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Volatility Transmission between Japan, U.K. and U.S. in Daily Stock Returns*

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Abstract: In the past, there are a lot of studies which conclude that the holiday, asymmetry and day-of-the-week effects influence stock price volatility. Most of the studies are based on a class of GARCH (Generalized Auto-Regressive Conditional Heteroskedasticity) models. No one examines these effects simultaneously using SV (Stochastic Volatility) models. In this paper, using the SV model, we examine whether these effects play an important role in stock price volatilities. Furthermore, we consider spillover effects between Japan, U.K. and U.S., where spillover effects in price level as well as volatility are taken into account.

Key Words: Daily Stock Returns, Holiday Effect, Asymmetry Effect, Day-of-the-Week Effect, Asymmetric Volatility Transmission, Spillover Effect in Level, and Spillover Effect in Volatility.

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1 Introduction

Market deregulation and the free flow of capital market have increased the globalization of financial markets and affected the nature of relationships among price movements across markets. The major world economies are now interdependent through trade and investment. Therefore, news about economic fundamentals in one country has implications for equity prices in other countries.

Data on the volatility of returns in financial markets provide additional information to data on returns alone. Ross (1989) showed that return volatility provides useful data on information flow. This development suggests that price volatility has significant implications for information linkages between markets. Thus, there is a growing literature on the linkages between conditional variances across financial markets and their implications for information transmission mechanism. Some example includes Hamao, Masulis and Ng (1990), Koutmos and Booth (1995), Kanas (1998), Ramchand and Susmel (1998), Ng (2000), and Baele (2003). These research has basically used ARCH (autoregressive conditional heteroskedasticity) -type models in order to analyze the volatility spillover.

Hamao, Masulis and Ng (1990) used a GARCH (generalized ARCH) model to analyze the volatility spillover of stock prices among three markets (Tokyo, London and New York) based on daily data from April 1, 1985 to March 31, 1988. They reported that a spillover effect to Tokyo from New York and London could be found.

Koutmos and Booth (1995) analyzed the volatility spillover of stock prices among the same three markets based on daily data from September 3, 1986 to December 1, 1993. A distinctive feature of this paper was that it explicitly considered the asymmetry of volatility using the EGARCH (exponential GARCH) model. They reported that there was a significant volatility spillover among the three markets and that there was an asymmetry in this spillover. In other words, a negative shock in one market increases the volatility in other markets more than a positive shock does. This showed that equity markets react sensitively to bad news in other markets.

Kanas (1998) analyzed the volatility spillover among three major European markets (London, Frankfurt and Paris) based on daily data from January 1, 1984 to December 7, 1993. Like Koutmos and Booth (1995), Kanas (1998) used the EGARCH model to explicitly consider the asymmetry of volatility. The analysis showed that volatility spillovers among the three markets were stronger since the equity market crash of 1987 than they were prior to that crash.

Ramchand and Susmel (1998) analyzed volatility spillover based on the weekly stock returns of major equity markets around the world compiled by the Morgan Stanley Capital International Perspective. The data cover the period from January 1980 to January 1990. A distinctive feature of this paper was its analysis using SWARCH (switching ARCH), which enables formulation of variance as state varying. The results showed that the correlation between the U.S. and other markets became 2.5 to 3.0 times higher on average when the U.S. market is in a higher variance state than it is in a low variance regime.

Ng (2000) used a GARCH model to analyze the volatility spillover in six Pacific-Basin countries (Hong Kong, Korea, Malaysia, Singapore, Taiwan, and Thailand) using weekly data. Ng (2000) divided the shocks impacting on this region into three categories according to source (local, regional and world), describing shocks from Japan as "regional shocks" and shocks from the U.S. as "world shocks." The results showed that: (1) both regional factors and world factors were important in relation to Pacific-Basin region volatility; and (2) liberalization events impacted on the relative importance of regional factors and world factors.

Baele (2003) analyzed the volatility spillover in 13 local European equity markets from aggregate European and U.S. markets using weekly data from January 1980 to August 2001. This paper uses the regime-switching volatility spillover model. The results showed that both the U.S. and E.U. had a large impact on local European markets, but the EU impact was strengthening.

In a lot of empirical studies, GARCH-type models are used for estimation on stock price volatility. As for SV (Stochastic Volatility) model, there are some empirical studies on the asymmetric effect in stock price volatility. However, no one examines all of holiday, day-of-the-week, asymmetric (leverage) and spill-over effects in both stock price level and its volatility simultaneously, using the SV model. In the past, main research topics on SV model are devoted to estimation methods and accordingly there are few empirical studies using SV model. In this paper, we focus on empirical studies about stock price volatility with SV model. Judging from past studies based on the other models such as GARCH models, it might be expected as: (i) a fall in the stock price yesterday leads to a rise in the stock price volatility today (e.g., Nelson (1991) and Glosten, Jagannathan and Runkle (1993)), which is called the asymmetry effect or the leverage effect, (ii) stock price on the day after holiday becomes volatile (e.g., Nelson (1991) and Watanabe (1999)), which is called the holiday effect (note that the holiday effect is taken as a proxy of the amount of information), (iii) we observe an increase in volatility on Monday when stock market is open because Monday is always after holiday, but we have a decrease in volatility on Tuesday as a counter-reaction against Monday (e.g., Fatemi and Park (1996), Coutts and Sheikh (2002) and Watanabe (2001)), which is referred to as the day-of-the-week effect, (iv) Japanese stock price level is positively correlated with U.K. and U.S. stock price levels (e.g., Koutmos and Booth (1995)), which is called the spillover effect in level, and (v) Japanese stock price volatility is also positively correlated with U.K. and U.S. stock price volatilities (e.g. Hamao, Masulis and Ng (1990) and Koutmos and Booth (1995)), which is related to the spillover effect in volatility.

Thus, this paper can be described as having two distinctive features. First, it analyzes the volatility spillover issue based on a SV (stochastic volatility) model. In the SV model, volatility is modeled as an unobserved latent variable. As is pointed out by Broto and Ruiz (2004), the SV model can capture the main empirical properties often observed in daily financial returns in a more appropriate way than GARCH type models. To our knowledge, there are no papers that analyze this issue based on a SV model, suggesting it could make a major contribution. Second, we take account of the holiday effect, the day-of-the-week effect, and the asymmetric effect (leverage effect) at the same time. The use of daily data enables us to analyze these effects in a systematic way. As long as we know, this is the first paper that has taken into consideration these effects simultaneously in the framework of the SV model. As for estimation, we utilize Bayesian procedure through MCMC (Markov Chain Monte Carlo), where flat prior densities are taken to exclude influence of prior information.

2 Data Description

Figure 1(a) represents the daily movement of the Nikkei 225 Stock Average (closing price, Japanese yen) from April 2, 1984 to February 2, 2007, where the vertical and horizontal axes indicate Japanese yen and time, respectively. The Nikkei 225 Stock Average data are taken from `http://table.yahoo.co.jp/t/` (Japanese website) after January 1, 1991 and `http://www.nikkei.co.jp/nkave/` (Japanese website) before December 31, 1990. In Figure 1(a), Japanese stock price extraordinarily decreases from 25746.56 on October 19, 1987 to 21910.08 on October 20, 1987, which corresponds to Black Monday on October 19, 1987 in the New York stock market. However, the stock price has been increasing until the end of 1989. The largest closing price is 38915.87 on December 29, 1989. Until the end of 1989, Japan experienced a rapid economic expansion based on vastly inflated stock and land prices, so-called the bubble economy. Since then, the collapse of Japan's overheated stock and real estate markets started. Especially, a drop in 1990 was really serious. That is, the stock price fell down from 38712.88 on January 4, 1990 to 20221.86 on October 1, 1990, which is almost 50% drop. Recently, since the value was 20833.21 on April 12, 2000, the stock price has been decreasing. It is 7607.88 on April 28, 2003, which is a minimum value during the period from January 4, 1985 to June 10, 2004. Recently, we have an increasing trend from April 28, 2003. Thus, Japanese stock price increased up to the end of 1989, decreased until around March or April in 1992, was relatively stable up to April in 2000, and has declined since then.

Figure 1(b) shows the natural log-difference, multiplied by 100, of the Nikkei stock average, which is roughly equal to the percent change of the daily data shown in Figure 1(a). Figure 1(b) displays the percent in the vertical axis and the time period in the horizontal axis. For comparison with Figure 1(a), Figure 1(b) takes the same time period as Figure 1(a), i.e., Figures 1(a) and 1(b) take the same scale in the horizontal axis. −16.1% on October 20, 1987 (October 19, 1987 in the Eastern

Figure 1: Nikkei 225 Stock Average (Japan, April 2, 1984 – February 2, 2007)

(a) Original Data (Closing Price, Japanese Yen and n = 5783)

(b) Percent Change Data (%)

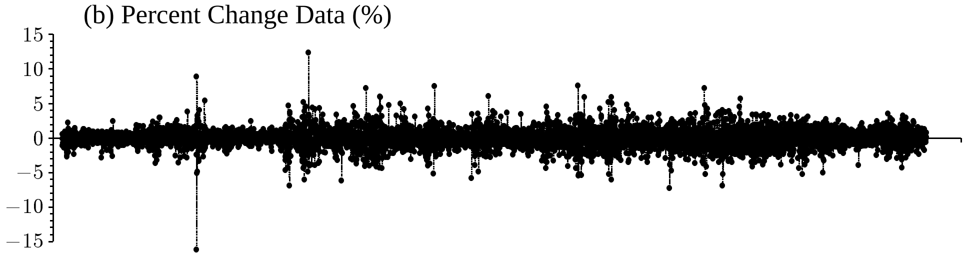
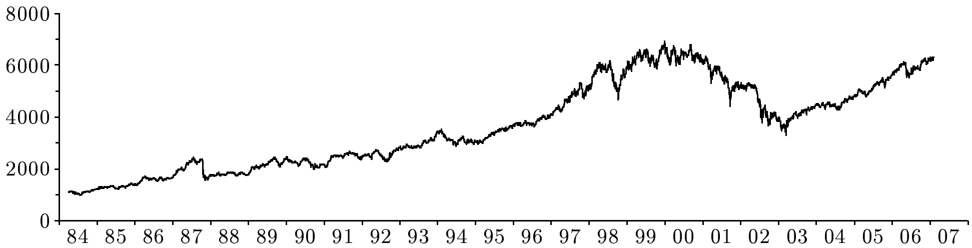


Figure 2: FTSE 100 Index (U.K., April 2, 1984 – February 2, 2007)

(a) Original Data (Closing Index, April 10, 1962=100 and n = 5771)



(b) Percent Change Data (%)

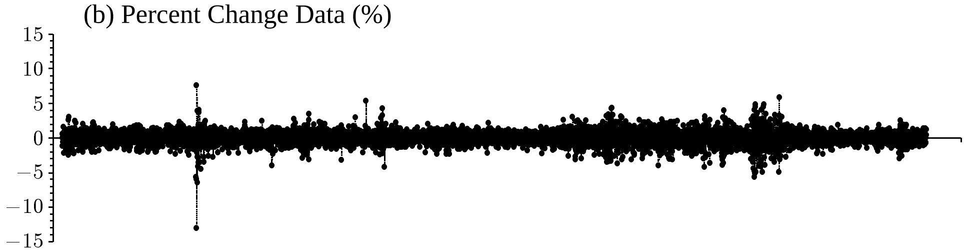
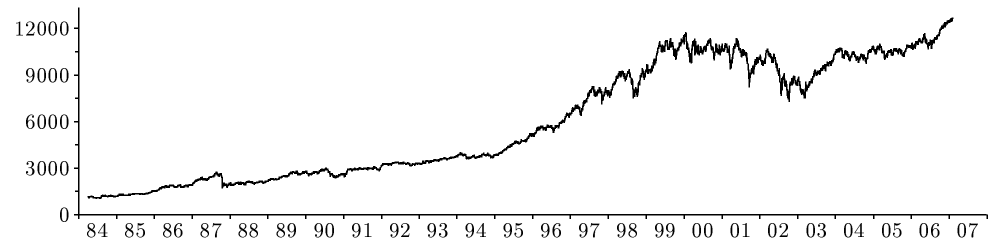
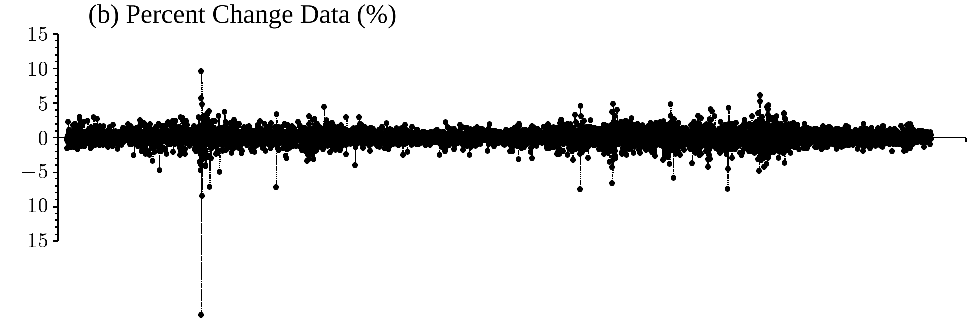


Figure 3: Dow Jones Industrial Average (U.S., April 2, 1984 – February 2, 2007)

(a) Original Data (Closing Price, U.S. Dollars and n = 5762)



(b) Percent Change Data (%)



Standard Time) is the largest drop (it is out of range in Figure 1(b)), which came from Black Monday in the New York stock market. 12.4% on October 2, 1990 is the largest rise, which corresponds to the unification of Germany occurred on October 1, 1990. The second largest rise in the stock price was 8.9% on October 21, 1987, which is a counter-reaction against the largest drop on October 20, 1987. Although there are some outliers, the percent changes up to the end of 1989 seem to be distributed within a relatively small range, i.e., variance of the percent change until the end of 1989 is small. After 1990, the percent changes are more broadly distributed. Thus, we can see that the percent change data of Japanese stock price are heteroskedastic. In any case, it may seem from Figure 1(b) that the percent change data are randomly distributed. In the next section, using the state space model we aim to examine the volatility in Japanese stock returns.

