

# ON ASYMMETRY, HOLIDAY AND DAY-OF-THE-WEEK EFFECTS IN VOLATILITY OF DAILY STOCK RETURNS: THE CASE OF JAPAN

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In this paper, we investigate volatility in Japanese stock returns, using the state-space model. The daily data of Nikkei 225 stock average from January 4, 1985 to June 10, 2004 are utilized and the stochastic volatility model is assumed for the noise component. We examine whether there are asymmetry, holiday and day-of-the-week effects in volatility. Moreover, we see whether U.S. stock price change influences the volatility in Japanese stock price, which is called U.S. stock price change effect in this paper (note that this is the asymmetry effect caused by U.S. stock market). It is also examined whether we have volatility transmission from U.S. to Japan. As a result, we empirically find that the asymmetry, holiday, U.S. stock price volatility transmission and Tuesday effects strongly influence the volatility in Japanese stock returns. Moreover, it is shown that both volatility and level in Japanese stock returns depend on U.S. stock returns.

*Key words and phrases:* Asymmetry effect, daily stock returns, day-of-the-week effect, holiday effect, Nikkei 225 stock average, stochastic variance model, U.S. stock price change effect, volatility, volatility transmission.

## 1. Introduction

There is a great amount of literature on empirical studies using financial data. In this paper, we discuss volatility in Japanese stock market. In the past, empirical studies have been done from various aspects on volatility, i.e., asymmetry effect (Melino and Turnbull (1990), Danielsson (1994), Engle and Ng (1993), Glosten *et al.* (1993), Harvey and Shephard (1996), Henry (1998), Watanabe (1999), Wu (2001), Blair *et al.* (2002), Chen and Kuan (2002), McKenzie (2002), So *et al.* (2002), Jacquier *et al.* (2004) and Yu (2002)), holiday effect (for example, Nelson (1991) and Watanabe (1999)), day-of-the-week effect (for example, Fatemi and Park (1996), Watanabe (2001), Hudson *et al.* (2002) and Coutts and Sheikh (2002)) and so on. Moreover, Hamao *et al.* (1990) and Koutmos and Booth (1995) discussed volatility transmission between U.S. and Japan, where they empirically found that U.S. stock price volatility influences Japanese stock price volatility. We examine whether Japanese stock price volatility depends on U.S. stock price change level, which is called the U.S. stock price change effect in this paper, and U.S. stock price change volatility, called the U.S. stock price volatility transmission effect. Engle and Ng (1993) discussed news impact on volatility and Watanabe (2000a) showed that there is a positive correlation be-

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tween volatility and trading volume. Thus, there is a lot of research on this topic.

Most of the papers which deal with volatility are based on a class of generalized autoregressive conditional heteroscedasticity (GARCH) models. As for the stochastic volatility model, since Jacquier *et al.* (1994) showed Bayesian procedure, Danielsson (1994), Harvey and Shephard (1996), So *et al.* (2002) and Blair *et al.* (2002) discussed the asymmetry effect on volatility. There are many papers on asymmetry effect, using the stochastic volatility model. However, there are very few articles on holiday and day-of-the-week effects in a class of the stochastic volatility models. As long as I know, Watanabe (1999) is the only one paper which deals with both asymmetry and holiday effects in Japanese stock market, but length of holidays, day-of-the-week effect and influence of U.S. stock price change are not taken into account in Watanabe (1999). Especially, no one examines the asymmetry, holiday (including length of holidays), day-of-the-week, U.S. stock price change level and its volatility transmission effects simultaneously, using the stochastic volatility model and Japanese stock price data. There are numerous papers dealing with an estimation problem of the stochastic volatility model, but there are few empirical applications.

In this paper, the percent change of Nikkei 225 stock average is represented as a sum of the deterministic part and the noise component. We assume that the noise component follows the stochastic volatility model. As for variance in the noise component, this paper is an extension of Watanabe (1999) in the sense that we incorporate all the asymmetry, holiday, day-of-the-week, U.S. stock price change and its volatility transmission effects into the stochastic volatility model using Japanese stock price data. We empirically obtain the results that the volatility in Japanese stock price has the asymmetry, holiday, day-of-the-week and U.S. stock price volatility transmission effects with the structural change in 1990 and that the percent change in Japanese stock price also depends on the U.S. stock price change effect with the structural change in 1990, i.e., a drop in U.S. stock price level results in a drop in Japanese stock price with unstability and we observe volatility transmission from U.S. to Japan.

## 2. Data description

Figure 1(a) represents the daily movement of the Nikkei 225 stock average (closing price, Japanese yen) from January 4, 1985 to June 10, 2004, where the vertical and horizontal axes indicate Japanese yen and time, respectively. 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.

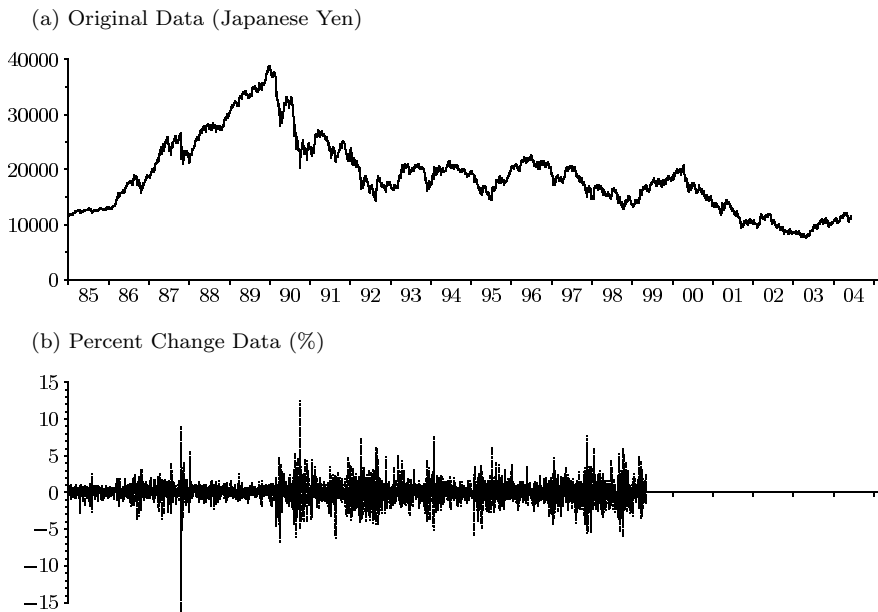


Figure 1. Nikkei stock average.

