equations (11) to (18), and to use the updating process to seek the estimates that maximize the log likelihood function. The standard errors are calculated by $H^{-1}(S'S)H^{-1}$ where H is the Hessian matrix and S is the score vector. In the second step, we examine whether this model can fully explain the volatility and the return correlations across markets. Such tests are conducted by Bollerslev and Wooldridge (1988)'s robust LM tests. The LM tests and standard errors that we construct here are robust to the density function, which will minimize the problem of non-normality of the shocks.

3. Primary Analysis

3.1. Data Summary

Because the effect of the Crash of 1987 on international stock returns has generated great interest in the literature, Table 1 reports the data summary for the Nikkei 225 and the Standard and Poor 500 (S&P 500) indices over the periods before, around, and after the Crash as well as the whole sample period. The stock returns on October 19, 1987 experienced the largest one-day drop in the history of major stock indices since 1885. The S&P 500 fell about 20.4 percent on October 19, 1987. During the two months around the Crash, the average daily returns for the S&P 500 decreased by 34.6 percent. As this financial shock was transmitted to the TSE on the following day, the average daily returns for the Nikkei 225 fell by 29.3 percent. Before and after this abnormal event, the two markets have a positive daily return. In general, the daily Nikkei 225 returns were higher than the S&P 500 returns before and after the Crash. Particularly after the Crash, the Nikkei 225 rebounded and surpassed the pre-Crash record high in the two years. On the last day of 1989, it reached 38915, or 77 percent above the day after the Black Monday (29190). The gain in the Nikkei 225 returns was larger than a 57 percent rebound of the S&P 500 returns from 224 to 353 during the same period. Further examination of Table 1 reveals that the distribution of stock returns is not normal. During the Crash period, the distribution of daytime stock returns became fatter tailed, indicating a more volatile movement of the stock prices.

Investigating the variance ratio of daytime returns to overnight returns also shows a pattern similar to that found by Amihud and Mendelson (1987), Oldfield and Rogalski (1980), and Stoll and Whaley (1990) in the NYSE before the

Crash. Despite different sample periods and stock returns, the variance ratio ranges from 4.26 to 5.40 in the NYSE. Amihud and Mendelson (1989) also show that this ratio amounts to 2.40 for the fifty most traded stocks in the TSE. Because we measure the 10:00 a.m. quote as the opening price, the variance ratio before the Crash is 3.1 in the S&P 500 and 1.60 in the Nikkei 225, smaller than the previous results. Around and after the Crash, the variance ratio drops.

Table 1 also reports the correlation between the overnight and the daytime returns in the NYSE and the TSE, which have an overlapping time segment. The correlation between the NKN and the SPD returns increases around the Crash, and drops after the Crash. Bennett and Kelleher (1988) report that daily correlations of returns for three major world stock markets ranged from 0.08 in 1980 to 0.26 in September 1987, and were much higher than those in the 1970s.

Our last observation from Table 1 is that the significant Ljung-Box statistics for the serial correlation of the twelfth order indicate evidence for serial correlation in the intra-daily stock returns. The evidence will be further examined in the next section for dependence between the daytime and the overnight returns.

3.2. Tests for Serial Dependence of Stock Returns

The fact that the close-to-close stock returns have positive autocorrelation has long been recognized in many studies. Poterba and Summers (1988) and Fama and French (1988) examine the proposition that stock prices take long temporary swings from fundamental values; the eventual reversal causes a negative correlation in some future holding period. Lo and MacKinlay (1989) investigate the importance of nonsynchronous trading in generating positive serial correlation, and show only weak evidence in favor of this interpretation. The role of noisy traders and positive feedback traders in inducing positive correlations of stock returns has been modeled by Campbell and Kyle (1988) and De Long, Shleifer, Summers, and Waldmann (1990).

It is well-known that price correlations exist in the high frequency data. In Table 2 we test for serial dependence of intra-daily stock returns. The results are presented for the SPD, the SPN, the NKD, and the NKN returns, and the standard errors are adjusted for heteroskedasticity of an unknown form. Table 2 shows some evidence for positive serial dependence of daytime returns on the overnight returns. This is different from the findings of negative serial dependence by Amihud and Mendelson (1989). As we measure the opening prices at thirty minutes or one hour after the market re-opens, the finding of positive significant impacts of the previous overnight returns on the daytime returns more likely indicates that price reversals last only for one hour or less. As shown in Table 2, White heteroskedasticity tests or Lagrangean multiplier tests for ARCH reveal that the volatility of stock returns is time-varying.

4. Aggregate Shock Model

A focus of attention in the study of world equities market has been how returns and volatilities in major markets are correlated and have changed as financial integration has progressed.[13] Using a vector autoregressions approach to model the transmission of daily stock returns, Eun and Shim (1989) have found that only United States stock returns can explain the movements of nine other world stock returns, but not vice versa. Hamao, Masulis, and Ng (1990), and King and Wadhwani (1990) also have given empirical support to this asymmetric transmission pattern between the New York market and the Tokyo market. The former paper estimated that the impact of the S&P 500 Daytime returns on the Nikkei overnight returns amounts to only 0.02 by the GARCH-in-mean model with MA(1) errors, whereas the latter work estimates the contagion coefficient implied by daily S&P 500 and Nikkei 225 returns ranging from 0.40 to 0.11.

In this section, we employ an aggregate stock return model, that is, we do not attempt to decompose unexpected daytime returns into global or local factors, but investigate whether the (non-decomposed) unexpected daytime returns in Tokyo have any impact on the overnight returns in New York. If any information revealed in Tokyo is relevant to the stock prices in New York, then New York investors will use it in pricing the New York stock returns. This will show international, contemporaneous spillovers from unexpected daytime returns of the Tokyo market to the unexpected overnight returns of the New York market. The contemporaneous spillovers themselves do not violate the efficient market hypothesis, but indicate that the unexpected returns in Tokyo contain some global information. The sensitivity coefficient of the contemporaneous spillovers is ϕ.

Conditional variances of unexpected returns in the two markets are 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 2.2. The results are reported in Table 3. In Table 4, a parallel investigation is done for daytime New York and overnight Tokyo 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 normal distribution. Therefore, we report the robust standard errors as calculated by Bollerslev and Wooldridge (1988).