Figure 2(a) displays the stock price index in U.K. and Figure 2(b) shows the stock price volatility (100 times the natural log-difference). The FTSE 100 Index data are taken from `http://uk.finance.yahoo.com/`. In U.K. stock market, we see in Figure 2(b) that there is a drastic drop (−13.03%) on October 20, 1987 (Black Monday in New York stock market). We have 7.60% on October 21, 1987, which is a counter-reaction of the large drop on the previous day. In Figure 2(a), there are some large drops (e.g., in 1987 and 1998) in U.K. stock price index. However, the stock price index have been increasing up to 6930.2 on December 30, 1999, which is the largest value during the estimation periods. Since then, the stock price index has been decreasing up to 3287.0 on March 12, 2003, which is more than 50% drop, compared with the largest value.

Figure 3(a) displays the stock price level in U.S. and Figure 3(b) shows the stock price volatility (100 times the natural log-difference). The Dow Jones Industrial Average data are taken from `http://finance.yahoo.com/`. In Figure 3(b), U.S. stock price has a tendency to rise up to 11722.98 on January 14, 2000. Since then, it has been decreasing up to 7286.27 on October 5, 2002 and increasing up to 10737.70 on February 11, 2004. In Figure 3(a), the largest drop is −25.63% on October 19, 1987 (Black Monday) and the second largest one is −8.38% on October 26, 1987, which might be also due to Black Monday. The counter-reactions against Black Monday are given by 5.72% on October 20, 1987 and 9.67% on October 21, 1987. From both Figures 2(a) and 3(a), in both U.K.and U.S., the bubble phenomena are observed around the end of 1999 or the beginning of 2000.

3 Setup of the Model

We consider that the original percent change data $r_t^{(j)}$ is given by a sum of the deterministic component and the irregular component for each time t, where j denotes a country. $j = 1, 2, 3$ is taken, where $j = 1$ indicates Japan, $j = 2$ denotes U.K., and $j = 3$ represents U.S. We take the following SV model:

$$r_t^{(j)} = z_t^{(j)}\alpha^{(j)} + \exp(\frac{1}{2}h_t^{(j)})\epsilon_t^{(j)}, \qquad \epsilon_t^{(j)} \sim N(0, 1), \tag{1}$$

$$h_t^{(j)} = x_t^{(j)}\gamma^{(j)} + \delta^{(j)}h_{t-1}^{(j)} + \eta_t^{(j)}, \qquad \eta_t^{(j)} \sim N(0, \sigma^{(j)2}), \tag{2}$$

for $j = 1, 2, 3$ and $t = 1, 2, \cdots, n$. n represents the sample size. $\epsilon_t^{(j)}$, $j = 1, 2, 3$ and $t = 1, 2, \cdots, n$, are mutually independently and normally distributed with mean zero and variance one. $\eta_t^{(j)}$, $j = 1, 2, 3$ and $t = 1, 2, \cdots, n$, are mutually independently and normally distributed with mean zero and variance $\sigma^{(j)2}$. $\alpha^{(j)}$, $h_t^{(j)}$, $\gamma^{(j)}$, $\delta^{(j)}$ and $\sigma^{(j)}$, $j = 1, 2, 3$, are the parameters to be estimated.

$r_t^{(1)}$, $r_t^{(2)}$ and $r_t^{(3)}$ are given by Figures 1(b), 2(b) and 3(b), respectively. $r_t^{(j)}$ indicates 100 times natural log-difference, which is approximated as the percent change of the stock price (hereafter we call $r_t^{(j)}$ the percent change of the stock price). The percent change of the stock price, $r_t^{(j)}$, consists of the deterministic component $z_t^{(j)}\alpha^{(j)}$ and the irregular component $\exp(\frac{1}{2}h_t^{(j)})\epsilon_t^{(j)}$.

$z_t^{(j)}$ denotes a $1 \times k_1$ vector of exogenous variables, which are assumed to be nonstochastic, and $\alpha^{(j)}$ represents a $k_1 \times 1$ parameter vector. $x_t^{(j)}$ indicates a $1 \times k_2$ vector of exogenous variables, which are also assumed to be nonstochastic, and $\gamma^{(j)}$ is a $k_2 \times 1$ parameter vector. $\exp(\frac{1}{2}h_t^{(j)})$ represents the volatility, which is assumed to be time-dependent and unobservable. $h_t^{(j)}$ depends on the exogenous variables $x_t^{(j)}$ as well as the lagged $h_{t-1}^{(j)}$. Thus, $r_t^{(j)}$ is observed, while $h_t^{(j)}$ is not observable. (1)

Table 1: Length of Holiday: H_t

H_t	1	2	3	4	5	6	7	8
Japan	244	904	110	14	13	9	0	1
U.K.	12	1077	79	42	0	0	0	0
U.S.	55	1109	138	1	0	1	0	0

is called the measurement equation, and (2) is referred to as the transition equation. Using the observed data $r_t^{(j)}$, we consider estimating unobservable component $h_t^{(j)}$.

Under the above setup, we estimate B_n and θ, where $B_n = (h_0, h_1, \cdots, h_n)$ and $\theta = (\alpha', \gamma', \delta, \sigma)$. The estimation procedure is discussed in Appendix A where the nonlinear non-Gaussian state-space model is estimated using Markov chain Monte Carlo (MCMC) methods. As for the parameter estimation, the Bayesian method is utilized because of its simplicity.

$z_t^{(j)}$ takes the constant term, $\tilde{r}_t^{(j')}$ for $j' \neq j$ and $r_{t-1}^{(j)}$, where $\tilde{r}_t^{(j')}$ indicates the most recent percent change data of the j'th country available at time t (closing time) in the jth country. Note that the subscript t in $z_t^{(j)}$ represents local time in the jth country. That is, the superscript (j) should be put in time t, but it is abbreviated to avoid messy notations. Thus, $\tilde{r}_t^{(j')}$ represents the spillover effect in price level from the j'th country to the jth country.

$x_t^{(j)}$ takes the constant term, $H_t^{(j)}$, $d_t^{(j)}$, $d_t^{(j')}$, $d_t^{(j'')}$, $\tilde{h}_t^{(j')}$, $\tilde{h}_t^{(j'')}$, Mo_t, Tu_t, We_t, Th_t, Fr_t and d_t^{90}, where $j' \neq j$, $j'' \neq j$ and $j' < j''$. $H_t^{(j)}$ represents the number of nontrading days between time $t-1$ and time t in the jth country. We have $d_t^{(j)} = 1$ when $r_{t-1}^{(j)}$ is negative and $d_t^{(j)} = 0$ otherwise. We take $d_t^{(j')} = 1$ when $\tilde{r}_t^{(j')}$ is negative and $d_t^{(j')} = 0$ otherwise. Similarly, we take $d_t^{(j'')} = 1$ when $\tilde{r}_t^{(j'')}$ is negative and $d_t^{(j'')} = 0$ otherwise. $\tilde{h}_t^{(j')}$ indicates the most recent volatility data of the j'th country available at time t in the jth country. $\tilde{h}_t^{(j'')}$ denotes the most recent volatility data of the j''th country available at time t in the jth country. Mo_t denotes Monday dummy, where $Mo_t = 1$ when time t is Monday and $Mo_t = 0$ otherwise. Similarly, Tu_t, We_t, Th_t and Fr_t represent Tuesday, Wednesday, Thursday and Friday dummies, respectively. We take $d_t^{90} = 1$ when time t is after the beginning of 1990 and $d_t^{90} = 0$ otherwise. From Figure 1(b), the stock returns after 1990 look like more volatile than those before 1990.

The stock returns become volatile when we have much information in the market. The amount of information is roughly equivalent to the number of nontrading days between time $t-1$ and time t, because longer holiday implies higher possibility that something happens in an economy. Thus, we can consider that the length of the period between trading days t and $t-1$ might be equivalent to the amount of information. Therefore, the number of nontrading days between trading days t and $t-1$ (i.e., the number of holidays between t and $t-1$, denoted by $H_t^{(j)}$) should be positively correlated with the volatility of $r_t^{(j)}$. This is known as the holiday effect.

Thus, $H_t^{(j)}$ represents a proxy variable of the amount of information. See Nelson (1991) for the holiday effect. Note that we usually have $H_t^{(j)} = 2$ when time $t-1$ is Friday, because the market is closed for two days (Saturday and Sunday). If Monday is a national holiday, we obtain $H_t^{(j)} = 3$, where time $t-1$ is Friday and time t is Tuesday. H_t is summarized in Table 1 for each country, which implies that in the case of Japan we have 244 data when $H_t = 1$, 904 data when $H_t = 2$, and etc. Note that in Japan the stock market was open on Saturday until the end of 1989 and 1 in the case of U.S. and $H_t = 6$ corresponds to September 11, 2001 – September 16, 2001 (terrorist attacks). Watanabe (1999) examined the holiday effect in Japanese stock market, where the length of holiday is not discussed.

It is well known that in the stock market a negative shock yesterday yields high volatility today but a positive shock yesterday does not, i.e., there is a negative relation between expected return and volatility (see Nelson (1991) and Glosten, Jagannathan and Runkle (1993)). This effect is known as the asymmetry effect or the leverage effect. Therefore, we examine how the sign of r_{t-1} affects the volatility. $d_t^{(j)}$ represents the dummy variable, where $d_t^{(j)} = 1$ if $r_{t-1}^{(j)} < 0$ and $d_t^{(j)} = 0$ otherwise. If the asymmetry effect is detected, we have the result that the coefficient of $d_t^{(j)}$ is significantly positive. In a lot of the past empirical research, the asymmetry effect is detected. Watanabe (1999) also discussed an asymmetry effect in the volatility. Jacquier, Polson and Rossi (2004) takes the asymmetry effect as a correlation between two errors $\epsilon_t^{(j)}$ and $\eta_t^{(j)}$, and Yu (2002) pointed out a problem in such a specification. Also, see Danielsson (1994) and So, Li and Lam (2002) for the asymmetry effect.