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 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 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 heteroscedastic. 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.

### 3. Setup of the model

In this section, the model is briefly described. The observed data  $y_t$  is denoted by:  $y_t = 100 \times \log(P_t/P_{t-1})$ , where  $P_t$  represents the Nikkei stock average displayed in Figure 1(a).  $y_t$ , which is shown in Figure 1(b), is approximately equal to the percent change of the Nikkei stock average. The daily data from January 4, 1985 to June 10, 2004 are utilized and the 100 times the log-differences from previous day are computed, i.e., the percent change data from January 5, 1985 to June 10, 2004 are available, where the sample size is given by  $n = 4914$ . To see the movement of the percent changes of the Nikkei stock average, we consider that the original data  $y_t$  is given by a sum of the deterministic component and the irregular component for each time  $t$ .

From Figure 1(b), we can see that there are a lot of outliers. This fact implies that the true distribution of the error term (i.e., irregular component) should be distributed more broadly than the normal distribution. In fact, the average, standard deviation, skewness and kurtosis obtained from the percent changes of the Nikkei stock average are computed as 0.0000, 1.4029,  $-0.1363$  and 10.3533, respectively, where the kurtosis is too large. Remember that skewness and kurtosis are 0 and 3 in the case of normal distributions. Moreover, 2.5, 5, 50, 95 and 97.5 percent points from the percent change data are given by  $-2.9277$ ,  $-2.2760$ , 0.0316, 2.1470 and 2.8660. Note that 2.5 percent point is  $-1.96 \times 1.4 = -2.744$  and 97.5 percent point is  $1.96 \times 1.4 = 2.744$  in the case of the normal distribution with mean zero and variance  $1.4^2$ . Thus, it is more appropriate for the irregular component to assume a non-Gaussian distribution with fat tails. Furthermore, we can observe in Figure 1(b) that the percent changes up to the end of 1989 seem to be distributed within a relatively small range (except for the periods around Black Monday), but the percent changes after 1990 are more broadly distributed. Thus, the percent change data of Japanese stock price are heteroscedastic. Taking into account the fat tails and heteroscedasticity, we assume that the percent change of Japanese stock price is specified as follows:

$$(3.1) \quad y_t = z_t \alpha + \exp\left(\frac{1}{2}\beta_t\right) \epsilon_t,$$

$$(3.2) \quad \beta_t = x_t \gamma + \delta \beta_{t-1} + v_t,$$

for  $t = 1, 2, \dots, n$ , where  $\epsilon_t \sim N(0, 1)$  and  $v_t \sim N(0, \sigma^2)$ .  $z_t$  denotes a  $1 \times k_1$  vector of exogenous variables, which are assumed to be nonstochastic, and  $\alpha$  represents a  $k_1 \times 1$  parameter vector.  $x_t$  indicates a  $1 \times k_2$  vector of exogenous variables, which are also assumed to be nonstochastic, and  $\gamma$  is a  $k_2 \times 1$  parameter

vector. We will discuss later on  $x_t$  and  $z_t$ .  $\exp((1/2)\beta_t)\epsilon_t$  indicates the irregular component, which is heteroscedastic.  $\exp((1/2)\beta_t)$  represents the volatility, which is assumed to be time-dependent and unobservable.  $\beta_t$  depends on the exogenous variables  $x_t$  as well as the lagged  $\beta_{t-1}$ . Thus,  $y_t$  is observed, while  $\beta_t$  is not observable. (3.1) is called the measurement equation, and (3.2) is referred to as the transition equation. Using the observed data  $y_t$ , we consider estimating unobservable component  $\beta_t$ .

Note that  $\exp((1/2)\beta_t)\epsilon_t$  with  $\beta_t = x_t\gamma + \delta\beta_{t-1} + v_t$  is non-Gaussian even if both  $\epsilon_t$  and  $v_t$  are Gaussian. However,  $\exp((1/2)\beta_t)\epsilon_t$  is conditionally Gaussian. Watanabe (2000b) has empirically shown that  $\epsilon_t$  is also non-Gaussian in the case of daily Japanese stock returns. However, for simplicity of discussion we assume in this paper that  $\epsilon_t$  is Gaussian. See Ghysels *et al.* (1996) and Taylor (1994) for the stochastic volatility model.

Under the above setup, we estimate  $B_n$  and  $\theta$ , where  $B_n = (\beta_0, \beta_1, \dots, \beta_n)$  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.

Depending on choice of  $x_t$  and  $z_t$ , we consider Models 1–12. In Models 1–10 we focus on volatility in the percent change of Japanese stock price, where  $k_1 = 0$  is taken. In Models 11 and 12, we assume that the percent change of Japanese stock price has the deterministic component as well as the irregular component, where  $z_t$  is taken into account.

**Model 1:**  $k_2 = 1$  and  $x_t = 1$  are taken, where  $\gamma$  reduces to a constant term. The constant term in (3.2) is related to the variance of the error term  $\exp((1/2)\beta_t)\epsilon_t$ . Model 1 is the simplest model of Models 1–12.

**Model 2 (Asymmetry Effect):** In Model 1, we have assumed that the error term  $\exp((1/2)\beta_t)\epsilon_t$  is symmetric in the sense that the volatility  $\exp((1/2)\beta_t)$  does not depend on a negative or positive sign of the percent change on the previous day. However, it is 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 *et al.* (1993)). This effect is known as the asymmetry effect in stock returns, or the leverage effect. In addition to Model 1, therefore, we examine in Model 2 how the sign of  $y_{t-1}$  affects the volatility.  $k_2 = 2$  and  $x_t = (1, d_t^-)$  are taken in Model 2.  $d_t^-$  represents the dummy variable, where  $d_t^- = 1$  if  $y_{t-1} < 0$  and  $d_t^- = 0$  otherwise. If the asymmetry effect is found, we have the result that the coefficient of  $d_t^-$  is significantly positive. In a lot of the past empirical research, the asymmetry effect is detected. Watanabe (1999) also discussed an asymmetry effect of the volatility. Jacquier *et al.* (2004) takes the asymmetry effect as a correlation between two errors  $\epsilon_t$  and  $v_t$ , and Yu (2002) pointed out a problem in such a specification. Also, see Danielsson (1994) and So *et al.* (2002) for the asymmetry effect.