The first salient feature in Tables 3 and 4 is the existence of contemporaneous spillover suggested by significant t statistics of ϕ. Put differently, information revealed in trading hours of a market has global impacts on stock returns in the other markets. Moreover, results in Tables 3 and 4 show that (i) before the Crash, the contemporaneous spillover was symmetric: Tokyo daytime returns affected New York overnight returns and vice versa; and (ii) after the Crash, the contemporaneous spillover became asymmetric: Tokyo daytime returns influenced the New York overnight returns, but New York daytime returns did not influence the Tokyo overnight returns. In a sense, Tokyo returns contained a statistically significant global factor, while New York returns did not.

The results (i) and (ii) are in sharp contrast to those of Hamao et al.

(1990), Becker, Finnerty, and Gupta (1990), and King and Wadhwani (1990). These researchers found that the stock returns of the U.S.A. can influence other stock markets in a sizable way, but not vice versa. This difference in results must come from the fact that we correct for non-synchronous trading by taking 10 a.m. as opening time, while Hamao et al. (1990) takes 9:01 a.m. for Tokyo and 9:30 a.m. for New York, and the fact that King and Wadhwani (1990) use daily (close-to-close) returns without decomposing into daytime and overnight returns. It is our understanding that our new finding offers a clear-cut conclusion to this issue.

Next, we examine the estimates of parameters in the variance process. The persistence of a shock to volatility is measured by the sum of α and β. The sum of α and β are more than 0.85 in all cases except for NKN after the crash (the sum was 0.70). We interpret these results as evidence for a persistent effect of a shock on volatility. Tables 3 and 4 show the lower persistence of volatility of the NKD, the NKN, and the SPD returns after the Crash. The conclusion here is that volatility would diminish much faster for the post-Crash period than for the pre-Crash period. This conclusion is in accordance with Engle and Mustafa (1989) and Schwert (1990). Neither the Monday dummy nor the Friday dummy shows significant effects on the returns in most cases. The overnight returns are more volatile during holidays partly because more no-trading hours and the clustering of foreign news during the domestic holidays raise the total volatility.

5. Signal Extraction Model

It is an implicit assumption in the aggregate shock model that all the news revealed during the trading hours of one market has global impacts on stock returns. Realistically, part of the information revealed through trading may affect the returns locally. Only a global factor influences the other market. If the market is efficient, the impacts of the global factor will be priced at the opening of the subsequent market. The question is how investors learn about the global factor when they do not have any precise information about the global and the local factors. In the signal extraction model, domestic investors are assumed to optimally extract the global information from the observed price changes. Consequently, the estimate of the global information is proportional to unexpected price changes with the proportional coefficient equal to the variance ratio of the global information to unexpected 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 2.4. After estimation, we test whether local factors, um_t, have a GARCH(1) term im the conditional variance processes. By evaluating the LM test statistics, we find that the null hypothesis of a GARCH(1), $\beta_{bm} = 0$, cannot be rejected at least at the 5% level. From Tables 5 and 6, we draw four conclusions:

First, in Table 5, we investigate how the New York investors extract the global factor from Tokyo daytime returns and how much New York overnight returns are sensitive to the estimated global factor. Table 6 is similarly done for Tokyo investors learning overnight from New York daytime returns. In Table 5, the coefficient of μ_{sn} is the sensitivity of New York overnight returns to the estimated global factors revealed in Tokyo daytime returns. The estimated global factor, wn^*_t, is the product of the time-varying signal extraction coefficient ($gn_t/(gn_t+hn_t)$) and estimated unexpected returns (en_t). Table 5 shows that the sensitivity μ increased after the Crash. Put differently, New York investors became more sensitive to what is revealed to be a global factor in Tokyo. Table 6 shows that the sensitivity μ' became statistically insignificant after the Crash. Tokyo investors' sensitivity to a global factor in New York became less statistically significant after the Crash.

Second, a coefficient of contemporaneous spillover is compared. Recalling that the sensitivity ϕ shown in Table 3 was with respect to the aggregate unexpected returns, we have to adjust for the signal extraction coefficient in order to compare the sensitivity obtained from Table 5. Let us denote $\mu(gm/(gm+hm))$, for suffix $m = n$ or s, as the time-varying sensitivity, comparable to ϕ in Table 3. Since $\mu(gm/(gm+hm))$ is time-varying, only its time-series average over the sample period is presented in Table 5. The estimated $\mu(gm/(gm+hm))$ for SPN is 0.075, 0.064, and 0.191 for the whole sample period, the periods before and after the Crash, respectively. Comparing ϕ in Table 3 with $\mu(gm/(gm+hm))$ in Table 5, we find a similar pattern: the sensitivity increased after the Crash, and the magnitude is similar, too. Comparing Tables 4 and 6, we also find that the sensitivities are similar. This shows a robustness in our procedures.

Third, the estimated variance ratio of the global factor to the local factor in the Tokyo market is presented as gm/hm. This is also time-varying, so that a time-series average over the sample period is presented. We find, as shown in Table 5, that the weight of the global factor revealed in Tokyo increased after the Crash. This suggests that the Tokyo stock returns after the Crash contain more of a global component than before. Table 6 also shows that the variance ratio of a global factor to a local factor increased in the New York market. However, recalling that the Tokyo investors' sensitivity μ became statistically not different from zero, an increase in the weight of the global factor in New York does not contribute to explaining the Tokyo overnight returns.

Fourth, we compare the performance of the aggregate shock model with the signal extraction model. The signal extraction model will be nested into the aggregate shock model because, if unexpected returns have no local impacts, then the two models become equivalent. We compute the Wald statistics, shown in the last rows of Tables 5 and 6, to examine the null hypothesis that the parameters in the conditional variance of the local factor equal zero. These show that the null hypothesis can be rejected in cases where the estimate of ϕ or μ is significant. The result suggests that if the stock returns contain some global effects, then the signal extraction approach is a better way to characterize the investors' use of the information in pricing opening quotes than the aggregate shock model.

6. Lagged International Spillovers

6.1 Lagged Returns Spillovers

In Tables 3 to 6, we investigate contemporaneous spillovers from daytime returns in one market to overnight returns in the other market. The two returns are defined in hours that are overlapping in real time. In this section, we investigate whether returns spillover from the daytime returns in one market to the daytime returns in the other market which starts trading several hours later. If the strict version of the efficient market hypothesis holds, we should not expect any (mean) spillovers of this type.