In this paper, we consider the asymmetry effects from foreign countries, i.e., for example, it might be expected that Japanese stock price becomes volatile when U.S. or U.K. stock price falls. For $j' \neq j$, $d_t^{j'}$ is taken as $d_t^{j'} = 1$ if the most recent percent change data of the stock price in the j'th country available at time t, which is denoted by $\tilde{r}_t^{(j')}$, is negative and $d_t^{(j')} = 0$ otherwise. j' may be replaced by j''. Remember that time t indicates local time in the jth country. In almost all the cases, $d_t^{(j')} = 1$ implies that the stock price in the j'th country at time $t-1$ is smaller than that at time $t-2$. However, when time $t-1$ is a holiday in the j'th country, $d_t^{(j')} = 1$ indicates that the stock price change in the j'th country from time $t-2$ to time $t-3$ is negative. Thus, $d_t^{(j')}$ also represents the asymmetry effect, but it is caused by the stock price change in the j'th country (note that $d_t^{(j)}$ indicates the asymmetry effect caused by the stock price change on the previous day in its own country). The effect on $d_t^{(j')}$ is called the asymmetry effect from the j'th country to distinguish $d_t^{(j')}$ and $d_t^{(j)}$. If the coefficient of $d_t^{(j')}$ is negative, i.e., if a drop in the stock price in the j'th country leads to an increase in the volatility of the stock price in the jth country, we might conclude that the stock price in the jth country becomes unstable if the economy in the j'th country falls down. Koutmos and Booth (1995) showed that Japanese stock market becomes volatile when U.S. economy falls down.

$\tilde{h}_t^{(j')}$ denotes the most recent stock price volatility in the j'th country available at time t (note that $\tilde{r}_t^{(j')}$ is utilized to obtain $d_t^{(j')}$), where j' may be replaced by j''. $\tilde{h}_t^{(j')}$ is taken as a proxy variable of the stock price volatility in the j'th country. Hamao, Masulis and Ng (1990) and Koutmos and Booth (1995) showed that there is an asymmetric volatility transmission between Japanese and U.S. stock prices. $\tilde{h}_t^{(j')}$ has the following two candidates:

(i)

$$\tilde{h}_t^{(j')} = \log\Big(\frac{1}{\min(t+L,n)+L-t}\sum_{j=-L+t}^{\min(t+L,n)} (r_t^{(j')} - \overline{r}_t^{(j')})^2\Big), \tag{3}$$

which corresponds to the log of the sample variance around time t. $\overline{r}_t^{(j')}$ is given by:

$$\overline{r}_t^{(j')} = \frac{1}{\min(t+L,n)+L-t+1}\sum_{j=-L+t}^{\min(t+L,n)} r_t^{(j')},$$

which represents the sample mean around time t and $L = 10$ is taken.

(ii)

$$\tilde{h}_t^{(j')} = \log|e_t^{(j')}|^2, \tag{4}$$

where $r_t^{(j')}$ is estimated by "const. + AR(p)" model and $e_t^{(j')}$ denotes the obtained residual. $p = 6$ for $j' = 1$, $p = 9$ for $j' = 2$, and $p = 2$ for $j' = 3$ are selected by AIC.

Thus, $\tilde{h}_t^{(j')}$ represents the spillover effect in stock price volatility from the j'th country to the jth country. Note that all the estimation periods in Section 4 are taken from April 16, 1984 to February 2, 2007 because we need some past data (i.e., $L = 10$ or $p = 9$) to compute $\tilde{h}_t^{(j')}$.

Watanabe (2000) empirically found that there is a structural change between 1989 and 1990 with respect to the holiday effect in Japan, and showed that we have the holiday effect after 1990 but do not have it before 1989. d_t^{90} indicates the structural change dummy which satisfies $d_t^{90} = 1$ when t is after January 1, 1990 and $d_t^{90} = 0$ otherwise.

Fatemi and Park (1996), Coutts and Sheikh (2002) and Watanabe (2001) discussed the day-of-the-week effect in the daily stock returns. Mo_t denotes the Monday dummy, which implies that $Mo_t = 1$ when time t is Monday and $Mo_t = 0$ otherwise. Tu_t, We_t, Th_t and Fr_t represent Tuesday, Wednesday, Thursday and Friday dummies, respectively. It might be expected that the coefficient of the Monday dummy Mo_t is positive, because we usually have a positive holiday effect on Monday. Also, possibly we have the Tuesday effect, which might be negative, because we might have a counter-reaction against the Monday effect and/or an influence of U.K. or U.S. stock market on Monday. Note that U.K. and U.S. stock markets are open between the closing time on Monday and the opening time on Tuesday in Japanese time zone. However, it is not easy to estimate the holiday effect and the Monday effect separately, because the holiday effect is observed every Monday when the market is open. Therefore, only the Tuesday effect is taken into account as the day-of-the-week effect. Also, see Appendix E.

For $\tilde{h}_t^{(j')}$, note as follows. In this paper, we examine whether the volatility in the jth country depends on that in the j'th country. That is, under the condition that there is no national holiday for all the three countries, $h_t^{(1)}$ depends on $h_{t-1}^{(2)}$ and $h_{t-1}^{(3)}$, $h_t^{(2)}$ is a function of $h_t^{(1)}$ and $h_{t-1}^{(3)}$, and $h_t^{(3)}$ depends on $h_t^{(1)}$ and $h_t^{(2)}$. This implies that we need to construct a multivariate SV model. That is, the three equations have to be estimated simultaneously. However, when we have different national holidays for each country, taking an example of $h_t^{(j)}$ for $j = 1$, we sometimes have the fact that $h_t^{(1)}$ depends on $h_{t-2}^{(2)}$ for some t. Accordingly, the likelihood function in this case cannot be explicitly written, because there is no regular rule on national holidays for each country. Therefore, $\tilde{h}_t^{(2)}$ and $\tilde{h}_t^{(3)}$ are taken as proxies of $h_{t-1}^{(2)}$ and $h_{t-1}^{(3)}$ for Japan (i.e., $j = 1$), where $\tilde{h}_t^{(j')}$, discussed above, represents the volatility transmission from the j'th country to the jth country. Given $\tilde{h}_t^{(j')}$ and $\tilde{h}_t^{(j'')}$, the jth equation is estimated independently. Thus, to avoid this complexity, we estimate the three equations separately in Sections 4.1 – 4.3. As an example of the past studies, Engle, Ito and Lin (1990) assume in the foreign exchange market that volatility is zero when a market is closed because of a national holiday. That is, on a national holiday, the stock price data is replaced by the most recently observed data, which implies that the holiday effect disappears because the length of the period between trading days t and $t-1$ is not taken into account at all. In Sections 4.1 – 4.3, we estimate a single equation for each country, because we want to examine both volatility transmission and holiday effects at the same time. Thus, the exact multivariate estimation is not feasible in practice. Instead, in Section 4.4 we consider a quasi multivariate estimation method.

4 Estimation Results and Discussions

4.1 Model Selection: Table 2

In Table 2, depending on combination of $x_t^{(j)}$ and $z_t^{(j)}$, we have Model XY, where X takes one of 1 – 8 and Y takes A, B or C. As for $x_t^{(j)}$, we take the following variables:

1: $x_t^{(j)} = 1$
2: $x_t^{(j)} = (1,\ H_t^{(j)})$
3: $x_t^{(j)} = (1,\ H_t^{(j)},\ d_t^{(j)},\ d_t^{(j')},\ d_t^{(j'')})$
4: $x_t^{(j)} = (1,\ H_t^{(j)},\ d_t^{(j)},\ d_t^{(j')},\ d_t^{(j'')},\ \tilde{h}_t^{(j')},\ \tilde{h}_t^{(j'')})$
5: $x_t^{(j)} = (Mo_t,\ Tu_t,\ We_t,\ Th_t,\ Fr_t)$
6: $x_t^{(j)} = (1,\ H_t^{(j)},\ d_t^{(j)},\ d_t^{(j')},\ d_t^{(j'')},\ \tilde{h}_t^{(j')},\ \tilde{h}_t^{(j'')},\ Tu_t)$
7: $x_t^{(j)} = (1,\ H_t^{(j)},\ d_t^{(j)},\ d_t^{(j')},\ d_t^{(j'')},\ \tilde{h}_t^{(j')},\ \tilde{h}_t^{(j'')},\ Tu_t,\ d_t^{90})$

Table 2: Surrogate for Marginal Likelihood: $\log f_R(R_n)$

	$z_t \backslash x_t$	1	2	3	4	5	6	7	8
	A	−8809.7	−8791.8	−8752.5	−8753.8	−8803.0*	−8749.9	−8751.1	−8751.3
	B	−8546.2	−8526.0	−8504.4	−8504.4	−8545.1	−8503.7	−8502.6	−8503.2
Japan	C	−8543.2	−8522.6	−8499.4	−8499.8	−8540.0	−8496.2	$\boxed{-8496.0}$	−8498.0
	A′	—	—	—	−8754.8	—	−8750.1	−8750.6	−8751.4
	B′	—	—	—	−8505.9*	—	−8505.3*	−8503.9	−8506.0*
	C′	—	—	—	−8501.2	—	−8497.1*	−8497.9	−8498.7
	A	−7377.4	−7376.9	−7358.1	−7354.9	−7376.6	−7352.8	−7352.7	−7352.7
U.K.	B	−7071.2	−7071.0	−7061.1	−7058.5	−7072.9	−7057.9	−7057.9	$\boxed{-7057.8}$
	A′	—	—	—	−7365.1*	—	−7362.3	−7363.2	−7362.5
	B′	—	—	—	−7067.5	—	−7067.2	−7069.1	−7068.7
	A	−7387.9	−7385.8	−7357.8	−7353.2	−7382.9	−7355.7	−7351.6	−7353.7*
U.S.	B	−6940.5	−6942.8*	−6921.3	−6909.8*	−6946.9	−6912.9	$\boxed{-6906.1}$	−6908.1*
	A′	—	—	—	−7354.7	—	−7353.8	−7356.0*	−7356.3
	B′	—	—	—	−6920.8*	—	−6922.8	−6919.8	−6920.7

Table 3: CPU Time (Minutes)

	$z_t \backslash x_t$	1	2	3	4	5	6	7	8
	A	96	100	117	135	116	146	158	157
Japan	B	147	150	168	186	167	195	208	209
	C	172	176	192	210	192	220	234	233

8: $x_t^{(j)} = (1,\ H_t^{(j)},\ d_t^{(j)},\ d_t^{(j')},\ d_t^{(j'')},\ \tilde{h}_t^{(j')},\ \tilde{h}_t^{(j'')},\ Tu_t,\ H_t^{(j)}d_t^{90})$

Note that j' and j'' satisfy $j' \neq j$, $j'' \neq j$ and $j' < j''$. We choose $z_t^{(j)}$ as follows:

A: $z_t^{(j)} = 0$

B: $z_t^{(j)} = (1,\ \tilde{r}_t^{(j')},\ \tilde{r}_t^{(j'')},\ r_{t-1}^{(j)})$

C: $z_t^{(j)} = (1,\ \tilde{r}_t^{(j')},\ \tilde{r}_t^{(j'')},\ r_{t-1}^{(j)},\ d_t^{90})$

Moreover, Y′ in Model XY′ implies that the proxy of volatility in the j'th country (i.e., $\tilde{h}_t^{(j')}$) is given by (4), which is shown in Section 3, while simply Y in Model XY indicates that $\tilde{h}_t^{(j')}$ is given by (3). Columns 4, 6, 7 and 8 in Table 2 represent that $\tilde{h}_t^{(j')}$ and $\tilde{h}_t^{(j'')}$ are included in $x_t^{(j)}$.

The surrogate for the marginal likelihood, denoted by $\log f_R(R_n)$ in this paper and discussed in Appendix B, is shown in Table 2 for each model and each country, and it is useful for model selection because the surrogate has the same information as the marginal likelihood (see Appendix B). The value with $*$ in the superscript indicates that the corresponding model is rejected at significance level 1% by the convergence diagnostic (CD) test. The CD is the test statistic that checks whether the Gibbs sequence is converged or not, which is proposed by Geweke (1992) and discussed in Appendix C. The model such that the CD is passed and the surrogate for the marginal likelihood is maximized results in the best model for each country. As a result, the value squared by the solid line implies the best model for each country. That is, Models 7C, 8B and 7B are chosen in Japan, U.K. and U.S., respectively. Table 3 represents CPU time in minutes for each model of A – C and 1 – 8 in the case of Japan, where Open Watcom F77/32 Compiler (Version 1.6), Dual Opteron 254 (2.8GHz) CPU and Microsoft Windows XP (Professional Edition) SP2 Operating System are utilized for computation. See `http://www.openwatcom.org` for the Open Watcom Compiler. The CPU times in the case of U.S. and U.K. are omitted from Table 3, because we can easily guess them from Table 3. Actually, It took about 235 hours to obtain all the computations in Table 2.