**Model 3 (Holiday Effect):** In Model 3, we discuss whether the number

of nontrading days affects the volatility. Nelson (1991) and Watanabe (2000a) have shown that there is a positive correlation between return volatility and trading volume. When we have much information in the market, the stock return becomes volatile. The volatility depends on the amount of information, which is roughly equivalent to the number of nontrading days between time  $t - 1$  and time  $t$ . Thus, in Model 3 we consider that the length of the period between trading days  $t$  and  $t - 1$  might be equivalent to the trading volume. 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  $DT_t$ ) should be positively correlated with the volatility of  $y_t$ . This is known as the holiday effect. See Nelson (1991) for the holiday effect. Model 3 is specified as:  $k_2 = 2$  and  $x_t = (1, DT_t)$ .  $DT_t$  indicates the number of nontrading days between time  $t$  and time  $t - 1$ . That is, when time  $t - 1$  is Friday we usually have  $DT_t = 2$ , because the market is closed for two days (Saturday and Sunday). If Monday is a national holiday, we obtain  $DT_t = 3$ , where time  $t - 1$  is Friday and time  $t$  is Tuesday. Thus,  $DT_t$  represents a proxy variable of the trading volume or the amount of information. Watanabe (1999) examined the holiday effect in Japanese stock market, where the length of holiday is not discussed.

**Model 4 (U.S. Stock Price Change Effect):** In Model 4, it is examined whether the volatility in the Japanese stock returns depends on either negative or positive sign of the U.S. stock price change. Model 4 is specified as:  $k_2 = 2$  and  $x_t = (1, d_t^{\text{US}})$ .  $d_t^{\text{US}}$  is taken as  $d_t^{\text{US}} = 1$  if the most recent percent change data of U.S. stock price (S&P 500 Index, closing price) available at time  $t$ , which is denoted by  $y_t^{\text{US}}$  in Model 4, is negative and  $d_t^{\text{US}} = 0$  otherwise. In almost all the cases,  $d_t^{\text{US}} = 1$  implies that U.S. stock price at time  $t - 1$  is smaller than U.S. stock price at time  $t - 2$ . However, when time  $t - 1$  is a holiday in U.S.,  $d_t^{\text{US}} = 1$  indicates that U.S. stock price change from time  $t - 2$  to time  $t - 3$  is negative. Thus,  $d_t^{\text{US}}$  also represents the asymmetry effect, but it is caused by the U.S. stock price change (note that  $d_t^-$  indicates the asymmetry effect caused by Japanese stock price change at the previous day). In this paper this effect is called the U.S. stock price change effect to distinguish  $d_t^{\text{US}}$  from  $d_t^-$ . If the coefficient of  $d_t^{\text{US}}$  is negative, i.e., if a drop in U.S. stock price leads to an increase in the volatility of Japanese stock price, we might conclude that Japanese stock prices become unstable if U.S. economy falls down (this result is empirically shown in Koutmos and Booth (1995)).

**Model 5 (U.S. Stock Price Volatility Transmission Effect):** In Model 5, it is examined whether the volatility in the Japanese stock returns depends on the volatility in the U.S. stock returns. Model 5 is specified as:  $k_2 = 2$  and  $x_t = (1, |y_t^{\text{US}}|)$ .  $y_t^{\text{US}}$  denotes the most recent percent change data of U.S. stock price (S&P 500 Index, closing price) available at time  $t$  (note that  $y_t^{\text{US}}$  is utilized to obtain  $d_t^{\text{US}}$  in Model 4). The absolute value of  $y_t^{\text{US}}$  is taken as a proxy variable of U.S. stock price volatility. Hamao *et al.* (1990) and Koutmos and Booth (1995) showed that there is an asymmetric volatility transmission between Japanese and U.S. stock prices.

**Model 6 (Asymmetry, Holiday, U.S. Stock Price Change, and U.S. Stock Price Volatility Transmission Effects):** In this model, Models 2–5 are combined. That is, asymmetry, holiday, U.S. stock price change and its volatility transmission effects are explicitly included in Model 6. The model is specified as:  $k_2 = 5$  and  $x_t = (1, d_t^-, DT_t, d_t^{\text{US}}, |y_t^{\text{US}}|)$ .

**Model 7 (Day-of-the-Week Effect):** Fatemi and Park (1996), Coutts and Sheikh (2002) and Watanabe (2001) discussed the day-of-the-week effect in the daily stock returns.  $k_2 = 5$  and  $x_t = (d_t^{\text{Mo}}, d_t^{\text{Tu}}, d_t^{\text{We}}, d_t^{\text{Th}}, d_t^{\text{Fr}})$  are taken in this model.  $d_t^{\text{Mo}}$  denotes the Monday dummy, which implies that  $d_t^{\text{Mo}} = 1$  when time  $t$  is Monday and  $d_t^{\text{Mo}} = 0$  otherwise.  $d_t^{\text{Tu}}, d_t^{\text{We}}, d_t^{\text{Th}}$  and  $d_t^{\text{Fr}}$  represent Tuesday, Wednesday, Thursday and Friday dummies, respectively. It might be expected that the coefficient of the Monday dummy  $d_t^{\text{Mo}}$  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.S. stock market on Monday. Note that U.S. stock market is open between Monday and Tuesday (i.e., on Monday night) in Japanese time zone.

**Model 8 (Asymmetry, Holiday, U.S. Stock Price Change, U.S. Stock Price Volatility Transmission and Tuesday Effects):** It is difficult to distinguish the holiday effect and the Monday effect, because in most of the cases we have  $DT_t = 2$  on Monday. It might be easily expected that  $DT_t$  is highly correlated with  $d_t^{\text{Mo}}$ . That is, inclusion of both the holiday effect and the Monday effect causes multicollinearity. According to the estimation results shown in the next section (see Model 7 in Table 2), clearly we have the Tuesday effect. In this model, therefore, the Tuesday effect is taken into account in addition to the asymmetry, holiday, U.S. stock price change and its volatility transmission effects. Therefore,  $k_2 = 6$  and  $x_t = (1, d_t^-, DT_t, d_t^{\text{US}}, |y_t^{\text{US}}|, d_t^{\text{Tu}})$  are taken in Model 8.