In Table 7, the Tokyo daytime return is a function of its preceding overnight returns and the New York daytime return (plus dummy variables). Note that the two regressors, the Tokyo overnight and the New York daytime returns, overlap in real time. The coefficient π shows the sensitivity of the Tokyo market returns to the New York daytime returns (of day t-1). The equation could be regarded as a causality test of whether New York daytime returns have any additional information (additional to Tokyo's own market overnight returns) in predicting Tokyo daytime returns. Alternatively, the equation may be interpreted as the test of lagged spillover effect from New York daytime returns to Tokyo daytime returns a half day later. In panel A of Table 7, the Lagrangean multiplier test shows that there is indeed such an effect in the post-Crash period, but not the pre-Crash period.

This result is somewhat counter-intuitive. If the market is efficient, one expects no spillovers from New York daytime returns to Tokyo daytime returns. Note that we have allowed one hour in the beginning of the day to avoid the nonsynchronous trading problem, giving a favorable setting for the efficient market hypothesis.[14] In panel B of Table 8, we re-estimate the model and find the impact of the S&P 500 daytime returns on the Nikkei 225 overnight returns amounting to 0.13. The significant t statistic confirms the findings of the Lagrangean multiplier test statistics. The estimates of other parameters in the mean and variance processes of Tokyo (New York) daytime returns are similar to those in Table 5 (Table 6), showing the robust results.

Recall that Tables 4 and 6 showed that the Tokyo overnight returns were insensitive to the New York daytime returns. Combining the lagged spillover result with the results in Tables 4 and 6 and with those in Table 8, the following scenario emerges. After the Crash, Tokyo investors became less confident in calculating the impact of New York daytime returns on Tokyo, taking time to react to the news. The spillover appears to last more than one hour after the opening of the Tokyo market. This, however, is a major puzzle from the efficient market point of view.

Table 8 shows that there is no lagged spillover from Tokyo daytime returns to New York daytime returns. All information revealed in the Tokyo daytime returns seems to be incorporated in the New York stock prices by 10:00 a.m., so that overnight returns are affected (Tables 3 and 5), but not daytime returns.

6.2 Lagged Volatility Spillovers

In this section, we will investigate what kinds of information influence the conditional variance of the global factor. The equation of gm has a GARCH process with an additional term to capture a possible effect from past shock, z. Several candidates we use for z are: the unexpected daytime returns of the foreign market, the global factor of the foreign market, the shocks revealed after the close of the foreign market but before the opening of the domestic market, and the overnight returns of the domestic market. These candidates contain information which is available to domestic investors at the opening of the market. Hence, we are able to perform a clean test to examine whether any of this information will generate volatility clustering across the border.

Table 9 shows that the conditional variance of Tokyo's global factor is influenced, for the post-Crash period, by the squared shocks observed between the New York close and the Tokyo open (or the estimated error terms of the New York overnight equations). Table 10 shows that New York's global factor, for the pre-Crash period, is influenced by the squared shocks observed between the Tokyo close and the New York open. However, on the whole, the effects of other possible realized volatility measures do not affect the conditional variance of the global factor. In particular, there is no statistically significant effect from the squared shocks in the global factor in one market to the conditional variance of the other market's global factor (see the second line of Tables 9 and 10).[15]

The results are different from those of Hamao et al. (1990) who found a volatility spillover from the New York daytime returns to the Tokyo daytime returns. This difference is likely attributable to their use of the opening quote of 9:01 a.m., which may contain some stale quotes, as opposed to our 10:00 a.m. Our result conforms more with that of Susmel and Engle (1990), who used hourly data and found that the volatility spillovers between New York and London equity markets only last for one hour after the market is open.

7. Conclusion

Using intra-daily data to decompose daily returns into daytime and overnight returns, this paper re-assesses several characteristics that have been found in the literature on the transmission of returns and volatility among world stock markets. Our data, methods, and findings contain several novel aspects. First, we define the opening price of a market as a price index thirty minutes (in New York) or one hour (in Tokyo) after the market is actually open, in order to minimize the problem of stale quotes or nonsynchronous trading. Second, we investigate contemporaneous correlations, Tokyo daytime with New York overnight, and New York daytime with Tokyo overnight. Our results show that the foreign daytime returns can significantly influence the domestic overnight returns, resulting in a price jump at the opening of the domestic market. Put differently, the bull or bear trend moves across the border. It has been suggested in the literature that spillovers take place in the direction from New York to other markets including Tokyo, but not in the opposite direction. In contrast, we find that returns and volatility spillovers are generally symmetric. Information (market fundamentals or psychology) revealed during the trading hours of one market are taken into account in the other markets when they open.

Second, we propose two models to describe the ways that investors learn information revealed in the foreign market during the overnight. One is the aggregate shock model, in which investors use the unexpected returns from the other model for setting opening prices. The second is the signal extraction model in which unexpected returns are decomposed into two parts, global and local factors, and in which investors optimally extract the information from the observed price changes. We compare these two models and find that the signal extraction model characterizes investors' behavior better than the aggregate shock model.

Third, several competing hypotheses regarding lagged spillovers in both returns and volatility are also tested. We find some evidence of the lagged return spillovers from New York daytime to Tokyo daytime in the period after the Crash. This is a puzzling finding. We conjecture that after the Crash, Tokyo participants needed more time to extract the global factor from the New York market, On the other hand, we also find that, in general, there is no volatility spillover from one market to the other several hours later.

ENDNOTES

1. See Solnik (1974a,b) and Abler and Dumas (1983) for models of international asset pricing.

2. Many studies have used daily returns in studying international transmission. Among them are King and Wadhwani (1990), von Furstenberg and Joen (1989), and Eun and Shim (1989). Without decomposing daily returns into overnight and daytime returns, it is impossible to test the type of questions related to an efficient market hypothesis. For example, King and Wadhwani (1990) show the signal extraction method that market participants of country A can use to infer from country B's stock returns, but their analysis cannot address the question of whether all adjustments are done at the opening of B's market.

3. King and Wadhwani (1990) report features (ii) and (iii); Hamao et al. (1990) document (i), (iii), and (iv); and Schwert (1990) reports (i).

4. Our framework is similar to King and Wadhwani (1990) in its use of the signal extraction method, but we decompose daily returns--that was the frequency of King and Wadhwani--into overnight and daytime returns. This finer frequency is also adopted in Hamao, Masulis, Ng (1990), but we define the opening price at 10 a.m. in order to avoid nonsynchronous trading problems which seem to bias their results in favor of volatility of spillovers. In addition, our model has several features, such as an explicit modeling of a signal extraction problem and a one-step estimation of a multi-variate (two country) GARCH problem, that are improved over Hamao, et al. (1990).