4.2 Parameter Estimates: Tables 4(a) – 4(c)

The estimation results are in Tables 4(a) – 4(c). AVE, STD, Skew and Kurt represent mean, standard deviation, skewness, kurtosis for each posterior distribution. If a posterior distribution is close to a normal distribution, we have 0 for skewness and 3 for kurtosis. 0.005, 0.025, 0.975 and 0.995 indicate percent points. If all the values in 0.005, 0.025, 0.975 and 0.995 have the same sign, we can judge that the corresponding coefficient is not statistically zero. CD represents the convergence diagnostic test statistic proposed by Geweke (1992), which implies that the value in CD is greater than 2.576 in absolute value if the Gibbs sequence is not converged (see Appendix C in detail discussion). The superscript $*$ is put in Table 2 when at least one of the CDs in $\theta = (\alpha', \gamma', \delta, \sigma)$ and $\log f_R(R_n|\Theta)$ is greater than 2.576 in absolute value (see Appendices A and B for the notation of $f_R(R_n|\Theta)$). The number of parameters is given by $k_1 + k_2 + 2 + n + 1$, i.e., $k_1 + k_2 + 2$ for the dimension of $\theta = (\alpha', \gamma', \delta, \sigma)$ and $n + 1$ for that of B_n. It is not possible to check individually if all the elements of B_n are converged. Therefore, the CD in $\log f_R(R_n|\Theta)$ gives us the overall convergence criterion (see Appendix D).

In Table 4(a), the findings are as follows: (i) there is a spillover effect in stock price level from U.S. to Japan, but no spillover effect from U.K. to Japan, (ii) we have a structural change in 1990 with respect to stock price level, i.e., the stock returns decrease after 1990, (iii) clearly there is a holiday effect in stock price volatility, (iv) a drop in the stock price yesterday yields an increase in the stock price volatility today (i.e., asymmetry effect), (v) according to the 95% interval constructed from the generated random draws, a drop in U.K. stock price causes an increase in the Japanese stock price volatility (i.e., asymmetry effect from U.K. stock market), but no asymmetry effect from the U.S. stock market is found, (vi)

Table 4: Estimation Results (April 16, 1984 – February 2, 2007)

(a) Model 7C with $(j, j', j'') = (1, 2, 3)$ — Japan $\qquad \log f_Y(Y_n) = -8496.0$

			AVE	STD	Skew	Kurt	0.005	0.025	0.975	0.995	CD
$z_t^{(j)}$	1	$\alpha_1^{(j)}$	0.0693	0.0151	0.001	3.005	0.0304	0.0397	0.0988	0.1082	1.259
	$\tilde{r}_t^{(j')}$	$\alpha_2^{(j)}$	−0.0190	0.0135	−0.004	2.993	−0.0539	−0.0454	0.0075	0.0157	1.029
	$\tilde{r}_t^{(j'')}$	$\alpha_3^{(j)}$	0.1215	0.0145	0.007	2.996	0.0842	0.0932	0.1499	0.1587	−1.677
	$r_{t-1}^{(j)}$	$\alpha_4^{(j)}$	0.2355	0.0137	0.009	2.991	0.2004	0.2087	0.2623	0.2709	−2.099
	d_t^{90}	$\alpha_5^{(j)}$	−0.0871	0.0227	0.001	2.995	−0.1456	−0.1316	−0.0425	−0.0284	−0.032
$x_t^{(j)}$	1	$\gamma_1^{(j)}$	−0.1818	0.0247	−0.098	3.006	−0.2478	−0.2314	−0.1343	−0.1207	−0.280
	$H_t^{(j)}$	$\gamma_2^{(j)}$	0.1217	0.0216	0.047	3.000	0.0673	0.0798	0.1645	0.1784	0.855
	$d_t^{(j)}$	$\gamma_3^{(j)}$	0.1753	0.0270	0.080	2.993	0.1077	0.1236	0.2290	0.2467	−1.967
	$d_t^{(j')}$	$\gamma_4^{(j)}$	0.0577	0.0251	0.018	2.992	−0.0067	0.0085	0.1073	0.1227	0.306
	$d_t^{(j'')}$	$\gamma_5^{(j)}$	0.0031	0.0258	−0.004	3.036	−0.0641	−0.0475	0.0536	0.0696	1.921
	$\tilde{h}_t^{(j')}$	$\gamma_6^{(j)}$	0.0253	0.0091	0.167	3.082	0.0032	0.0082	0.0440	0.0504	−0.241
	$\tilde{h}_t^{(j'')}$	$\gamma_7^{(j)}$	0.0051	0.0076	0.015	3.061	−0.0145	−0.0098	0.0201	0.0250	0.900
	Tu_t	$\gamma_8^{(j)}$	−0.1189	0.0580	−0.019	3.045	−0.2705	−0.2333	−0.0058	0.0311	−1.243
	d_t^{90}	$\gamma_9^{(j)}$	0.0661	0.0154	0.280	3.161	0.0302	0.0380	0.0984	0.1100	1.112
		$\delta^{(j)}$	0.9284	0.0098	−0.306	3.174	0.9003	0.9078	0.9462	0.9512	−0.446
		$\sigma^{(j)}$	0.2563	0.0189	0.187	3.015	0.2110	0.2209	0.2950	0.3081	0.731
$\log f_R(R_n \mid \Theta)$			−8222.6	24.014	0.041	3.023	−8283.6	−8269.2	−8175.0	−8159.6	0.520

(b) Model 8B with $(j, j', j'') = (2, 1, 3)$ — U.K. $\qquad \log f_Y(Y_n) = -7057.8$

			AVE	STD	Skew	Kurt	0.005	0.025	0.975	0.995	CD
$z_t^{(j)}$	1	$\alpha_1^{(j)}$	0.0309	0.0101	−0.002	2.996	0.0049	0.0111	0.0506	0.0567	0.159
	$\tilde{r}_t^{(j')}$	$\alpha_2^{(j)}$	0.1279	0.0087	0.001	3.012	0.1054	0.1108	0.1450	0.1504	1.193
	$\tilde{r}_t^{(j'')}$	$\alpha_3^{(j)}$	−0.0892	0.0140	−0.002	3.000	−0.1254	−0.1166	−0.0618	−0.0532	0.050
	$r_{t-1}^{(j)}$	$\alpha_4^{(j)}$	0.2153	0.0134	0.005	2.994	0.1807	0.1889	0.2417	0.2498	−1.691
$x_t^{(j)}$	1	$\gamma_1^{(j)}$	−0.0935	0.0208	−0.054	3.016	−0.1483	−0.1345	−0.0533	−0.0410	−1.180
	$H_t^{(j)}$	$\gamma_2^{(j)}$	0.0683	0.0261	0.029	3.058	0.0013	0.0173	0.1199	0.1373	1.684
	$d_t^{(j)}$	$\gamma_3^{(j)}$	0.0906	0.0224	0.029	3.082	0.0332	0.0469	0.1350	0.1501	−0.208
	$d_t^{(j')}$	$\gamma_4^{(j)}$	0.0272	0.0201	0.030	3.028	−0.0243	−0.0120	0.0668	0.0795	0.941
	$d_t^{(j'')}$	$\gamma_5^{(j)}$	0.0452	0.0228	0.021	3.045	−0.0134	0.0006	0.0901	0.1047	0.533
	$\tilde{h}_t^{(j')}$	$\gamma_6^{(j)}$	0.0135	0.0044	0.241	3.182	0.0031	0.0054	0.0226	0.0259	−0.457
	$\tilde{h}_t^{(j'')}$	$\gamma_7^{(j)}$	0.0413	0.0080	0.397	3.341	0.0233	0.0270	0.0584	0.0651	−0.734
	Tu_t	$\gamma_8^{(j)}$	−0.0957	0.0504	−0.059	2.996	−0.2277	−0.1952	0.0020	0.0297	−0.368
	$H_t^{(j)} d_t^{90}$	$\gamma_9^{(j)}$	−0.0444	0.0181	−0.128	3.124	−0.0939	−0.0811	−0.0098	0.0009	−0.114
		$\delta^{(j)}$	0.9273	0.0118	−0.432	3.352	0.8916	0.9019	0.9481	0.9533	0.468
		$\sigma^{(j)}$	0.1607	0.0158	0.310	3.155	0.1245	0.1320	0.1941	0.2061	−0.905
$\log f_R(R_n \mid \Theta)$			−6918.4	18.215	0.020	3.033	−6965.2	−6954.1	−6882.4	−6870.7	−1.062

Table 4: Estimation Results (April 16, 1984 – February 2, 2007) — Continued

(c) Model 7B with $(j, j', j'') = (3, 1, 2)$ — U.S. $\log f_Y(Y_n) = -6906.1$

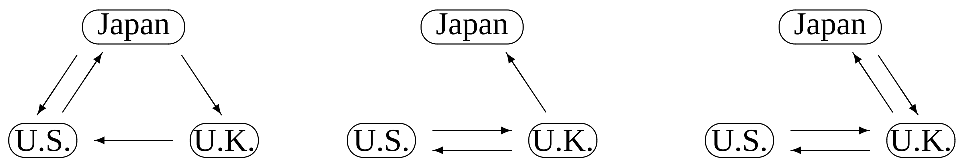
			AVE	STD	Skew	Kurt	0.005	0.025	0.975	0.995	CD
$z_t^{(j)}$	1	$\alpha_1^{(j)}$	0.0402	0.0096	−0.001	3.002	0.0154	0.0214	0.0589	0.0649	0.140
	$\tilde{r}_t^{(j')}$	$\alpha_2^{(j)}$	0.0324	0.0081	0.008	3.008	0.0115	0.0166	0.0484	0.0534	1.627
	$\tilde{r}_t^{(j'')}$	$\alpha_3^{(j)}$	0.3686	0.0129	0.000	3.001	0.3353	0.3433	0.3939	0.4018	−2.177
	$r_{t-1}^{(j)}$	$\alpha_4^{(j)}$	−0.0812	0.0132	−0.002	2.997	−0.1150	−0.1070	−0.0555	−0.0473	1.535
$x_t^{(j)}$	1	$\gamma_1^{(j)}$	−0.1598	0.0271	−0.079	3.038	−0.2318	−0.2140	−0.1077	−0.0917	1.377
	$H_t^{(j)}$	$\gamma_2^{(j)}$	0.0699	0.0268	0.008	3.019	0.0012	0.0175	0.1227	0.1394	0.007
	$d_t^{(j)}$	$\gamma_3^{(j)}$	0.1564	0.0317	0.038	2.988	0.0762	0.0948	0.2190	0.2389	−0.177
	$d_t^{(j')}$	$\gamma_4^{(j)}$	0.0452	0.0270	0.012	3.047	−0.0246	−0.0078	0.0983	0.1158	−2.059
	$d_t^{(j'')}$	$\gamma_5^{(j)}$	0.0561	0.0285	−0.003	3.048	−0.0179	0.0001	0.1121	0.1300	−0.483
	$\tilde{h}_t^{(j')}$	$\gamma_6^{(j)}$	0.0115	0.0077	0.177	3.215	−0.0075	−0.0030	0.0272	0.0329	−0.072
	$\tilde{h}_t^{(j'')}$	$\gamma_7^{(j)}$	0.1016	0.0193	0.540	3.560	0.0605	0.0686	0.1442	0.1618	−1.191
	Tu_t	$\gamma_8^{(j)}$	0.0261	0.0609	0.010	2.999	−0.1301	−0.0929	0.1462	0.1831	0.071
	d_t^{90}	$\gamma_9^{(j)}$	−0.0631	0.0173	−0.315	3.259	−0.1133	−0.0996	−0.0317	−0.0228	0.945
		$\delta^{(j)}$	0.8458	0.0266	−0.581	3.633	0.7617	0.7867	0.8909	0.9015	1.305
		$\sigma^{(j)}$	0.2833	0.0293	0.354	3.185	0.2178	0.2308	0.3458	0.3685	−0.885
$\log f_R(R_n\|\Theta)$			−6627.5	27.680	0.137	3.043	−6695.6	−6680.0	−6571.4	−6552.6	−0.413

the spillover effect in stock price volatility is found from U.K. to Japan but not from U.S. to Japan, (vii) the stock price volatility has Tuesday effect as a counter-reaction against Monday effect, (viii) there is a structural change in 1990 regarding the stock price volatility, (ix) we have SV effect because the 99% interval is between 0.9003 and 0.9512, and (x) all the estimates except for $\gamma_6^{(j)}$, $\gamma_9^{(j)}$, $\delta^{(j)}$ and $\sigma^{(j)}$ are very similar to normal distribution because skewness and kurtosis are close to 0 and 3, respectively. As for (vii), inclusion of both the holiday effect and the Monday effect causes multicollinearity. All the Mondays have the holiday effect, i.e., $H_t^{(j)} = 2$ for most of Mondays. Thus, it is not easy to estimate the holiday effect and the Monday effect, separately. Therefore, the Monday effect is not taken into account. See Appendix E for the day-of-the-week effect.