**Model 9 (Asymmetry, Holiday, U.S. Stock Price Volatility Transmission and Tuesday Effects with Structural Change in Holiday Effect):** 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.  $k_2 = 6$  and  $x_t = (1, d_t^-, DT_t, |y_t^{\text{US}}|, d_t^{\text{Tu}}, DT_t d_t^{90})$  are taken in Model 8, where  $d_t^{90}$  denotes the dummy variable which is given by  $d_t^{90} = 1$  in the periods after the beginning of 1990 and  $d_t^{90} = 0$  otherwise. According to the estimation results shown in the next section (see Models 6 and 8 in Table 2), the coefficient of  $d_t^{\text{US}}$  is not significant and therefore in Models 9–12 we exclude  $d_t^{\text{US}}$ .

**Model 10 (Asymmetry, Holiday, U.S. Stock Price Volatility Transmission and Tuesday Effects with Structural Change in Constant Term):** We examine that there is a structural change between 1989 and 1990 with respect to the constant term. This model considers that the structural change occurs because of the sudden shift of the constant term, rather than the shift of the holiday effect. Therefore,  $k_2 = 6$  and  $x_t = (1, d_t^-, DT_t, |y_t^{\text{US}}|, d_t^{\text{Tu}}, d_t^{90})$  are taken

in Model 10.

**Model 11 (AR(1) and U.S. Stock Price Change in Deterministic Component):** In Models 6 and 8, we consider whether U.S. stock price change yesterday and Japanese stock price change yesterday affect Japanese stock price volatility today. In Model 11, we consider whether Japanese stock returns at time  $t$  depend on both Japanese stock returns at time  $t - 1$  and U.S. stock returns available at time  $t$ . Therefore,  $k_1 = 3$  and  $z_t = (1, y_{t-1}, y_t^{\text{US}})$  is taken in Model 11.  $x_t$  is given by Model 10, i.e.,  $k_2 = 6$  and  $x_t = (1, d_t^-, DT_t, |y_t^{\text{US}}|, d_t^{\text{TU}}, d_t^{90})$ . If the change in U.S. stock price is negative and the change in Japanese stock price is also negative, i.e., if the coefficient of  $y_t^{\text{US}}$  is negative, a recession in U.S. economy leads to a recession in Japanese economy.

**Model 12 (AR(1), U.S. Stock Price Change and Structural Change in Deterministic Component):** In Model 12, taking into account the structural change in 1990, we examine whether U.S. stock price returns affect Japanese stock returns in level. We take  $k_1 = 4$  and  $z_t = (1, y_{t-1}, y_t^{\text{US}}, d_t^{90})$  in Model 12.  $x_t$  is given by Model 10, i.e.,  $k_2 = 6$  and  $x_t = (1, d_t^-, DT_t, |y_t^{\text{US}}|, d_t^{\text{TU}}, d_t^{90})$ .

#### 4. Results and discussion

In Models 1–10, we consider the cases of  $k_1 = 0$ , where the stock returns are represented only by the noise component which follows the stochastic volatility given by (3.2). In Models 11 and 12, the deterministic component is incorporated with Model 10. For Models 1–12, the log-likelihood functions are computed in Table 1. For Models 6–12, the coefficient estimates are shown in Table 2. For Models 1, 10 and 12, the movements of volatility estimates are displayed in Figure 2.

##### 4.1. Results in Table 1

In Table 1,  $\log f_Y(Y_n)$  indicates the marginal log-likelihood function of  $Y_n = \{y_1, y_2, \dots, y_n\}$ , which is utilized for model comparison.  $k_1$  is the number of elements in  $z_t$  and  $k_2$  denotes the number of elements in  $x_t$ . The marginal density of  $Y_n$ ,  $f_Y(Y_n)$ , is obtained by integrating out the joint density of  $Y_n$ ,  $B_n$  and  $\theta$  with respect to  $B_n$  and  $\theta$ . See Appendix B for computation of the marginal likelihood  $f_Y(Y_n)$ .

The marginal log-likelihood function  $\log f_Y(Y_n)$  is given by  $-7575.5$  in Model 1 and  $-7546.0$  in Model 2. Since Model 2 is much larger than Model 1, the former is preferred to the latter. Thus, the asymmetry effect is detected. Similarly, we can see the holiday effect from Models 1 and 3, the U.S. stock price change

Table 1. Marginal log-likelihood function  $\log f_Y(Y_n)$  for Models 1–12.

Model	$\log f_Y(Y_n)$	$k_1$	$k_2$	Model	$\log f_Y(Y_n)$	$k_1$	$k_2$	Model	$\log f_Y(Y_n)$	$k_1$	$k_2$
1	-7575.5	0	1	5	-7564.7	0	2	9	-7507.7	0	6
2	-7546.0	0	2	6	-7521.7	0	5	10	-7504.0	0	6
3	-7556.1	0	2	7	-7573.0	0	5	11	-7309.3	3	6
4	-7572.8	0	2	8	-7515.3	0	6	12	-7297.9	4	6



effect from Models 1 and 4, the U.S. stock price volatility transmission effect from Models 1 and 5, and the day-of-the-week effect from Models 1 and 6. Comparing Models 6 and 8, the Tuesday effect plays an important part in Japanese stock market. Moreover, from Models 8 and 9, it is shown that we have a structural change in the holiday effect, which is consistent with Watanabe (2001). From Models 8 and 10, we can observe that we have a structural change in the constant term, too. Comparing Models 9 and 10, Model 10 is better than Model 9. Actually I have estimated the model such that  $d_t^{90}$ , in addition to Model 9, is included in  $x_t$ , which is not reported in the table. The obtained results are: a lot of coefficient estimates are not significant and accordingly it is not plausible to include both  $d_t^{90}$  and  $DT_t d_t^{90}$  in  $x_t$ .

Comparing Models 1–10, Model 10 should be selected from the  $\log f_Y(Y_n)$  criterion. We can conclude that the volatility in Japanese stock price has asymmetry, holiday, day-of-the-week (especially, Tuesday) and U.S. stock price volatility transmission effects with structural change in the constant term. In particular, an increase in the volatility after 1990 is not due to the structural change in the holiday effect. It might be appropriate to consider that the other exogenous shock caused the structural change in the volatility after 1990.