5. The Standard and Poor 500 (S&P 500) is the equity-value weighted arithmetic mean of 500 stocks selected by Standard and Poor. The hourly data of S&P 500 are kindly provided to us by Dr. J. Harold Mukherlin. The Nikkei 225 (Nikkei 225) is a price-weighted simple average of 225 stock prices selected by Nikkei. The equity-value weighted index in Tokyo is TOPIX, which covers all stocks in the first section of the TSE. Because of its broad coverage, the nonsynchronous trading and stale quotes problems become serious if we use TOPIX. Moreover, the opening TOPIX is very hard to obtain.

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

7. 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.

8. Large order imbalances at the opening of the day are likely to result, due to divergent beliefs of investors regarding overnight news. As pointed out by Brock and Kleidon (1989), large overnight changes in underlying pricing of stocks are not fully reflected the opening price, but extend over several trades at the beginning of the day. Put differently, it may take some time for investors to rebalance their portfolios after the opening. This produces volatility continuation or spillover.

9. In Tokyo, the bid or ask price may be substituted for the stale quote in the process of groping for an equilibrium price.

10. See Gibbons and Hess (1981) who reported the existence of day-of-week effects.

11. As noted above, our approach is similar to the one by King and Wadhwani (1990). Our approach is an improvement on theirs, in that time-varying variances are considered, daytime and overnight returns are separated, and thus updating procedures are explicitly specified.

12. Note that $hm^{*}_{t-1} = gm^{*}_{t-1}$ because the aggregate shock is observed. In order to see this, after wn is observed, un = en - wn, where wn is known. Hence, the conditional variance of en equals the conditional variance of un.

13. The examination of monthly international stock returns and their implications of financial integration have long been discussed. Recently, several papers have studied correlations in high frequency stock returns. In one of the early studies, Hilliard (1979) concluded that daily contemporaneous returns among ten world stock markets were not so highly correlated, even during the 1973-1974 oil crisis.

14. Hamao et al. (1990) find a similar spillover effect from New York returns to Tokyo returns. However, they speculate that it is due to the beginning-of-the-day nonsynchronous trading problem, because they use 9:01 a.m. We have used 10:00 a.m. as open so that the efficient market hypothesis will work, but still find evidence of spillovers. King and Wadhwani (1990) find similar effects, but since they use the close-to-close returns of the two markets, they cannot judge from their results whether the spillover effect is resolved in overlapping hours or in lagged hours.

15. This means that there are no "meteor shower" effects (in the sense of Engle, Ito and Lin (1990)) in the stock price indices of Tokyo and New York.

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Table 1 Data Summary

	Whole period	Before Crash	Around Crash	After Crash
	9/28/85-12/29/89	9/28/85-9/30/87	10/1/87-12/31/87	1/1/88-12/29/89
A: NKD				
Mean	0.069**	0.021	-0.226	0.154**
Variance	0.707	0.507	5.257	0.346
Skewness	-4.014**	-0.078	-3.252*	0.210
Kurtosis	73.983**	6.461**	23.461**	7.725**
LB(12)	23.074**	25.262**	12.100	12.562
B: NKN				
Mean	0.036*	0.121**	-0.067	-0.035*
Variance	0.240	0.306	1.036	0.067
Skewness	-0.249**	-0.298**	-0.511	0.837**
Kurtosis	15.113**	8.662**	8.662**	9.241**
LB(12)	49.698**	16.251	7.043	12.049
C: SPD				
Mean	0.042	0.088**	-0.358	0.045
Variance	1.118	0.635	8.452	0.682
Skewness	-6.317**	-0.357**	-4.654**	-1.635**
Kurtosis	112.831**	5.118**	33.042**	20.005**
LB(12)	20.699*	5.822	11.998	14.243*
D: SPN				
Mean	0.019*	0.026	-0.088	0.025
Variance	0.393	0.216	3.433	0.197
Skewness	0.671**	-0.945**	0.740**	0.165
Kurtosis	22.364**	10.796**	10.796**	9.633**
LB(12)	173.202**	60.546**	8.489	14.119
Contemporaneous Corr. Coeff.				
NKD & SPN	0.007	0.137	-0.104	0.170
NKN & SPD	0.222	0.212	0.400	0.042

Notes:

(1) Single asterisk (*) indicates the significance at a 10% level and double asterisks (**) indicate the significance at a 5% level.

(2) In the row of mean, asterisks indicate the significance at a 5% level for the null hypothesis that mean equals zero.

(3) In the rows of skewness and kurtosis, asterisks indicate the significance for the null hypothesis of the normal distribution.

(4) LB(12) indicates the Ljung-Box statistics for the serial correlation of order twelve.

Table 2 Tests for Serial Dependence

	Whole period		Before Crash		After Crash	
Exog. Var.	9/29/85-12/29/89		9/29/85-9/30/87		1/1/88-12/29/89	
A: Dependent Variable: NKD_t						
Constant	0.062**	(0.029)	0.006	(0.034)	0.165**	(0.031)
NKN_{t-1}	0.383**	(0.159)	0.132*	(0.070)	0.135	(0.198)
NKD_{t-1}	-0.093	(0.078)	0.011	(0.063)	-0.032	(0.054)
R^2	0.054		0.011		0.004	
White:	81.715	(0.000)	14.086	(0.002)	79.336	(0.000)
ARCH(1):	7.066	(0.007)	13.649	(0.002)	13.789	(0.000)
ARCH(5):	22.697	(0.000)	28.023	(0.000)	17.773	(0.003)
B: Dependent Variable: NKN_t						
Constant	0.029*	(0.017)	0.104**	(0.024)	-0.041	(0.121)
NKD_t	0.044	(0.073)	0.176**	(0.043)	0.064**	(0.023)
NKN_{t-1}	0.144**	(0.047)	0.108**	(0.053)	0.059	(0.058)
R^2	0.031		0.068		0.026	
White:	272.439	(0.000)	6.854	(0.077)	6.385	(0.094)
ARCH(1):	37.668	(0.000)	1.822	(0.177)	0.028	(0.867)
ARCH(5):	55.788	(0.000)	21.772	(0.001)	1.277	(0.937)
C: Dependent Variable: SPD_t						
Constant	0.034	(0.036)	0.090	(0.036)	0.057	(0.031)
SPN_t	0.277	(0.178)	0.042	(0.101)	0.190**	(0.093)
SPD_{t-1}	0.026	(0.094)	-0.062	(0.050)	-0.212**	(0.074)
R^2	0.027		0.004		0.052	
White:	358.897	(0.000)	9.321	(0.025)	10.448	(0.015)
ARCH(1):	7.301	(0.007)	1.353	(0.245)	10.675	(0.001)
ARCH(5):	8.006	(0.155)	4.055	(0.542)	11.714	(0.039)
Dependent Variable: SPN_t						
Constant	0.021	(0.021)	0.012	(0.021)	0.019	(0.020)
SPD_{t-1}	-0.028	(0.088)	0.149**	(0.029)	0.062*	(0.035)
SPN_{t-1}	-0.004	(0.108)	0.064	(0.048)	0.042	(0.801)
R^2	0.002		0.070		0.016	
White:	590.935	(0.000)	4.075	(0.254)	5.583	(0.134)
ARCH(1):	418.151	(0.000)	0.444	(0.505)	0.208	(0.648)
ARCH(5):	476.872	(0.000)	6.618	(0.251)	10.035	(0.074)