In Table 4(b), we have the following results: (i) we have a spillover effect in the stock price level from Japan to U.K., (ii) there is a holiday effect in U.K. stock market, (iii) a drop in the stock price yesterday results in an increase in the stock price volatility today (i.e., asymmetry effect), (iv) a drop in U.S. stock price gives us an increase in U.K. stock price volatility (i.e., asymmetry effect from U.S. stock market), but no asymmetry effect from Japanese stock market is found, (v) we can observe volatility transmission from both U.S. and Japan to U.K., where the volatility spillover effect from U.S. is larger than that from Japan, (vi) there is no Tuesday effect, (vii) we have a structural change in 1990 with respect to the holiday effect

Figure 4: Spillover Effects between Japan, U.K. and U.S.

(a) Spillover Effects in Level (b) Asymmetry Effects (c) Spillover Effects in Volatility



The arrow represents a direction of influence between two countries.

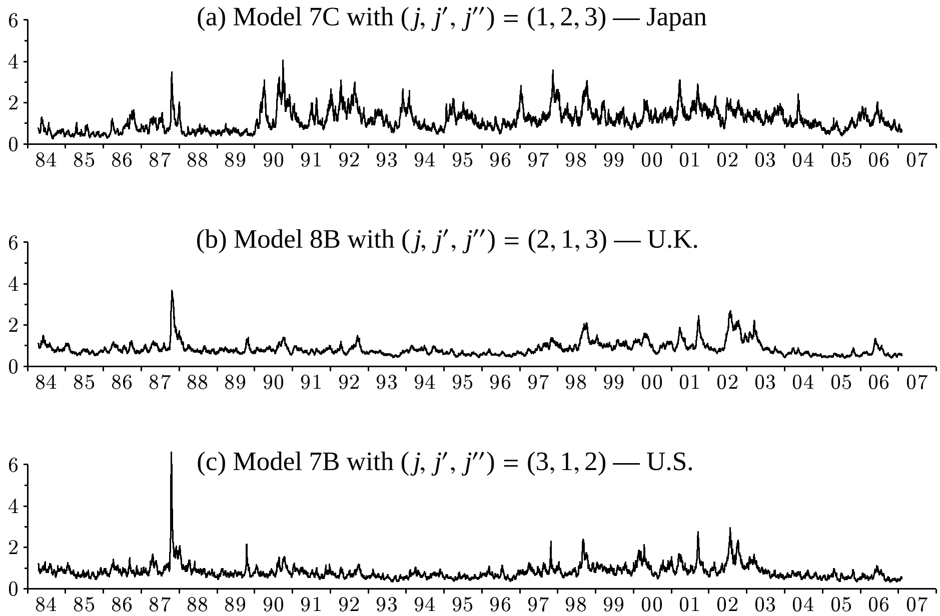
in U.K. stock volatility, where U.K. stock returns are less volatile after 1990, and (viii) except for $\gamma_6^{(j)}$, $\gamma_7^{(j)}$, $\gamma_9^{(j)}$, $\delta^{(j)}$ and $\sigma^{(j)}$, the posterior distributions are close to a normal distribution.

In Table 4(c), we can observe the following findings: (i) we have a spillover effect in U.S. stock price level from Japan to U.S. and the effect from U.K. to U.S., where the spillover effect from U.K. is larger than that from Japan, (ii) there is a holiday effect in U.S. stock market, (iii) a drop in the stock price yesterday gives us an increase in the stock price volatility today (i.e., asymmetry effect), (iv) U.S. stock price volatility has an asymmetry effect from U.K. stock price volatilities, but not from Japan, (v) we have volatility transmission from U.K. to U.S. but not from Japan to U.S., (vi) there is no Tuesday effect, (vii) there is a structural change in 1990 with respect to U.S. stock price volatility, i.e., U.S. stock returns after 1990 are less volatile than those before 1990, and (viii) except for $\gamma_1^{(j)}$, $\gamma_6^{(j)}$, $\gamma_7^{(j)}$, $\gamma_9^{(j)}$, $\delta^{(j)}$ and $\sigma^{(j)}$, the posterior distributions are close to a normal distribution.

Thus, for all the three countries, stock price volatility depends on the holiday, asymmetry and day-of-the-week effects, except for the Tuesday effect in U.K. and U.S. Note that the holiday effect is regarded as a kind of the Monday effect because in most of the cases we have $H_t = 2$ when t is Monday. Accordingly, as for the day-of-the-week effect, Japan has both Monday and Tuesday effects, U.K. has Tuesday effect, and U.S. has Monday effect. These results are consistent with the past studies, i.e., Nelson (1991), Glosten, Jagannathan and Runkle (1993), Danielsson (1994), Watanabe (1999), So, Li and Lam (2002), and Jacquier, Polson and Rossi (2004) for the asymmetry effect, Nelson (1991) and Watanabe (1999) for the holiday effect, and Fatemi and Park (1996), Watanabe (2001), Coutts and Sheikh (2002) for the day-of-the-week effect.

The two spillover effects and asymmetry effect between Japan, U.K. and U.S. are summarized in Figures 4(a) – (c). The arrow represents a direction of influence between two countries. Japanese stock returns influence U.K. and U.S. stock returns in level from Figure 4(a), where there is an interaction between U.S. and Japanese stock prices in level. From Figure 4(b), a drop in U.S. stock price yields an increase

Figure 5: The Movements of Volatility — $\mathrm{E}(\exp(\frac{1}{2}h_t^{(j)})|R_n) \approx (1/N)\sum_{i=1}^{N}\exp(\frac{1}{2}h_{t,i}^{(j)})$



in U.K. stock price volatility and a drop in U.K. stock price indicates an increase in U.S. and Japanese stock price volatilities, i.e., U.U. and U.K. stock returns have asymmetry effects with each other. Japanese and U.K. stock returns influence with each other and U.K. and U.S. stock returns also influence with each other in a sense of volatility transmission from Figure 4(c). See Koutmos and Booth (1995) for the asymmetry effect between two countries, and Hamao, Masulis and Ng (1990) for the volatility spillover effect.

4.3 Volatility Estimates: Figures 5(a) – 5(c)

In Figures 5(a) – 5(c), the volatility is displayed by $\exp(\frac{1}{2}h_t)$ in (1), which represents a fluctuation in the stock price. When there is a sharp fluctuation in the stock price, we sometimes have a big gain but sometimes a big loss. Thus, the volatility implies a risk in a sense. In Figures 5(a) – 5(c), the movements in the volatility estimates are shown for each country. The volatility is evaluated as the following conditional expectation: $\mathrm{E}(\exp(\frac{1}{2}h_t)|R_n) \approx (1/N)\sum_{i=1}^{N}\exp(\frac{1}{2}h_{t,i})$, where $h_{t,i}$ denotes the ith random draw of h_t given R_n and N represents the number of random draws. See Appendix A for the notations.

On October 19, 1987 in the Eastern Standard Time (so-called Black Monday), the stock price drastically fell down in New York stock market, which influenced Japanese and U.K. stock prices on October 20, 1987 in each local time zone. On

Black Monday, the volatility extremely increases, as shown in Figures 5(a) – 5(c), but it is observed that the volatility is temporary and the volatility in U.S. is much larger than the volatilities in U.K. and Japan.

Since 1990, Japanese stock price drastically starts to decrease (see Figure 1(b)), which represents the bubble-burst phenomenon. However, the volatility increases after the bubble burst. Thus, it is shown in Figure 5(a) that we have larger volatility after the bubble burst in 1990 than before that. In other words, Japanese economy becomes more unstable after the bubble burst. The results in Table 4(a) (see the coefficient of $d_t^{(j)}$ in $x_t^{(j)}$) and Figure 5(a) support those in Watanabe (2000), where it is mentioned that the structural change in 1990 occurs in the Japanese stock market.

In both U.K. and U.S. stock markets, the stock price volatility increases from 1997 to 2003, in addition to the periods around Black Monday (see Figures 5(b) and 5(c)). The periods from 1997 to 2003 are sometimes interpreted as the bubble periods. During the estimation periods (especially after 1990), Japanese stock prices are more volatile than U.K. and U.S. stock prices.

4.4 Multivariate Estimation: Table 5

In Sections 4.1 – 4.3, we have considered estimating the three equations separately. As mentioned in the last paragraph of Section 3, it is not easy to estimate the three equations simultaneously using daily data, because we often have the case where one stock market is closed due to a national holiday but another two markets are open, i.e., data is available in one country, but not observed in another two countries. Therefore, the exact simultaneous estimation is not possible. In this section, instead, we consider a quasi simultaneous estimation method using Japan, U.K. and U.S. stock returns. The estimation procedure is as follows.

(i) For $t = 1, 2, \cdots, T$ and $j = 1, 2, 3$, store the estimates of $h_t^{(j)}$ obtained in Tables 4(a) – (c), where $\mathrm{E}(h_t^{(j)}|R_n) \approx (1/N)\sum_{i=1}^N h_{t,i}^{(j)}$ is taken as the estimate of $h_t^{(j)}$. Note that $h_{t,i}^{(j)}$ is denoted by the ith random draw of $h_t^{(j)}$. Thus, we take Model 7C for Japan, Model 8B for U.K. and Model 7C for U.S., where the volatility (3) shown in Section 3 is used for the most recently available stock price volatility.

(ii) Based on the estimates of $h_t^{(j)}$, we obtain $\tilde{h}_t^{(j')}$ as the most recent stock price volatility in the j'th country available at time t in country j. Given country j, we obtain $\tilde{h}_t^{(j')}$ and $\tilde{h}_t^{(j'')}$ based on $h_t^{(j')}$ and $h_t^{(j'')}$, where $(j, j', j'') = (1, 2, 3)$, (2,1,3) and (3,1,2).

(iii) For each of $(j, j', j'') = (1, 2, 3)$, (2,1,3) and (3,1,2), estimate (1) and (2) to update $h_t^{(j)}$ using the $\tilde{h}_t^{(j')}$ and $\tilde{h}_t^{(j'')}$ obtained in Step (ii). Model 7C for Japan, Model 8B for U.K. and Model 7C for U.S. are chosen for the estimation models.

(iv) Repeat (ii) and (iii) until sum of the three likelihoods is maximized.