Furthermore, taking into account the deterministic component included in Japanese stock returns, Models 11 and 12 are estimated. Both Models 11 and 12 have the same volatility specification as Model 10. Model 11 takes much larger marginal log-likelihood function than Model 10, which implies that both U.S. stock returns and Japanese stock returns yesterday influence Japanese stock returns today. However, from the estimation results shown in Model 12 of Table 2, Japanese stock change yesterday is not significant and accordingly U.S. stock change is an important factor to explain Japanese stock change today, although these results are not observed from Table 1. Comparing Models 10 and 12, it is shown that Japanese stock price change as well as its volatility has structural change in 1990, because the marginal log-likelihood of Model 12 is larger than that of Model 10. From Models 11 and 12, since Model 12 is much larger than Model 11 in the marginal log-likelihood, Model 12 is better than Model 11. As a result, Model 12 is the best model, comparing Models 1–12. That is, from Table 1, it is shown that (i) the volatility in Japanese stock returns is explained by asymmetry, holiday, day-of-the-week and U.S. stock price volatility transmission effects with the structural change in the constant term, and (ii) Japanese stock price change depends on U.S. stock price change together with the structural change in 1990.

#### 4.2. Results in Table 2

In Table 2, AVE, STD, Skewness and Kurtosis represent the arithmetic average, standard deviation, skewness and kurtosis, which represent the features of the posterior density of  $\theta$ . Judging from Skewness and Kurtosis, almost all the posterior distributions are very similar to normal distributions. The posterior density of  $\delta$  is skewed to the left, which is a well known fact in the case of AR(1) coefficient estimate (see, for example, Tanizaki (2004)), and the posterior

Table 2. Estimation results in Models 6–12.

$\theta$	$\gamma_1$	$\gamma_2$	$\gamma_3$	$\gamma_4$	$\gamma_5$	$\gamma_6$	$\delta$	$\sigma$
<b>Model 6</b> ( $\log f_Y(Y_n) = -7521.7$ )								
$x_t$	1	$d_t^-$	$DT_t$	$d_t^{\text{US}}$	$ y_t^{\text{US}} $	$\beta_{t-1}$		
AVE	-0.1811	0.1892	0.1153	0.0331	0.0410	0.9582	0.2093	
STD	0.0169	0.0218	0.0173	0.0213	0.0078	0.0042	0.0147	
Skewness	-0.074	0.052	0.065	-0.008	0.097	-0.236	0.158	
Kurtosis	3.031	3.006	2.983	3.018	3.034	3.120	3.102	
0.005	-0.2260	0.1340	0.0722	-0.0224	0.0215	0.9463	0.1735	
0.025	-0.2148	0.1471	0.0820	-0.0088	0.0260	0.9495	0.1816	
0.050	-0.2093	0.1538	0.0871	-0.0020	0.0284	0.9510	0.1858	
0.500	-0.1809	0.1890	0.1151	0.0331	0.0409	0.9584	0.2090	
0.950	-0.1536	0.2254	0.1440	0.0681	0.0540	0.9650	0.2340	
0.975	-0.1484	0.2325	0.1498	0.0748	0.0567	0.9661	0.2392	
0.995	-0.1386	0.2463	0.1608	0.0880	0.0619	0.9682	0.2499	
CD	0.0404	-0.3139	0.4089	0.2882	-0.7101	0.4009	-0.4232	
<b>Model 7</b> ( $\log f_Y(Y_n) = -7573.0$ )								
$x_t$	$d_t^{\text{Mo}}$	$d_t^{\text{Tu}}$	$d_t^{\text{We}}$	$d_t^{\text{Th}}$	$d_t^{\text{Fr}}$	$\beta_{t-1}$		
AVE	0.1956	-0.1645	0.0438	-0.0527	0.0121	0.9811	0.1886	
STD	0.0390	0.0419	0.0429	0.0427	0.0410	0.0026	0.0140	
Skewness	0.002	0.022	0.035	0.016	0.007	-0.354	0.178	
Kurtosis	2.996	3.006	3.039	3.029	2.983	3.186	3.103	
0.005	0.0959	-0.2715	-0.0663	-0.1624	-0.0936	0.9735	0.1547	
0.025	0.1190	-0.2460	-0.0397	-0.1360	-0.0683	0.9756	0.1622	
0.050	0.1310	-0.2329	-0.0263	-0.1229	-0.0555	0.9766	0.1661	
0.500	0.1956	-0.1647	0.0434	-0.0528	0.0119	0.9812	0.1883	
0.950	0.2596	-0.0952	0.1148	0.0178	0.0798	0.9851	0.2122	
0.975	0.2717	-0.0815	0.1283	0.0314	0.0927	0.9857	0.2173	
0.995	0.2962	-0.0555	0.1555	0.0585	0.1176	0.9868	0.2277	
CD	-0.1168	0.3245	-2.0703	-0.0003	2.1992	0.6629	-0.5142	
<b>Model 8</b> ( $\log f_Y(Y_n) = -7515.3$ )								
$x_t$	1	$d_t^-$	$DT_t$	$d_t^{\text{US}}$	$ y_t^{\text{US}} $	$d_t^{\text{Tu}}$	$\beta_{t-1}$	
AVE	-0.1516	0.1910	0.1198	0.0345	0.0401	-0.1661	0.9591	0.2072
STD	0.0193	0.0216	0.0170	0.0211	0.0078	0.0523	0.0043	0.0147
Skewness	-0.073	0.051	0.073	0.016	0.124	-0.027	-0.278	0.223
Kurtosis	3.059	3.002	3.010	3.040	3.056	3.064	3.154	3.144
0.005	-0.2030	0.1364	0.0768	-0.0199	0.0208	-0.3037	0.9470	0.1722
0.025	-0.1903	0.1491	0.0869	-0.0068	0.0252	-0.2698	0.9502	0.1798
0.050	-0.1838	0.1558	0.0922	-0.0001	0.0275	-0.2526	0.9518	0.1839
0.500	-0.1514	0.1908	0.1195	0.0345	0.0399	-0.1658	0.9593	0.2067
0.950	-0.1203	0.2270	0.1483	0.0694	0.0532	-0.0808	0.9657	0.2323
0.975	-0.1142	0.2340	0.1538	0.0763	0.0559	-0.0640	0.9669	0.2377
0.995	-0.1027	0.2477	0.1646	0.0897	0.0613	-0.0314	0.9690	0.2487
CD	-0.5382	0.6441	1.6903	1.1261	0.6639	-1.8770	-1.1708	0.9682

Table 2. (Continued.)