Notes:
(1) Standard errors are adjusted to heteroskedasticity with an unknown form.
(2) "White" is White's (1982) heteroskedastcity test statistics and ARCH(p) is the Lagrange multiplier tests for ARCH processes of order p. The p-value is in the parenthesis.

Table 3 Aggregate Shock Model for Stock Returns
- NKD and SPN

Stage 1:

$NKD_t = c_{nd} + a_{nd} NKN_{t-1} + b_{nd} DM_t + d_{nd} DF_t + en_t$

$en_t | \Omega(TKO_t) \sim N(0, qn_t)$

$qn_t = \omega_{qn} + \beta_{qn} qn_{t-1} + \alpha_{qn} en^2_{t-1} + \gamma_{qn} DM_t + \delta_{qn} DF_t$

Stage 2:

$SPN_t = c_{sn} + a_{sn} SPD_{t-1} + b_{sn} DM_t + \phi_{sn} en_t + vn_t$

$vn_t | \Omega(TKC_t) \sim N(0, kn_t)$

$kn_t = \omega_{kn} + \beta_{kn} kn_{t-1} + \alpha_{kn} vn^2_{t-1} + \gamma_{kn} DM_t$

	Whole period 9/29/85-12/29/89		Before Crash 9/29/85-9/30/87		After Crash 1/1/88-12/29/89	
	Coeff.	St. Error	Coeff.	St Error	Coeff.	St. Error
Stage 1:						
c_{nd}	0.120**	(0.022)	0.028	(0.032)	0.175*	(0.034)
a_{nd}	0.022	(0.320)	0.124	(0.078)	0.026	(0.171)
b_{nd}	-0.080	(0.224)	-0.168**	(0.067)	-0.068	(0.062)
d_{nd}	-0.031	(0.070)	0.025	(0.061)	-0.080	(0.057)
ω_{qn}	0.029†	(0.055)	0.013*	(0.010)	0.013**	(0.038)
β_{qn}	0.729**	(0.290)	0.870**	(0.026)	0.830*	(0.121)
α_{qn}	0.202†	(0.350)	0.116**	(0.029)	0.057†	(0.038)
γ_{qn}	0.066†	(0.127)	-0.060	(0.048)	0.125†	(0.091)
δ_{qn}	-0.003	(0.107)	0.042	(0.052)	-0.030	(0.078)
log L	-1204.787		-469.525		-425.568	
Skewness	-5.322**		-0.489**		0.049	
Kurtosis	90.758**		5.061**		7.191**	
LB(12)	10.562		12.120		12.174	
LBS(12)	0.200		14.452		2.600	
Stage 2:						
c_{sn}	0.058**	(0.014)	0.058**	(0.019)	0.053**	(0.020)
a_{sn}	0.075**	(0.036)	0.137**	(0.027)	0.033†	(0.038)
b_{sn}	-0.191**	(0.037)	-0.215**	(0.053)	-0.133**	(0.040)
ϕ_{sn}	0.082**	(0.029)	0.083**	(0.025)	0.103**	(0.036)
ω_{sn}	0.010	(0.011)	-0.007	(0.009)	0.020†	(0.013)
β_{sn}	0.791**	(0.081)	0.804**	(0.099)	0.950**	(0.047)
α_{sn}	0.156*	(0.083)	0.098**	(0.042)	0.018†	(0.017)
δ_{sn}	0.020†	(0.048)	0.113*	(0.059)	-0.071†	(0.045)
log L	-689.435		-274.065		-262.319	
Skewness	-0.574**		-0.598**		-0.539**	
Kurtosis	9.104**		6.164**		7.751**	
LB(12)	16.601		10.187		12.000	
LBS(12)	5.834		12.816		2.694	

Notes:

(1) † indicates significance at a 5 % level when the standard errors are calculated from the outer product of scores.

(2) The statistics of skewness and kurtosis are for the standardized residuals $en_t/(qn_t)^{1/2}$ or $vn_t/(kn_t)^{1/2}$.

(3) LB(12) and LBS(12) are the Ljung Box statistics for the standardized residual and its square, respectively.

Table 4 Aggregate Shock Model for Stock Returns - SPD and NKN

Stage 1:

$SPD_t = c_{sd} + a_{sd} SPN_t + b_{sd} DM_t + d_{sd} DF_t + es_t$

$es_t | \Omega(NYO_t) \sim N(0, qs_t)$

$qs_t = \omega_{qs} + \beta_{qs} qs_{t-1} + \alpha_{qs} en^2_{t-1} + \gamma_{qs} DM_t + \delta_{qs} DF_t$

Stage 2:

$NKN_t = c_{nn} + a_{nn} SPD_{t-1} + b_{nn} DM_t + \phi_{nn} es_t + vs_t$

$vs_t | \Omega(NYC_t) \sim N(0, ks_t)$

$ks_t = \omega_{ks} + \beta_{ks} ks_{t-1} + \alpha_{ks} vs^2_{t-1} + \gamma_{ks} DM_t$