Table 5: Multivariate Estimation (April 16, 1984 – February 2, 2007)

			(a) Model 7C — Japan $(j, j', j'') = (1, 2, 3)$			(b) Model 8B — U.K. $(j, j', j'') = (2, 1, 3)$			(c) Model 7B — U.S. $(j, j', j'') = (3, 1, 2)$		
			AVE	0.025	0.975	AVE	0.025	0.975	AVE	0.025	0.975
$z_t^{(j)}$	1	$\alpha_1^{(j)}$	0.0695	0.0399	0.0991	0.0295	0.0103	0.0488	0.0394	0.0211	0.0578
	$\tilde{r}_t^{(j')}$	$\alpha_2^{(j)}$	−0.0192	−0.0457	0.0073	0.1290	0.1123	0.1458	0.0318	0.0164	0.0474
	$\tilde{r}_t^{(j'')}$	$\alpha_3^{(j)}$	0.1214	0.0932	0.1497	−0.0892	−0.1164	−0.0618	0.3673	0.3423	0.3923
	$r_{t-1}^{(j)}$	$\alpha_4^{(j)}$	0.2362	0.2095	0.2630	0.2154	0.1894	0.2415	−0.0803	−0.1059	−0.0546
	d_t^{90}	$\alpha_5^{(j)}$	−0.0888	−0.1335	−0.0442						
$x_t^{(j)}$	1	$\gamma_1^{(j)}$	−0.1849	−0.2355	−0.1370	−0.0605	−0.1001	−0.0210	−0.1449	−0.1984	−0.0914
	$H_t^{(j)}$	$\gamma_2^{(j)}$	0.1236	0.0808	0.1672	0.0460	−0.0011	0.0933	0.0476	−0.0006	0.0963
	$d_t^{(j)}$	$\gamma_3^{(j)}$	0.1777	0.1246	0.2323	0.0760	0.0317	0.1195	0.1399	0.0780	0.2020
	$d_t^{(j')}$	$\gamma_4^{(j)}$	0.0587	0.0089	0.1081	0.0209	−0.0187	0.0614	0.0441	−0.0099	0.0982
	$d_t^{(j'')}$	$\gamma_5^{(j)}$	0.0047	−0.0472	0.0563	0.0220	−0.0230	0.0669	0.0521	−0.0055	0.1096
	$\tilde{h}_t^{(j')}$	$\gamma_6^{(j)}$	0.0335	0.0048	0.0649	0.0148	0.0047	0.0253	−0.0019	−0.0213	0.0174
	$\tilde{h}_t^{(j'')}$	$\gamma_7^{(j)}$	0.0016	−0.0250	0.0279	0.0735	0.0542	0.0960	0.1506	0.1194	0.1841
	Tu_t	$\gamma_8^{(j)}$	−0.1195	−0.2345	−0.0032	−0.0497	−0.1332	0.0329	0.0516	−0.0563	0.1593
	d_t^{90}	$\gamma_9^{(j)}$	0.0725	0.0412	0.1086				−0.0382	−0.0747	−0.0021
	$H_t^{(j)}d_t^{90}$	$\gamma_9^{(j)}$				−0.0272	−0.0678	0.0131			
		$\delta^{(j)}$	0.9247	0.9015	0.9446	0.9125	0.8938	0.9285	0.8304	0.8056	0.8539
		$\sigma^{(j)}$	0.2646	0.2267	0.3069	0.1838	0.1582	0.2147	0.3235	0.2911	0.3580
$\log f_R(R_n\|\Theta)$			−8216.4	−8264.8	−8166.7	−6902.6	−6938.8	−6865.9	−6586.2	−6635.6	−6536.4

The results are in Table 5. The difference between Tables 4(a) – (c) and 5 are: (i) there is no asymmetry effect between U.K. and U.S., i.e., the two arrows between U.K. and U.S. in Figure 4(b) disappear, (ii) the holiday effects also disappears in U.K. and U.S., and (iii) in U.K. the structural change in the holiday effect vanishes. Thus, by estimating the three equations simultaneously, there is no holiday effect in both U.K. and U.S. However, these effects are quite small even in the case of Tables 4(a) – (c), because zero is very close to the 95% interval for each case. Therefore, Tables 4(a) – (c) are not too different from Table 5. In addition, we have the almost same figures as Figures 5(a) – (c) in the volatility estimates.

5 Summary

In this paper, we have investigated stock price volatilities in Japan, U.K. and U.S. using the SV model. Note that there are no other papers which include the asymmetry, holiday and day of the week effects as well as the spillover effects in stock price level and volatility simultaneously. Furthermore, we use the Bayesian procedure through MCMC to estimate the model.

We have found that the holiday, asymmetry and day-of-the-week effects play an important role in volatility, although no Tuesday effect in U.K. and U.S. is observed (see Tables 4(a) – (c)). Moreover, in addition to these effects, we have examined whether there are spillover effects between Japan, U.K. and U.S. with respect to stock price level and volatility. As a result, U.S. stock price volatility interacts U.K. stock price volatility and Japanese stock price volatility also interacts U.K. stock price volatility (see Figure 4(c)). Moreover, we can observe inter-transmission between Japan and U.S. in price level (see Figure 4(a)). It has been shown that the structural change in 1990 are included in Japanese, U.K. and U.S. stock price volatilities (see Tables 4(a) – (c)). Most of these results are consistent with past studies such as Hamao, Masulis and Ng (1990), Koutmos and Booth (1995), Kanas (1998), Ramchand and Susmel (1998), Ng (2000), and Baele (2003).

Appendix A: Estimation Procedure

Under the setup shown in Section 2, the density function of r_t given h_t, and that of h_t given h_{t-1} are obtained as $f_r(r_t|h_t)$ and $f_h(h_t|h_{t-1})$, which are given by:

$$f_r(r_t|h_t) = \frac{1}{\sqrt{2\pi \exp(h_t)}} \exp\Big(-\frac{1}{2\exp(h_t)}(r_t - z_t\alpha)^2\Big), \tag{5}$$

$$f_h(h_t|h_{t-1}) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\Big(-\frac{1}{2\sigma^2}(h_t - x_t\gamma - \delta h_{t-1})^2\Big), \tag{6}$$

where the superscript (j) is abbreviated hereafter. (5) is derived from (1), and (6) comes from (2). Let us denote $R_n = (r_1, r_2, \cdots, r_n)$, $B_n = (h_0, h_1, \cdots, h_n)$ and $\theta = (\alpha',$ γ', δ, $\sigma)$. In this model, B_n and θ has to be estimated. Given θ, the density function of R_n given B_n and that of B_n are given by:

$$f(R_n|B_n, \theta) = \prod_{t=1}^{n} f_r(r_t|h_t), \qquad f(B_n|\theta) = \prod_{t=1}^{n} f_h(h_t|h_{t-1}).$$

Therefore, given θ, the joint density of R_n and B_n is:

$$f(R_n, B_n|\theta) = \prod_{t=1}^{n} f_r(r_t|h_t) f_h(h_t|h_{t-1}).$$

Here, we estimate the unknown parameters by Bayes method. Setting prior densities sometimes leads to *ad hoc* and unrealistic results. To exclude influence of prior information, the prior densities are assumed to be diffuse, i.e.,

$$f_\alpha(\alpha) \propto \text{const.}, \quad f_{h_0}(h_0) \propto \text{const.}, \quad f_{\gamma\delta}(\gamma, \delta) \propto \text{const.}, \quad f_\sigma(\sigma^2) \propto \frac{1}{\sigma^2}. \tag{7}$$

Thus, from (5) – (7), the joint density function of R_n, B_n and θ is obtained as:

$$f(R_n, B_n, \theta) \equiv f(R_n, \Theta_n) \propto \frac{1}{\sigma^2} \prod_{t=1}^{n} f_r(r_t|h_t) f_h(h_t|h_{t-1}), \tag{8}$$

where $\Theta = (B_n, \theta)$. The conditional density function of B_n and θ given R_n is:

$$f(B_n, \theta|R_n) \equiv f(\Theta_n|R_n) \propto \frac{1}{\sigma^2} \prod_{t=1}^{n} f_r(r_t|h_t) f_h(h_t|h_{t-1}). \tag{9}$$

Let us define $B_t^+ = (h_t, h_{t+1}, \cdots, h_n)$. We consider generating random draws of $\Theta = (B_n, \theta)$. From (8), we can derive the following conditional densities:

$$f(h_t|B_{t-1}, B_{t+1}^+, \theta) \propto \begin{cases} \dfrac{1}{\sqrt{\exp(h_t)}} \exp\Big(-\dfrac{1}{2\exp(h_t)}(r_t - z_t\alpha)^2\Big) \\ \qquad \times \exp\Big(-\dfrac{1}{2\sigma^2}(h_{t+1} - x_{t+1}\gamma - \delta h_t)^2\Big) \\ \qquad \times \exp\Big(-\dfrac{1}{2\sigma^2}(h_t - x_t\gamma - \delta h_{t-1})^2\Big), \\ \qquad\qquad\qquad \text{for } t = 1, 2, \cdots, n-1, \\ \dfrac{1}{\sqrt{\exp(h_t)}} \exp\Big(-\dfrac{1}{2\exp(h_t)}(r_t - z_t\alpha)^2\Big) \\ \qquad \times \exp\Big(-\dfrac{1}{2\sigma^2}(h_t - x_t\gamma - \delta h_{t-1})^2\Big), \\ \qquad\qquad\qquad \text{for } t = n, \end{cases} \tag{10}$$

$$h_0 \mid B_1^+, \theta \sim N\Big(\frac{h_1 - x_1\gamma}{\delta},\ \frac{\sigma^2}{\delta^2}\Big), \tag{11}$$

$$\begin{pmatrix} \gamma \\ \delta \end{pmatrix} \Big| B_n, \alpha, \sigma^2 \sim N\Big((\sum_{t=1}^{n} x_t^{*\prime} x_t^*)^{-1} \sum_{t=1}^{n} x_t^{*\prime} h_t,\ \sigma^2(\sum_{t=1}^{n} x_t^{*\prime} x_t^*)^{-1}\Big), \tag{12}$$

for $x_t^* = (x_t,\ h_{t-1})$,

$$\alpha \mid B_n, \gamma, \delta, \sigma^2 \sim N\Big((\sum_{t=1}^{n} z_t' z_t e^{-h_t})^{-1} \sum_{t=1}^{n} z_t' r_t e^{-h_t},\ (\sum_{t=1}^{n} z_t' z_t e^{-h_t})^{-1}\Big), \tag{13}$$

$$\sigma^2 \mid B_n, \alpha, \gamma, \delta \sim IG\Big(\frac{n}{2},\ \frac{2}{\sum_{t=1}^{n}(h_t - x_t\gamma - \delta h_{t-1})^2}\Big). \tag{14}$$

where $X \sim IG(a, b)$ indicates $1/X \sim G(a, b)$ and the density function given by $G(a, b)$ is proportional to $x^{a-1}e^{-x/b}$, which is called the gamma distribution with parameters a and b.

Using the above conditional densities (10) – (14), the Gibbs sampler can be performed to generate random draws of B_n and θ. It is hard to generate the random draws of h_t from (10). Therefore, the Metropolis-Hastings algorithm is utilized for random number generation of h_t. See, for example, Chib and Greenberg (1995) and Tierney (1994) for the Metropolis-Hastings algorithm. Also, see Jacquier, Polson and Rossi (1994) for Bayesian estimation of the stochastic volatility model. The Metropolis-Hastings algorithm requires the sampling density. Let $f_*(h_t)$ be the sampling density of h_t. We take the sampling density $f_*(h_t)$ as follows:

$$f_*(h_t) \propto \begin{cases} f_r^*(h_t) f_h(h_{t+1}|h_t) f_h(h_t|h_{t-1}), & \text{for } t = 1, 2, \cdots, n-1, \\ f_r^*(h_t) f_h(h_t|h_{t-1}), & \text{for } t = n, \end{cases}$$

where $f_r^*(h_t)$ denotes the normal distribution in which mean is the mode of $f_r(r_t|h_t)$, i.e., $\mu_t^* \equiv \log(r_t - z_t\alpha)^2$, and variance is the inverse of the information matrix of $f_r(r_t|h_t)$ evaluated at the mode, i.e., $\sigma_t^{*2} \equiv (\frac{1}{2}e^{-h_t}(r_t - z_t\alpha)^2)^{-1} = 2$ (note that $h_t = \log(r_t - z_t\alpha)^2$ is substituted into the information matrix). Thus, $f_*(h_t)$ results in the normal distribution with mean $\tau_t b_t$ and variance τ_t, where $(b_t, \tau_t^{-1}) = ((x_t\gamma + \delta h_{t-1})/\sigma^2 + (h_{t+1} - x_{t+1}\gamma)\delta/\sigma^2 + \mu_t^*/\sigma_t^{*2},\ 1/\sigma^2 + \delta^2/\sigma^2 + 1/\sigma_t^{*2})$ for $t = 1, 2, \cdots, n-1$ and $(b_t, \tau_t^{-1}) = ((x_t\gamma + \delta h_{t-1})/\sigma^2 + \mu_t^*/\sigma_t^{*2},\ 1/\sigma^2 + 1/\sigma_t^{*2})$ for $t = n$. Through the random draws from the sampling density, the random draws of h_t from the target density (10) are generated. Let $h_{t,i}$ be the ith random draw of h_t given R_n, δ_i be the ith random draw of δ given R_n, and σ_i be the ith random draw of σ given R_n. Let us denote $B_{t,i} = (h_{0,i}, h_{1,i}, \cdots, h_{t,i})$, $B_{t,i}^+ = (h_{t,i}, h_{t+1,i}, \cdots, h_{n,i})$ and $\theta_i = (\alpha_i', \gamma_i', \delta_i, \sigma_i)$. The random draw generation procedure is shown as follows.