$\theta$	$\gamma_1$	$\gamma_2$	$\gamma_3$	$\gamma_4$	$\gamma_5$	$\gamma_6$	$\delta$	$\sigma$
<b>Model 9</b> ( $\log f_Y(Y_n) = -7507.7$ )								
$x_t$	1	$d_t^-$	$DT_t$	$ y_t^{\text{US}} $	$d_t^{\text{Tu}}$	$DT_t d_t^{90}$	$\beta_{t-1}$	
AVE	-0.1399	0.1967	0.0074	0.0606	-0.2055	0.1374	0.9373	0.2278
STD	0.0190	0.0223	0.0249	0.0093	0.0532	0.0249	0.0070	0.0168
Skewness	-0.087	0.047	-0.036	0.149	-0.020	0.191	-0.258	0.233
Kurtosis	3.082	3.007	2.987	3.048	3.031	3.047	3.111	3.156
0.005	-0.1911	0.1402	-0.0576	0.0379	-0.3445	0.0780	0.9176	0.1879
0.025	-0.1781	0.1535	-0.0419	0.0430	-0.3103	0.0908	0.9228	0.1965
0.050	-0.1716	0.1603	-0.0339	0.0457	-0.2932	0.0979	0.9253	0.2011
0.500	-0.1396	0.1965	0.0075	0.0604	-0.2053	0.1366	0.9376	0.2273
0.950	-0.1091	0.2337	0.0481	0.0764	-0.1186	0.1796	0.9483	0.2566
0.975	-0.1032	0.2410	0.0558	0.0796	-0.1017	0.1882	0.9502	0.2629
0.995	-0.0918	0.2552	0.0706	0.0860	-0.0688	0.2057	0.9535	0.2752
CD	-0.3127	0.6579	1.9262	0.3750	-1.3710	-0.4285	-0.3066	0.5604
<b>Model 10</b> ( $\log f_Y(Y_n) = -7504.0$ )								
$x_t$	1	$d_t^-$	$DT_t$	$ y_t^{\text{US}} $	$d_t^{\text{Tu}}$	$d_t^{90}$	$\beta_{t-1}$	
AVE	-0.1849	0.1971	0.1039	0.0666	-0.2215	0.0691	0.9298	0.2369
STD	0.0231	0.0228	0.0182	0.0103	0.0535	0.0117	0.0085	0.0182
Skewness	-0.168	0.050	0.060	0.182	-0.018	0.388	-0.350	0.251
Kurtosis	3.149	3.007	3.024	3.109	3.042	3.346	3.293	3.183
0.005	-0.2489	0.1396	0.0578	0.0415	-0.3615	0.0429	0.9049	0.1939
0.025	-0.2324	0.1530	0.0687	0.0471	-0.3269	0.0482	0.9117	0.2030
0.050	-0.2239	0.1600	0.0744	0.0501	-0.3098	0.0511	0.9151	0.2080
0.500	-0.1843	0.1969	0.1037	0.0662	-0.2213	0.0684	0.9303	0.2362
0.950	-0.1479	0.2350	0.1343	0.0840	-0.1342	0.0895	0.9431	0.2680
0.975	-0.1412	0.2424	0.1401	0.0877	-0.1174	0.0941	0.9453	0.2748
0.995	-0.1279	0.2570	0.1514	0.0952	-0.0837	0.1038	0.9492	0.2888
CD	-0.8076	0.8293	1.5113	1.0906	-1.2700	0.8411	-1.0047	1.0220

densities of  $\sigma$  and the coefficients of  $|y_t^{\text{US}}|$  and  $d_t^{90}$  are skewed to the right. 0.005, 0.025, 0.050, 0.500, 0.950, 0.975 and 0.995 denote 0.5%, 2.5%, 5%, 50%, 95%, 97.5% and 99.5% values. CD shows the convergence diagnostic test statistic, which is compared with the standard normal distribution. If CD is less than 1.96 in absolute value, we can judge that MCMC works well at significance level 5%. We can see from Table 2 that MCMC works well for all the Models 6–12. See Appendix C for computation on AVE, STD, Skewness, Kurtosis, 0.005, 0.025, 0.050, 0.500, 0.950, 0.975, 0.995 and CD. The CD's in Table 2 are related to the convergence diagnostic tests for individual coefficient estimates. Furthermore, we discuss the criterion on overall convergence in Appendix D, where it is shown that all the Gibbs sequences in Models 1–12 converge.

Model 1 is a basic model, and it is modified to obtain more realistic models, i.e., Models 2–12. Some modifications are given by incorporating the following

Table 2. (Continued.)