	Whole period 9/29/85-12/29/89		Before Crash 9/29/85-9/30/87		After Crash 1/1/88-12/29/89	
	Coeff.	St. Error	Coeff.	St. Error	Coeff.	St. Error
Stage 1:						
c_{sd}	0.026	(0.030)	0.086*	(0.035)	-0.014	(0.038)
a_{sd}	0.224**	(0.066)	0.090	(0.099)	0.290**	(0.116)
b_{sd}	0.142**	(0.066)	0.107	(0.094)	0.143†	(0.082)
d_{sd}	0.040	(0.095)	-0.014	(0.083)	0.107	(0.104)
ω_{qs}	0.014	(0.063)	0.008	(0.049)	0.054	(0.047)
β_{qs}	0.799**	(0.338)	0.865**	(0.088)	0.761**	(0.114)
α_{qs}	0.083†	(0.252)	0.054*	(0.036)	0.092†	(0.086)
γ_{qs}	-0.218	(0.386)	0.187	(0.140)	-0.185	(0.490)
δ_{qs}	0.556*	(0.304)	0.009	(0.106)	0.300	(0.582)
log L	-1376.708		-595.592		-579.534	
Skewness	-1.813**		-0.359**		-1.285**	
Kurtosis	19.032**		4.700**		12.746**	
LB(12)	10.018		6.638		14.495	
LBS(12)	16.691		4.806		2.631	
Stage 2:						
c_{nn}	-0.030**	(0.012)	0.059**	(0.021)	-0.047**	(0.011)
a_{nn}	0.057*	(0.033)	0.163**	(0.034)	0.049**	(0.022)
b_{nn}	0.027†	(0.026)	0.155**	(0.032)	0.004	(0.017)
ϕ_{nn}	0.039†	(0.055)	0.199**	(0.061)	0.017	(0.037)
ω_{ks}	-0.007**	(0.004)	-0.013	(0.011)	0.034	(0.007)
β_{ks}	0.904**	(0.053)	0.797**	(0.082)	0.035**	(0.073)
α_{ks}	0.082**	(0.042)	0.143**	(0.038)	0.035	(0.023)
γ_{ks}	0.054**	(0.016)	0.151**	(0.061)	0.110*	(0.029)
log L	-520.434		-330.016		24.197	
Skewness	-0.764**		-0.348**		0.462**	
Kurtosis	13.799**		6.241**		5.493**	
LB(12)	49.888		34.072		8.960	
LBS(12)	4.345		9.721		3.691	

Notes: see Table 3.

Table 5 Signal Extraction Model for Stock Returns
- NKD and SPN

Model:

Mean eq. : $NKD_t = c_{nd} + a_{nd}\ NKN_{t-1} + b_{nd}\ DM_t + d_{nd}\ DF_t + wn_t + un_t$
$SPN_t = c_{sn} + a_{sn}\ SPD_{t-1} + b_{sn}\ DM_t + \mu_{sn}\ wn^*_t + vn_t$

Var. eq. : $wn_t|\Omega(TKO_t) \sim N(0, gn_t)$, $un_t|\Omega(TKO_t) \sim N(0, hn_t)$, $vn_t|\Omega(TKC_t) \sim N(0, kn_t)$
$gn_t = \omega_{gn} + \beta_{gn}\ gn_{t-1} + \alpha_{gn}[(wn^*_{t-1})^2 + gn^*_{t-1}] + \gamma_{gn} DM_t + \delta_{gn}\ DF_t$
$hn_t = \omega_{hn} + \alpha_{hn}\ [(un^*_{t-1})^2 + hn^*_{t-1}] + \gamma_{hn}\ DM_t + \delta_{hn}\ DF_t$
$kn_t = \omega_{kn} + \beta_{kn}\ kn_{t-1} + \alpha_{kn}\ vn^2_{t-1} + \gamma_{kn}\ DM_t$

	Whole Period 9/28/85-12/31/89		Before Crash 9/28/85-7/31/87		After Crash 1/1/88-12/31/89	
Parameter	Coeff.	St. Error	Coeff.	St. Error	Coeff.	St. Error
c_{nd}	0.120**	(0.021)	0.038	(0.032)	0.182†	(0.031)
a_{nd}	-0.008	(0.437)	0.114†	(0.080)	-0.001	(0.108)
b_{nd}	-0.061	(0.301)	-0.157**	(0.072)	-0.070	(0.058)
d_{nd}	-0.044	(0.080)	0.038	(0.060)	-0.097*	(0.054)
ω_{gn}	0.008	(0.011)	0.013	(0.020)	0.004	(0.051)
α_{gn}	0.151†	(0.198)	0.108**	(0.053)	0.108	(0.177)
β_{gn}	0.829†	(0.174)	0.867**	(0.054)	0.663	(0.426)
γ_{gn}	-0.002	(0.152)	-0.025	(0.058)	0.174	(0.115)
δ_{gn}	-0.011	(0.123)	-0.008	(0.082)	-0.054	(0.076)
ω_{hn}	0.022**	(0.026)	0.003	(0.035)	0.083	(0.053)
α_{hn}	0.948†	(0.612)	0.964**	(0.145)	0.948	(0.612)
γ_{hn}	0.111†	(0.250)	-0.018	(0.066)	-0.071	(0.103)
δ_{hn}	0.001	(0.180)	0.058	(0.080)	0.063	(0.064)
c_{sn}	0.059**	(0.016)	0.052**	(0.019)	0.053**	(0.020)
a_{sn}	0.094**	(0.042)	0.143**	(0.027)	0.059	(0.040)
b_{sn}	-0.199**	(0.051)	-0.204**	(0.054)	-0.163**	(0.044)
μ_{sn}	0.192*	(0.112)	0.126**	(0.045)	0.219*	(0.131)
ω_{kn}	0.008	(0.011)	-0.012	(0.011)	0.040**	(0.015)
α_{kn}	0.134†	(0.096)	0.072**	(0.034)	0.085**	(0.044)
β_{kn}	0.797**	(0.100)	0.834**	(0.097)	0.785**	(0.085)
γ_{kn}	0.037†	(0.045)	0.139**	(0.060)	-0.081	(0.051)
Log L	-1857.779		-748.281		-646.516	
gn/hn	0.645		0.064		6.889	
μ gn/(hn+gn)	0.075		0.064		0.191	
GARCH(1)	3.204*		3.085*		0.038	
Wald(4)	43.533**		161.383**		83.850**	

Notes: (1) gn/hn is the ratio of the sample average of gn_t to the sample average of hn_t

(2) GARCH(1) is the test statistics for a GARCH(1) term in hn_t, i.e., null hypothesis is that $\beta_{hn} = 0$.