(i) Take appropriate initial values of B_n and θ as $B_{n,-M}$ and θ_{-M}.

(ii) The Metropolis-Hastings algorithm is performed to generate random draws of h_t, $t = 1, 2, \cdots, n$, from (10), which is shown in (a) – (c).

  (a) Generate a random draw of h_t from the sampling density $f_*(h_t)$, denoted by h_t^*, and compute $\omega(h_{t,i-1}, h_t^*) = \min\Big(\dfrac{f_r(r_t|h_t^*)/f_*(h_t^*)}{f_r(r_t|h_{t,i-1})/f_*(h_{t,i-1})},\ 1\Big)$.

  (b) Set $h_{t,i} = h_t^*$ with probability $\omega(h_{t,i-1}, h_t^*)$ and $h_{t,i} = h_{t,i-1}$ otherwise.

  (c) Repeat Steps (a) and (b) for $t = 1, 2, \cdots, n$.

(iii) Generate $h_{0,i}$ from (11), $(\gamma_i', \delta_i)'$ from (12), α_i from (13), and σ_i from (14).

(iv) Repeat Steps (ii) and (iii) for $i = -M + 1, -M + 2, \cdots, N$.

Note that the order of Steps (ii) and (iii) does not matter. Implementing Steps (i) – (iv), $M + N$ random draws are generated for B_n and θ. Taking into account convergence of the Gibbs sampler, the first M random draws are discarded and the last N random draws are used for further analysis. $M = 10^5$ and $N = 10^6$ are taken in this paper. To see whether the last N random draws converge to the random draws generated from the target density, there are a lot of convergence diagnostic (CD) test statistics. The CD proposed by Geweke (1992) is utilized in this paper, which is discussed in Appendix C.

In this paper the nonlinear non-Gaussian state space modeling with the Markov chain Monte Carlo method is used for estimation, which is discussed in Geweke and Tanizaki (2001). Also, see Carlin, Polson and Stoffer (1992), Carter and Kohn (1994, 1996), Chib and Greenberg (1996), Geweke and Tanizaki (1999) and Tanizaki (2001, 2003, 2004) for state space modeling. The estimation procedure shown in this appendix, called the single-move sampler, is not very efficient and it is well known that convergence of the Gibbs sampler is very slow, because h_0, h_1, $\cdots$, h_n are highly correlated with each other. There are various more efficient procedures for precision of generated random draws, e.g., Watanabe and Omori (2004). However, they are quite complicated in computer programming and they are computationally intensive. Therefore, in this paper the simplest algorithm (but inefficient algorithm) is utilized with sufficiently large number of random draws (i.e., $M = 10^5$ and $N = 10^6$).

Appendix B: Surrogate for Marginal Likelihood

In order to compare Models 1 – 8 and A – C in Section 3, integrating out B_n and θ we usually consider deriving the density of R_n, denoted by $f_R(R_n)$, where R_n denotes all the observed data, i.e., $R_n = \{r_1, r_2, \cdots, r_n\}$. Because z_t and x_t are assumed to be nonstochastic, it is not in R_n. Newton and Raftery (1994), Chib (1995), Dey, Chang and Ray (1996) and Gelfand (1996) proposed computation of the marginal likelihood $f_R(R_n)$. Also, see Geisser and Eddy (1979), Gelfand and Dey (1994) and Omori (2001). However, in this paper $f_R(R_n)$ is diffuse because the prior densities of θ and h_0 are assumed to be diffuse. See (7) for the priors. Define $\Theta = (B_n, \theta)$ and $\Theta_i = (B_{i,n}, \theta_i)$. Therefore, we consider the model selection using the cross-validation predictive density, which is given by:

$$
\begin{aligned}
f(r_t|R_{t-1}, R^+_{t+1}) &= \frac{f_R(R_n)}{f_R(R_{t-1}, R^+_{t+1})} = \Big(\frac{f_R(R_{t-1}, R^+_{t+1})}{f_R(R_n)}\Big)^{-1} = \Big(\int \frac{f_R(R_{t-1}, R^+_{t+1}, \Theta)}{f_R(R_n)}\,\mathrm{d}\Theta\Big)^{-1} \\
&= \Big(\int \frac{f_R(R_{t-1}, R^+_{t+1}, \Theta)}{f_R(R_n, \Theta)} f(\Theta|R_n)\,\mathrm{d}\Theta\Big)^{-1} = \Big(\int \frac{1}{f_R(r_t|R_{t-1}, R^+_{t+1}, \Theta)} f(\Theta|R_n)\,\mathrm{d}\Theta\Big)^{-1} \\
&\approx \Big(\frac{1}{N}\sum_{i=1}^{N} \frac{1}{f_R(r_t|R_{t-1}, R^+_{t+1}, \Theta_i)}\Big)^{-1} = \Big(\frac{1}{N}\sum_{i=1}^{N} \frac{1}{f_r(r_t|h_{i,t})}\Big)^{-1}.
\end{aligned}
$$

which are based on the cross-validation predictive density. Note that we utilize $f_R(R_n) = f_R(R_n, \Theta)/f(\Theta|R_n)$ in the fourth equality and $f_R(r_t|R_{t-1}, R^+_{t+1}, \Theta_i) = f_r(r_t|h_{t,i})$ in the last equality. $f(r_t|R_{t-1}, R^+_{t+1})$ is a proper density while both $f_R(R_n)$ and $f_R(R_{t-1}, R^+_{t+1})$ are diffuse. $B_{n,i}$ and θ_i represent the ith random draws of B_n and θ given R_n.

Thus, in this paper we take the product of cross-validation predictive densities as the the surrogate for marginal likelihood $f_R(R_n)$. The product of cross-validation predictive densities is given by:

$$\prod_{t=1}^{n} f(r_t|R_{t-1}, R_{t+1}^{+}) \approx \prod_{t=1}^{n}\Big(\frac{1}{N}\sum_{i=1}^{N}\frac{1}{f_r(r_t|h_{i,t})}\Big)^{-1}$$

is called the surrogate for marginal likelihood $f_R(R_n)$. According to Besag (1975), $f_R(R_n)$ is equivalent to the set $\{f(r_t|R_{t-1}, R_{t+1}^{+}),\ t = 1, 2, \cdots, n\}$, in the sense that each uniquely determines the other. Hence, in terms of model assessment, examining the observed R_n with respect to $f_R(R_n)$ is the same as with respect to the set $f(r_t|R_{t-1}, R_{t+1}^{+})$. See Dey, Chang and Ray (1996). Geisser and Eddy (1979) showed that the surrogate for marginal likelihood is very useful for model selection even when the prior densities are improper. In this paper (especially in Table 2), accordingly, $\log f_R(R_n)$ should be read as $\sum_{t=1}^{n} \log f(r_t|R_{t-1}, R_{t+1}^{+})$.

Appendix C: AVE, STD, Skew and Kurt and CD

For a random variable X and its Gibbs sequence x_i, $i = 1, 2, \cdots, N$, under some regularity conditions it is known that we have the following property:

$$\frac{1}{N}\sum_{i=1}^{N} g(x_i) \longrightarrow \mathrm{E}(g(X)),$$

where $g(\cdot)$ is any continuous function, which is typically specified as $g(x) = x^m$, $m = 1, 2, 3, 4$. Then, $(1/N)\sum_{i=1}^{N} x_i^m$ is a consistent estimate of $\mathrm{E}(X^m)$, provided that variance of $(1/N)\sum_{i=1}^{N} x_i^m$ is finite, which comes from the law of large numbers. The random variable X takes B_n or θ in this paper. In Table 4, AVE, STD, Skew and Kurt are defined as $\overline{x} = (1/N)\sum_{i=1}^{N} x_i$, $s = ((1/N)\sum_{i=1}^{N}(x_i - \overline{x})^2)^{1/2}$, $(1/N)\sum_{i=1}^{N}(x_i - \overline{x})^3/s^{3/2}$ and $(1/N)\sum_{i=1}^{N}(x_i - \overline{x})^4/s^2$, which are consistent estimates of $\mu = \mathrm{E}(X)$, $\sigma = (\mathrm{E}(X-\mu)^2)^{1/2}$, $\mathrm{E}(X-\mu)^3/\sigma^{3/2}$ and $\mathrm{E}(X-\mu)^4/\sigma^2$ even in the case where x_1, x_2, $\cdots$, x_N are serially correlated. Note that AVE, STD, Skew and Kurt in Table 4 represent a shape of each posterior density. 0.005, 0.025, 0.975 and 0.995 are also given by 0.5%, 2.5%, 97.5% and 99.5% point values by sorting the N random draws in order of size for each element of θ.

To check convergence of the Gibbs sequence, Geweke (1992) proposed the convergence diagnostic test statistic, denoted by CD, and its asymptotic property as follows:

$$\mathrm{CD} = \frac{\overline{x}_a - \overline{x}_b}{\sqrt{s_a^2/N_a + s_b^2/N_b}} \longrightarrow N(0,1),$$

where $\overline{x}_a$ denotes the arithmetic average from the first N_a random draws out of x_1, x_2, $\cdots$, x_N, and $\overline{x}_b$ indicates the arithmetic average from the last N_b random draws, i.e.,

$$\overline{x}_a = \frac{1}{N_a}\sum_{i=1}^{N_a} x_i, \qquad \overline{x}_b = \frac{1}{N_b}\sum_{i=N-N_b+1}^{N} x_i.$$

$N - N_a - N_b$ random draws in the middle are not utilized for the diagnostic test. As for s_a^2 and s_b^2, because x_1, x_2, $\cdots$, x_N are serially correlated. variances of $\overline{x}_a$ and $\overline{x}_b$ are estimated as:

$$s_a^2 = \Gamma_a^{(0)} + 2\sum_{j=1}^{L}\Big(1+\frac{j}{L+1}\Big)\Gamma_a^{(j)}, \qquad s_b^2 = \Gamma_b^{(0)} + 2\sum_{j=1}^{L}\Big(1+\frac{j}{L+1}\Big)\Gamma_b^{(j)},$$

which are based on Newey and West (1987). The sample autocovariances $\Gamma_a^{(j)}$ and $\Gamma_b^{(j)}$ are given by $\Gamma_a^{(j)} = (1/N_a)\sum_{i=j+1}^{N_a}(x_i-\overline{x}_a)(x_{i-j}-\overline{x}_a)$ and $\Gamma_b^{(j)} = (1/N_b)\sum_{i=N-N_b+j+1}^{N}(x_i-\overline{x}_b)(x_{i-j}-\overline{x}_b)$, for $j = 0, 1, \cdots, L$. In this paper, $N_a = 0.1N = 10^5$, $N_b = 0.5N = 5\times 10^5$ and $L = 10^3$ are taken.

Appendix D: Overall Convergence Criterion

In each model of Table 4, CD represents the convergence diagnostic test based on each element of θ. The number of parameters included in (1) and (2) is given by $(n+1)+(k_1+k_2+2)$, i.e., the dimension of B_n is $n+1$ and that of θ is k_1+k_2+2. It is not easy to evaluate all the CDs at the same time. Therefore, in this appendix we consider the overall convergence diagnostic test for each model. The ith random draw of $\log f_R(R_n|\Theta)$ is given by $\log f_R(R_n|\Theta_i)$, where $\Theta = (B_n, \theta)$ and $\Theta_i = (B_{n,i}, \theta_i)$. As for the overall convergence diagnostic test, we consider checking convergence of $\log f_R(R_n|\Theta_i) \equiv \sum_{t=1}^{n} \log f_r(r_t|h_{i,t})$. In $\log f_R(R_n|\Theta_i)$ of Table 4, all the CDs are less than 2.576 in absolute value. Therefore, we can conclude that the Gibbs sequence $\{\log f_R(R_n|\Theta_i)\}_{i=1}^{N}$ converges at significance level 1%.

The acceptance probability at time t is given by $(1/N)\sum_{i=1}^{N} I_{(h_{t,i}\neq h_{t,i-1})}$, which corresponds to the probability such that the random draw is updated in Step (ii)(a) of Appendix A, where $I_{(\cdot)}$ is the indicator function which satisfies $I_{(A)} = 1$ if A is true and $I_{(A)} = 0$ otherwise. Thus, we can compute n acceptance probabilities for $t = 1$, 2, $\cdots$, n. The arithmetic average from the n acceptance probabilities is 0.934 in Table 4(a), 0.962 in Table 4(b) and 0.928 in Table 4(c). Especially, the minimum acceptance rates are given by 0.619 in Table 4(a), 0.685 in Table 4(b) and 0.423 in Table 4(c). which corresponds to Black Monday, i.e., a drastic drop in U.S. stock price. The outliers shown in Figures 1(b) – 3(b) result in relatively small acceptance probabilities. In practice, however, the acceptance probability 0.423 is not too low.