$\theta$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\gamma_1$	$\gamma_2$	$\gamma_3$	$\gamma_4$	$\gamma_5$	$\gamma_6$	$\delta$	$\sigma$
<b>Model 11</b> ( $\log f_Y(Y_n) = -7309.3$ )												
$(z_t, x_t)$	1	$y_{t-1}$	$y_t^{US}$	1	$d_t^-$	$DT_t$	$ y_t^{US} $	$d_t^{Tu}$	$d_t^{g0}$	$\beta_{t-1}$		
AVE	0.0319	0.0016	0.2887	-0.1690	0.1708	0.1052	0.0477	-0.1681	0.0601	0.9371	0.2354	
STD	0.0129	0.0145	0.0151	0.0217	0.0227	0.0183	0.0090	0.0534	0.0107	0.0077	0.0184	
Skewness	-0.007	-0.001	0.006	-0.136	0.056	0.066	0.181	0.028	0.362	-0.337	0.171	
Kurtosis	3.001	3.001	2.999	3.009	3.053	3.024	3.092	3.010	3.233	3.176	2.995	
0.005	-0.0014	-0.0357	0.2499	-0.2274	0.1130	0.0589	0.0260	-0.3047	0.0362	0.9149	0.1908	
0.025	0.0066	-0.0268	0.2591	-0.2131	0.1269	0.0699	0.0309	-0.2721	0.0410	0.9208	0.2008	
0.050	0.0107	-0.0222	0.2639	-0.2057	0.1340	0.0755	0.0335	-0.2556	0.0437	0.9238	0.2061	
0.500	0.0319	0.0016	0.2887	-0.1685	0.1706	0.1050	0.0474	-0.1684	0.0595	0.9375	0.2348	
0.950	0.0531	0.0254	0.3136	-0.1341	0.2085	0.1357	0.0629	-0.0795	0.0786	0.9490	0.2667	
0.975	0.0571	0.0299	0.3184	-0.1277	0.2160	0.1419	0.0660	-0.0623	0.0828	0.9509	0.2731	
0.995	0.0651	0.0388	0.3277	-0.1160	0.2308	0.1537	0.0725	-0.0301	0.0915	0.9545	0.2855	
CD	0.0085	-0.5242	0.1640	0.9268	-0.5032	-1.2721	-0.2243	-0.3230	-0.5200	0.7558	-0.8461	
<b>Model 12</b> ( $\log f_Y(Y_n) = -7297.9$ )												
$(z_t, x_t)$	1	$y_{t-1}$	$y_t^{US}$	$d_t^{g0}$	1	$d_t^-$	$DT_t$	$ y_t^{US} $	$d_t^{Tu}$	$d_t^{g0}$	$\beta_{t-1}$	
AVE	0.0861	-0.0019	0.2860	-0.1361	-0.1813	0.1851	0.1095	0.0502	-0.1708	0.0626	0.9344	0.2425
STD	0.0163	0.0144	0.0150	0.0256	0.0224	0.0233	0.0186	0.0091	0.0540	0.0110	0.0079	0.0188
Skewness	-0.004	0.004	0.010	0.001	-0.134	0.038	0.053	0.169	-0.014	0.393	-0.344	0.209
Kurtosis	2.997	3.003	3.000	2.991	3.060	3.020	2.970	3.072	2.965	3.321	3.216	3.081
0.005	0.0441	-0.0391	0.2473	-0.2021	-0.2419	0.1261	0.0628	0.0281	-0.3104	0.0379	0.9113	0.1976
0.025	0.0541	-0.0302	0.2567	-0.1863	-0.2266	0.1398	0.0735	0.0330	-0.2771	0.0430	0.9176	0.2074
0.050	0.0593	-0.0256	0.2613	-0.1783	-0.2190	0.1471	0.0791	0.0356	-0.2599	0.0457	0.9206	0.2127
0.500	0.0861	-0.0019	0.2860	-0.1361	-0.1807	0.1850	0.1093	0.0500	-0.1706	0.0619	0.9348	0.2418
0.950	0.1130	0.0219	0.3108	-0.0940	-0.1453	0.2235	0.1404	0.0657	-0.0820	0.0818	0.9467	0.2745
0.975	0.1181	0.0265	0.3156	-0.0859	-0.1387	0.2311	0.1465	0.0688	-0.0655	0.0861	0.9487	0.2813
0.995	0.1279	0.0354	0.3249	-0.0701	-0.1259	0.2461	0.1580	0.0753	-0.0336	0.0953	0.9523	0.2946
CD	0.6097	0.4339	-0.0676	0.6704	-0.3030	0.2323	1.2697	-0.2728	0.0001	-0.2141	-0.0452	0.0088

effects: (i) asymmetry effect, (ii) holiday effect, (iii) U.S. stock price change effect, (iv) U.S. stock price volatility transmission effect, (v) day-of-the-week effect, and (vi) structural change, which affect Japanese stock price volatility, and (vii) inclusion of the deterministic component in the stock returns. The feature in each model is as follows: (i) is given by Model 2, (ii) corresponds to Model 3, (iii) is Model 4, (iv) is Model 5, and (v) is equivalent to Model 7. Model 6 includes (i)–(iv), and Model 8 has (i)–(v). Models 9 and 10 are characterized by (i)–(vi). Model 9 has (vi) with respect to (ii), while Model 10 has (vi) in the constant term. Models 11 and 12 have all of (i)–(vii).

The asymmetry, holiday, U.S. stock price change and its volatility transmission effects are simultaneously incorporated in Model 6. The results are shown in Table 2. The coefficient of  $d_t^-$  represents the asymmetry effect in the volatility, that of  $DT_t$  indicates the holiday effect, that of  $d_t^{US}$  shows the U.S. stock price change effect, and that of  $|y_t^{US}|$  denotes the U.S. stock price volatility transmission effect. It is shown from Table 2 that the coefficients of  $d_t^-$ ,  $DT_t$  and  $|y_t^{US}|$  are statistically non-zero but the coefficient of  $d_t^{US}$  is not significant. The coefficient estimate of  $d_t^-$  is 0.1892 and it is significantly positive, because the percent points are given by 0.1340 for 0.005 (0.5% point) and 0.2463 for 0.995 (99.5% point). This implies that the negative stock price change yesterday becomes unstable in the stock price today. This result is consistent with the past research, e.g., Nelson (1991), Glosten *et al.* (1993) and Watanabe (1999). The coefficient estimate of  $DT_t$  is 0.1153 and it is significantly positive, judging from the percent points, i.e., 0.0722 for 0.005 (0.5% point) and 0.1608 for 0.995 (99.5% point). Thus, the holiday effect is detected in Japanese stock price volatility, which is also supported by Watanabe (1999). Furthermore, the estimate in  $d_t^{US}$  is 0.0331 and it is not significant, because the 95% interval is between  $-0.0088$  and  $0.0748$ . The estimate in  $d_t^{US}$  is smaller than that in  $d_t^-$ , because it might be natural to consider that the asymmetry effect from Japanese stock market has a larger impact than that from U.S. stock market. The coefficient estimate of  $|y_t^{US}|$  is given by 0.0410, which is significantly greater than zero because the 99% interval is between 0.0215 and 0.0619. Therefore, the size in U.S. stock price change (i.e., U.S. stock price volatility) affects Japanese stock price volatility. Thus, it has been shown from Table 2 that the asymmetry effect (or the leverage effect), the number of nontrading days and the U.S. stock price volatility depend on the volatility in Japanese stock price.

In Model 7, the day-of-the-effect is estimated. Monday effect is positive, Tuesday effect is negative, but the other effects are not significant. Monday effect is almost equivalent to the holiday effect, because we have  $DT_t = 2$  on Monday in many cases. The coefficient estimate of  $d_t^{Mo}$  should be twice as large as that of  $DT_t$ . As it is expected, we obtain the result that  $\gamma_1$  in Model 7 is 0.1956 while  $\gamma_3$  in Model 6 is 0.1153. The negative Tuesday effect indicates a counter reaction against the positive Monday effect.