(3) Wald (4) is the test statistics for the null hypothesis that $\omega_{hn} = \alpha_{hn} = \delta_{hn} = \gamma_{hn} = 0$

Table 6 Signal Extraction Model for Stock Returns - SPD and NKN

Model:

Mean eq. : $SPD_t = c_{sd} + a_{sd}\ SPN_{t-1} + b_{sd}\ DM_t + d_{sd}\ DF_t + ws_t + us_t$

$NKN_t = c_{nn} + a_{nn}\ NKD_{t-1} + b_{nn}\ DM_t + \mu_{nn}\ ws^*_t + vs_t$

Var. eq. : $ws_t|\Omega(NYO_t) \sim N(0, gs_t)$, $us_t|\Omega(NYO_t) \sim N(0, hs_t)$, $vn_t|\Omega(NYC_t) \sim N(0, ks_t)$

$gs_t = \omega_{gs} + \beta_{gs}\ gs_{t-1} + \alpha_{gs}[(ws^*_{t-1})^2 + gs^*_{t-1}] + \gamma_{gs}\ DM_t + \delta_{gs}\ DF_t$

$hs_t = \omega_{hs} + \alpha_{hs}[(us^*_{t-1})^2 + hs^*_{t-1}] + \gamma_{hs}\ DM_t + \delta_{hs}\ DF_t$

$ks_t = \omega_{ks} + \beta_{ks}\ ks_{t-1} + \alpha_{ks}\ vs^2_{t-1} + \gamma_{ks}\ DM_t$

	Whole Period 9/28/85-12/31/89		Before Crash 9/28/85-7/31/87		After Crash 1/1/88-12/31/89	
Parameter	Coeff.	St. Error	Coeff.	St. Error	Coeff.	St. Error
c_{sd}	0.021†	(0.031)	0.084†	(0.045)	0.018	(0.037)
a_{sd}	0.203*	(0.066)	0.040	(0.086)	0.238**	(0.087)
b_{sd}	0.143*	(0.063)	0.145	(0.089)	0.106	(0.096)
d_{sd}	0.042†	(0.084)	0.029	(0.081)	0.114	(0.107)
ω_{gs}	-0.001	(0.045)	-0.046	(0.034)	0.016	(0.067)
α_{gs}	0.082†	(0.119)	0.211†	(0.172)	0.099	(0.202)
β_{gs}	0.874**	(0.135)	0.748**	(0.138)	0.884**	(0.196)
γ_{gs}	-0.036	(0.423)	0.111†	(0.167)	0.093	(0.235)
δ_{gs}	0.116	(0.345)	0.201	(0.187)	-0.147	(0.208)
ω_{hs}	0.053	(0.101)	0.307**	(0.114)	0.085	(0.225)
α_{hs}	0.771**	(0.219)	-0.047	(0.153)	0.185	(0.323)
γ_{hs}	0.023	(0.157)	-0.091	(0.142)	0.064	(0.153)
δ_{hs}	0.280†	(0.428)	-0.170	(0.156)	0.108	(0.698)
c_{nn}	-0.022†	(0.015)	0.059**	(0.020)	-0.042**	(0.011)
a_{nn}	0.073*	(0.021)	0.163**	(0.034)	0.019	(0.022)
b_{nn}	0.074†	(0.048)	0.203**	(0.060)	0.004	(0.037)
μ_{nn}	0.091†	(0.061)	0.265**	(0.120)	0.012	(0.021)
ω_{kn}	0.001	(0.009)	-0.011	(0.011)	0.031**	(0.005)
α_{kn}	0.195**	(0.082)	0.146**	(0.038)	0.049*	(0.027)
β_{kn}	0.668**	(0.152)	0.791**	(0.080)	0.038	(0.036)
γ_{kn}	0.098†	(0.063)	0.139**	(0.057)	0.096*	(0.029)
Log L	-1859.807		-924.033		-540.342	
gs/hs	5.135		2.089		6.890	
μ gs/(gs+ks)	1.195		0.179		0.007	
GARCH(1)	0.067		1.691		0.662	
Wald(4)	21.644**		7.893*		2.584	

Notes: see Table 5

Table 7 Lagged Return Spillovers: New York Daytime to Tokyo Daytime

Model:

Mean eq. : $NKD_t = c_{nd} + a_{nd} NKN_{t-1} + b_{nd} DM_t + d_{nd} DF_t + \pi_{nd} SPD_{t-1} + wn_t + un_t$

$SPN_t = c_{sn} + a_{sn} SPD_{t-1} + b_{sn} DM_t + \mu_{sn} wn^*_t + vn_t$

Var. eq. : $wn_t | \Omega(TKO_t) \sim N(0, gn_t)$, $un_t | \Omega(TKO_t) \sim N(0, hn_t)$, $vn_t | \Omega(TKC_t) \sim N(0, kn_t)$

$gn_t = \omega_{gn} + \beta_{gn} gn_{t-1} + \alpha_{gn}[(wn^*_{t-1})^2 + gn^*_{t-1}] + \gamma_{gn} DM_t + \delta_{gn} DF_t$

$hn_t = \omega_{hn} + \alpha_{hn}[(un^*_{t-1})^2 + hn^*_{t-1}] + \gamma_{hn} DM_t + \delta_{hn} DF_t$

$kn_t = \omega_{kn} + \beta_{kn} kn_{t-1} + \alpha_{kn} vn^2_{t-1} + \gamma_{kn} DM_t$

Panel A: LM Test for Null hypothesis: $\pi_{nd} = 0$; Alternative hypothesis: $\pi_{nd} \neq 0$

	Whole Period 9/28/85-12/31/89	Before Crash 9/28/85-7/31/87	After Crash 1/1/88-12/31/89
test stat.	0.393	0.004	12.852**

Panel B: Estimated Results for the mean equation of NKD

	Whole Period 9/28/85-12/31/89		Before Crash 9/28/85-7/31/87		After Crash 1/1/88-12/31/89	
Parameter	Coeff.	St. Error	Coeff.	St. Error	Coeff.	St. Error
c_{nd}	0.119**	(0.021)	0.035	(0.032)	0.174**	(0.032)
a_{nd}	-0.001	(0.334)	0.119†	(0.077)	-0.029	(0.101)
b_{nd}	-0.047	(0.054)	0.037	(0.060)	-0.081	(0.053)
d_{nd}	-0.065	(0.299)	-0.156**	(0.071)	-0.071	(0.057)
π_{nd}	0.091	(0.057)	0.007	(0.034)	0.130**	(0.033)
α_{gn}	0.140	(0.158)	0.105**	(0.050)	0.086	(0.161)
β_{gn}	0.837	(0.162)	0.872**	(0.051)	0.695	(0.378)

Table 8 **Lagged Return Spillovers: Tokyo Daytime to New York Daytime**

Model:

Mean eq. : $SPD_t = c_{sd} + a_{sd}\, SPN_{t-1} + b_{sd}\, DM_t + d_{sd}\, DF_t + \pi_{sd}\, NKD_t + ws_t + us_t$

$$NKN_t = c_{nn} + a_{nn}\, NKD_{t-1} + b_{nn}\, DM_t + \mu_{nn}\, ws^*_t + vs_t$$

Var. eq. : $ws_t|\Omega(NYO_t) \sim N(0, gs_t)$, $us_t|\Omega(NYO_t) \sim N(0, hs_t)$, $vn_t|\Omega(NYC_t) \sim N(0, ks_t)$

$$gs_t = \omega_{gs} + \beta_{gs}\, gs_{t-1} + \alpha_{gs}[(ws^*_{t-1})^2 + gs^*_{t-1}] + \gamma_{gs}\, DM_t + \delta_{gs}\, DF_t$$

$$hs_t = \omega_{hs} + \alpha_{hs}[(us^*_{t-1})^2 + hs^*_{t-1}] + \gamma_{hs}\, DM_t + \delta_{hs}\, DF_t$$

$$ks_t = \omega_{ks} + \beta_{ks}\, ks_{t-1} + \alpha_{ks}\, vs^2_{t-1} + \gamma_{ks}\, DM_t$$

Panel A: LM test for Null hypothesis: $\pi_{sd} = 0$; Alternative hypothesis: $\pi_{sd} \neq 0$

	Whole Period	Before Crash	After Crash
LM Test for $\pi_{sd}=0$	1.363	0.066	0.018

Panel B: Estimated coefficients for the mean equation of SPD

	Whole Period 9/28/85-12/31/89		Before Crash 9/28/85-7/31/87		After Crash 1/1/88-12/31/89	
Parameter	Coeff.	St. Error	Coeff.	St. Error	Coeff.	St. Error
c_{sd}	0.024	(0.031)	0.084**	(0.045)	0.007	(0.043)
a_{sd}	0.206**	(0.066)	0.040	(0.086)	0.209**	(0.102)
π_{sd}	-0.004	(0.039)	0.010	(0.042)	0.008	(0.076)
b_{sd}	0.139**	(0.064)	0.145	(0.089)	0.136	(0.085)
d_{sd}	0.042	(0.085)	0.029	(0.081)	0.114	(0.108)
α_{nd}	0.080	(0.109)	0.211	(0.171)	0.120	(0.161)
β_{nd}	0.879**	(0.119)	0.748**	(0.138)	0.864	(0.150)

Table 9 Lagged Volatility Spillovers to Tokyo Global Factor

Model:

Mean eq. : $NKD_t = c_{nd} + a_{nd}\, NKN_{t-1} + b_{nd}\, DM_t + d_{nd}\, DF_t + wn_t + un_t$

$SPN_t = c_{sn} + a_{sn}\, SPD_{t-1} + b_{sn}\, DM_t + \mu_{sn}\, wn^*_t + vn_t$

Var. eq. : $wn_t|\Omega(TKO_t) \sim N(0, gn_t)$, $un_t|\Omega(TKO_t) \sim N(0, hn_t)$, $vn_t|\Omega(TKC_t) \sim N(0, kn_t)$

$gn_t = \omega_{gn} + \beta_{gn}\, gn_{t-1} + \alpha_{gn}[(wn^*_{t-1})^2 + gn^*_{t-1}] + \gamma_{gn}\, DM_t + \delta_{gn}\, DF_t + \lambda_{gn} z_t$

$hn_t = \omega_{hn} + \beta_{hn}\, hn_{t-1} + \alpha_{hn}[(un^*_{t-1})^2 + hn^*_{t-1}] + \gamma_{hn}\, DM_t + \delta_{hn}\, DF_t$

$kn_t = \omega_{kn} + \beta_{kn}\, kn_{t-1} + \alpha_{kn}\, vn^2_{t-1} + \gamma_{kn}\, DM_t$

Null hypothesis: $\lambda_{nd} = 0$ Alternative hypothesis: $\lambda_{nd} \neq 0$

Var. for z	Notation	Whole Period	Before Crash	After Crash
N.Y. Daytime Returns:	SPD^2_{t-1}	0.961	2.142	0.192
N.Y. Global Factor:	$(ws^*_{t-1})^2 + gs^*_{t-1}$	1.108	1.631	0.161
TK. Overnight Shocks:	vs^2_{t-1}	0.784	0.034	6.304**
TK. Overnight Returns:	$NKN_{t-1}{}^2$	1.847	3.129*	0.124

Table 10 Lagged Volatility Spillovers to New York Global Factor

Model:

Mean eq. : $SPD_t = c_{sd} + a_{sd}\, SPN_{t-1} + b_{sd}\, DM_t + d_{sd}\, DF_t + ws_t + us_t$

$NKN_t = c_{nn} + a_{nn}\, NKD_{t-1} + b_{nn}\, DM_t + \mu_{nn}\, ws^*_t + vs_t$

Var. eq. :

$ws_t|\Omega(NYO_t) \sim N(0,gs_t),\ us_t|\Omega(NYO_t) \sim N(0,hs_t),\ vn_t|\Omega(NYC_t) \sim N(0,ks_t)$

$gs_t = \omega_{gs} + \beta_{gs}\, gs_{t-1} + \alpha_{gs}[(ws_{t-1})^2 + gs_{t-1}] + \gamma_{gs}\, DM_t + \delta_{gs}\, DF_t + \lambda_{gs}\, z_t$

$hs_t = \omega_{hs} + \beta_{hs}\, hs_{t-1} + \alpha_{hs}[(us_{t-1})^2 + hs_{t-1}] + \gamma_{hs}\, DM_t + \delta_{hs}\, DF_t$

$ks_t = \omega_{ks} + \beta_{ks}\, ks_{t-1} + \alpha_{ks} vs^2_{t-1} + \gamma_{ks}\, DM_t$

Null hypothesis: $\lambda_{gs} = 0$ Alternative hypothesis: $\lambda_{gs} \neq 0$

Var. for z	Notation	Whole Period	Before Crash	After Crash
TK. Daytime Returns:	NKD^2_{t-1}	1.048	3.291*	0.346
TK. Global Factor:	$wn^{*}_{t-1}{}^2 + gn^{*}_{t-1}$	1.075	0.001	0.699
N.Y. Overnight shock:	$vn_{t-1}{}^2$	1.065	11.427**	0.906
N.Y. Overnight Return:	$SPN_t{}^2$	2.682	3.786*	0.864