Thus, the CDs in Tables 4 and the acceptance rates show that the MCMC procedure taken in Models 1 – 8 and A – C works well without any problem.

Table 6: Day-of-the-Week Effect

			(a) Model 5C — Japan $(j, j', j'') = (1,2,3)$			(b) Model 5B — U.K. $(j, j', j'') = (2,1,3)$			(c) Model 5B — U.S. $(j, j', j'') = (3,1,2)$		
			AVE	0.025	0.975	AVE	0.025	0.975	AVE	0.025	0.975
$z_t^{(j)}$	1	$\alpha_1^{(j)}$	0.0756	0.0453	0.1059	0.0396	0.0202	0.0590	0.0520	0.0335	0.0705
	$\tilde{r}_t^{(j')}$	$\alpha_2^{(j)}$	−0.0240	−0.0503	0.0024	0.1291	0.1123	0.1459	0.0292	0.0137	0.0448
	$\tilde{r}_t^{(j'')}$	$\alpha_3^{(j)}$	0.1254	0.0972	0.1537	−0.0944	−0.1217	−0.0671	0.3631	0.3381	0.3882
	$r_{t-1}^{(j)}$	$\alpha_4^{(j)}$	0.2415	0.2145	0.2686	0.2161	0.1904	0.2418	−0.0808	−0.1065	−0.0551
	d_t^{90}	$\alpha_5^{(j)}$	−0.0719	−0.1169	−0.0270						
$x_t^{(j)}$	Mo_t	$\gamma_1^{(j)}$	0.0976	0.0147	0.1829	−0.0034	−0.0740	0.0674	0.0010	−0.0775	0.0793
	Tu_t	$\gamma_2^{(j)}$	−0.1145	−0.2201	−0.0091	−0.0941	−0.1931	0.0078	−0.0264	−0.1321	0.0805
	We_t	$\gamma_3^{(j)}$	0.0033	−0.1072	0.1139	0.0112	−0.0996	0.1210	−0.0607	−0.1717	0.0510
	Th_t	$\gamma_4^{(j)}$	0.0153	−0.0955	0.1276	0.0034	−0.1034	0.1139	−0.0070	−0.1146	0.0998
	Fr_t	$\gamma_5^{(j)}$	0.0137	−0.0917	0.1179	0.0499	−0.0524	0.1497	0.0284	−0.0717	0.1276
		$\delta^{(j)}$	0.9795	0.9717	0.9864	0.9848	0.9783	0.9902	0.9742	0.9630	0.9837
		$\sigma^{(j)}$	0.1995	0.1736	0.2285	0.1257	0.1143	0.1452	0.1768	0.1462	0.2107

Appendix E: Day-of-the-Week Effect

In this appendix, we focus on the day-of-the-week effect for each country, where z_t in Table 6 take the same variables as z_t in Tables 4(a) – 4(c), and the five dummies (Mo_t, Tu_t, We_t, Th_t and Fr_t) are included in x_t. Note that the convergence diagnostic (CD) test is passed for the three cases even though CD is not shown in Table 6. As a result, both Monday and Tuesday effects play an important role in Japanese stock price volatility (see Table 6(a)). The day-of-the-week effect is not important for U.K. and U.S. stock price volatilities (see Tables 6(b) and (c)).

In any case, the stock price volatility depends on at most Monday and Tuesday effects. Wednesday, Thursday and Friday dummies are not significant at all in Tables 6(a) – 6(c). It is not easy to distinguish Monday effect and holiday effect, because all the Mondays when the stock market is open have holiday effect, i.e., $H_t^{(j)} = 2$ for most of Mondays. Thus, inclusion of both Mo_t and $H_t^{(j)}$ in $x_t^{(j)}$ results in multicollinearity. Therefore, in Tables 4(a) – 4(c), Tu_t is incorporated.

References

Baele, L., (2003), "Volatility Spillover Effects in European Equity Markets," Working Paper No.2003-114, Tilburg University.

Besag, J., (1975), "Spatial Interaction and the Statistical Analysis of Lattice Systems," *Journal of the Royal Statistical Society, Ser. B*, **36**, 192-236.

Broto, C. and Ruiz, E., (2004), "Estimation Methods for Stochastic Volatility Models: A Survey," *Journal of Economic Survey*, **18**, 613-649.

Carlin, B.P., Polson, N.G. and Stoffer, D.S. (1992). "A Monte Carlo Approach to Nonnormal and Nonlinear State Space Modeling," *Journal of the American Statistical Association*, **87**, 493-500.

Carter, C.K. and Kohn, R. (1994). "On Gibbs Sampling for State Space Models," *Biometrika*, **81**, 541-553.

Carter, C.K. and Kohn, R. (1996). "Markov Chain Monte Carlo in Conditionally Gaussian State Space Models," *Biometrika*, **83**, 589-601.

Chib, S. (1995). "Marginal Likelihood from the Gibbs Output," *Journal of the American Statistical Association*, **90**, 1313-1321.

Chib, S. and Greenberg, E. (1995). "Understanding the Metropolis-Hastings Algorithm," *The American Statistician*, **49**, 327-335.

Chib, S. and Greenberg, E. (1996). "Markov Chain Monte Carlo Simulation Methods in Econometrics," *Econometric Theory*, **12**, 409-431.

Coutts, J.A. and Sheikh, M.A. (2002). "The Anomalies that Aren't There: The Weekend, January and Pre-Holiday Effects on the All Gold Index on the Johannesburg Stock Exchange 1987-1997," *Applied Financial Economics*, **12**, 863-871.

Danielsson, J. (1994). "Stochastic Volatility in Asset Prices Estimation with Simulated Maximum Likelihood," *Journal of Econometrics*, **64**, 375-400.

Dey, D.K., Chang, H. and Ray, S.C. (1996). "Bayesian Approach in Model Selection for the Binary Response Data," in Advances in Econometrics, Vol.11 (Part A): Bayesian Computational Methods and Applications, edited by Hill, R.C., 145-175, JAI Press.

Engle, R.F., Ito, T. and Lin, W.L. (1990), "Meteor Showers or Heat Waves? Heteroskedastic Intra-Daily Volatility in the Foreign Exchange Market," *Econometrica*, **58**, 525-542.

Fatemi, A.M. and Park, J. (1996). "Seasonal Patterns in Japanese ADR Returns and the US Stock Market Influence," *Japan and the World Economy*, **8**, 65-79.

Geisser, S. and Eddy, W.F. (1979). "A Predictive Approach to Model Selection," *Journal of the American Statistical Association*, **74**, 153-160.

Gelfand, A.E. (1996). "Model Determination Using Sampling-Based Methods," in *Markov Chain Monte Carlo in Practice*, edited by Gilks, W.R., Richardson, S. and Spiegelhalter, D.J., Chap.9, 145-161,

Gelfand, A.E. and Dey, D.K. (1994). "Bayesian Model Choice: Asymptotics and Exact Calculations," *Journal of the Royal Statistical Society. Ser.B*, **56**, 501-514.

Gelfand, A.E., Dey, D.K. and Chang, H. (1992). "Model Determination using Predictive Distributions with Implementation via Sampling-Based Methods," *Bayesian Statistics 4*, 147-167.

Geweke, J. (1992). "Evaluating the Accuracy of Sampling-based Approaches to the Calculation of Posterior Moments," in *Bayesian Statistics 4*, edited by Bernardo, J.M., Berger, J.O., Dawid, A.P. and Smith, A.F.M., 169-193, Oxford University Press.

Geweke, J. and Tanizaki, H. (1999). "On Markov Chain Monte-Carlo Methods for Nonlinear and Non-Gaussian State-Space Models," *Communications in Statistics, Simulation and Computation*, **28**, 867-894.

Geweke, J. and Tanizaki, H. (2001). "Bayesian Estimation of State-Space Model Using the Metropolis-Hastings Algorithm within Gibbs Sampling," *Computational Statistics and Data Analysis*, **37**, 151-170.

Glosten, L.R., Jagannathan, R. and Runkle, D.E. (1993). "On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks," *The Journal of Finance*, **48**, 1779-1801.

Hamao, Y., Masulis, R.W. and Ng, V. (1990). "Correlations in Price Changes and Volatility across International Stock Markets," *Review of Financial Studies*, **3**, 281-307.

Jacquier, E., Polson, N.G. and Rossi, P.E. (1994). "Bayesian Analysis of Stochastic Volatility Models," *Journal of Business and Economic Statistics*, **14**, 371-417 (with discussion).

Jacquier, E., Polson, N.G. and Rossi, P.E. (2004). "Bayesian Analysis of Stochastic Volatility Models with Fat-tails and Correlated Errors," *Journal of Econometrics*, **122**, 185-212.

Kanas, A. (1998), "Volatility Spillovers across Equity Markets: European Evidence," *Applied Financial Economics*, **8**, 245-256.

Koutmos, G. and Booth, G. (1995). "Asymmetric Volatility Transmission in International Stock Markets," *Journal of International Money and Finance*, **14**, 747-762.

Nelson, D.B. (1991). "Conditional Heteroskedasticity in Asset Returns: A New Approach," *Econometrica*, **59**, 347-370.

Newton, M.A. and Raftery, A.E. (1994). "Approximate Bayesian Inference with the Weighted Likelihood Bootstrap," *Journal of the Royal Statistical Society, Ser.B*, **56**, 3-48.

Ng, A. (2000), "Volatility Spillover Effects from Japan and the US to the Pacific-Basin," *Journal of International Money and Finance*, **19**, 207-233.

Omori, Y. (2001). "Recent Developments in Markov Chain Monte Carlo Method," *Journal of the Japan Statistical Society*, **31**, 305-344 (in Japanese).

Ramchand, L. and Susmel, R. (1998), "Volatility and Cross Correlation across Major Stock Markets," *Journal of Empirical Finance*, **5**, 397-416.

Ross, S.A. (1989), "Information and Volatility: The No-Arbitrage Martingale Approach to Timing and Resolution Irrelevancy," *Journal of Finance*, **44**, 1-17.

So, M.K.P., Li, W.K. and Lam K. (2002). "A Threshold Stochastic Volatility Model," *Journal of Forecasting*, **21**, 473-500.

Tanizaki, H. (2001), "Estimation of Unknown Parameters in Nonlinear and Non-Gaussian State Space Models," *Journal of Statistical Planning and Inference*, **96**, 301-323.

Tanizaki, H. (2003). "Nonlinear and Non-Gaussian State-Space Modeling with Monte Carlo Techniques: A Survey and Comparative Study," in *Handbook of Statistics, Vol.21 (Stochastic Processes: Theory and Applications)*, Chap.22, edited by Rao, C.R. and Shanbhag, D.N., 871-929, Elsevier Science.

Tanizaki, H. (2004). *Computational Methods in Statistics and Econometrics*, Mercel Dekker.

Tierney, L. (1994). "Markov Chains for Exploring Posterior Distributions," *The Annals of Statistics*, **22**, 1701-1762.

Watanabe, T. (1999). “A Non-linear Filtering Approach to Stochastic Volatility Models with an Application to Daily Stock Returns,” *Journal of Applied Econometrics*, **14**, 101-121.

Watanabe, T. (2000). “Excess Kurtosis of Conditional Distribution for Daily Stock Returns: The Case of Japan,” *Applied Economics Letters*, **7**, 353-355.

Watanabe, T. (2001). “Price Volatility, Trading Volume, and Market Depth: Evidence from the Japanese Stock Index Futures Market,” *Applied Financial Economics*, **11**, 651-658.

Watanabe, T. and Omori, Y. (2004). “A Multi-move Sampler for Estimating Non-Gaussian Time Series Models: Comments on Shephard & Pitt (1997),” *Biometrika*, **91**, 246-248.

Yu, J. (2002). “MCMC Methods for Estimating Stochastic Volatility Models with Leverage Effects: Comments on Jacquier, Polson and Rossi (2002),” Working Paper, Department of Economics, University of Auckland.