In addition to the asymmetry, holiday, U.S. stock price change and its volatility transmission effects, the Tuesday effect is introduced in Model 8. Inclusion

of both the holiday effect and the day-of-the-week effect causes multicollinearity. During the estimation period, we have 922 Mondays when the stock market is open. All the Mondays have the holiday effect. There are 119 Mondays with  $DT_t = 1$ , 767 Mondays with  $DT_t = 2$ , 22 Mondays with  $DT_t = 3$ , 4 Mondays with  $DT_t = 4$ , 5 Mondays with  $DT_t = 5$ , 4 Mondays with  $DT_t = 6$ , and 1 Monday with  $DT_t = 8$  (i.e.,  $119 + 767 + \dots = 922$ ). In Japan the stock market was open on Saturday until the end of 1989, and accordingly we have 119 Mondays with  $DT_t = 1$ . As for the holiday effect except for Monday, we have 77 days when Tuesday has the holiday effect, 35 days when Wednesday has it, 31 days when Thursday has it, 31 days when Friday has it, and 5 days when Saturday has it. Thus, we have 1101 days when we have the holiday effect (i.e.,  $922 + 77 + 35 + 31 + 31 + 5 = 1101$ ). Most of the holiday effects appear on Monday (922 out of 1101), and most of Mondays have  $DT_t = 2$  (767 out of 922). 119 Mondays with  $DT_t = 1$  appear before the end of 1989. Thus, as expected, it is not easy to estimate the holiday effect and the Monday effect, separately. Therefore, only the Tuesday effect is taken into account in Model 8. From the estimation results in Model 8, all the exogenous variables except for  $\gamma_4$  influence the volatility in the stock returns (at least by the 99% interval).

In Model 9, the structural change in the holiday effect is introduced, but the asymmetry effect from U.S. stock market (i.e., U.S. stock price change effect) is excluded because in Models 6 and 8 the coefficient of  $d_t^{\text{US}}$  is not significant. According to Watanabe (2000b), there was a structural change around 1990 with respect to the holiday effect in Japanese stock market, where an EGARCH model is applied. From the percent points in Model 9 of Table 2, the coefficient of  $DT_t$  is not significant, but that of  $DT_t d_t^{90}$  is clearly greater than zero. Thus, no holiday effect is detected before the end of 1989, but the holiday effect appears after the beginning of 1990.

In Model 10, we assume that we have the structural change in the constant term, rather than the holiday effect. From the percent points, all the coefficients of  $d_t^-$ ,  $DT_t$ ,  $|y_t^{\text{US}}|$ ,  $d_t^{\text{TU}}$  and  $d_t^{90}$  are significantly different from zero (at least by the 99% interval). As a result, we have the asymmetry effect, the holiday effect, the U.S. stock price volatility transmission effect, the Tuesday effect (one of the day-of-the-week effects) and the structural change in the constant term. Moreover, comparing Models 9 and 10 with respect to  $\log f_Y(Y_n)$  in Table 1, Model 10 is better than Model 9. Accordingly, it might be concluded that Model 10 is the best model of Models 1–10, where the volatility in Japanese stock prices depends on the asymmetry, holiday, U.S. stock price volatility transmission and Tuesday effects with the structural change in the constant term.

In Models 11 and 12, we assume that the percent change of stock price consists of two components, i.e., one is the deterministic component and another is the irregular component. The specifications in the noise component are discussed in Models 1–10, where we have obtained the result that Model 10 is the best model for the volatility specification. As for the estimation results in volatility specification, Models 11 and 12 are very similar to Model 10 (see  $\gamma_1$ – $\gamma_6$ ,  $\delta$  and

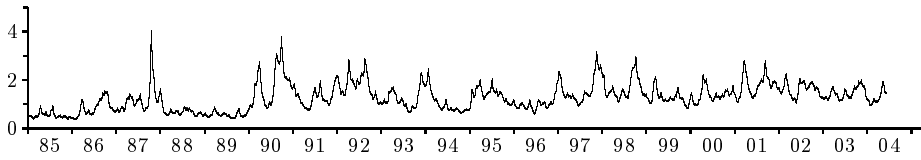
$\sigma$  in Models 10–12). In Model 11, it is shown from the estimates of  $\alpha_2$  and  $\alpha_3$  that Japanese stock price change today does not depend on Japanese stock price change yesterday, but depends on U.S. stock price change. Model 11 implies that Japanese stock returns have the movements similar to U.S. stock returns (i.e., Japanese economy is strongly affected by U.S. economy). In Model 12, we find that the percent change in Japanese stock price has the structural change not only in the volatility but also in the level. In other words, it is observed from  $\alpha_4$  and  $\gamma_6$  in Model 12 that in Japanese stock market we have low returns and high volatility after the bubble burst in 1990.

Finally, we examine whether there is a stochastic volatility effect (i.e.,  $\delta$ ) in Japanese stock market. From Figure 1(b), the percent change data  $y_t$  likely has heavier tails than a normal random variable and it seems to be heteroscedastic over time  $t$ . Therefore, we consider the stochastic volatility model in this paper. From the percent points shown in Models 6–12 of Table 2, the stochastic volatility effect  $\delta$  is significantly greater than zero and less than one, but it is very close to one for all the models, i.e., 0.9582 in Model 6, 0.9811 in Model 7, 0.9591 in Model 8, 0.9373 in Model 9, 0.9298 in Model 10, 0.9371 in Model 11 and 0.9344 in Model 12. Accordingly, the volatility effect persistently continues over time.

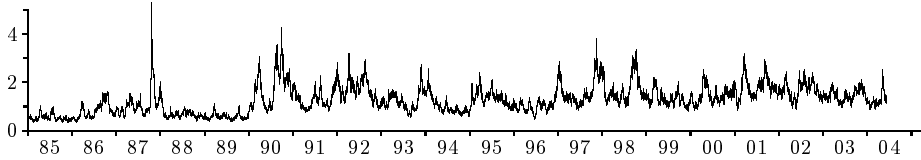
### 4.3. Results in Figure 2

The volatility is given by  $\exp((1/2)\beta_t)$ , 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. We assume that the error is heteroscedastic as in Models 1–12, because clearly the percent changes are heteroscedastic from Figure 1(b). In Figures 2(a)–(c), the movements in the volatility estimates are shown for Models 1, 10 and 12. The volatility is evaluated as:  $E(\exp((1/2)\beta_t) | Y_n) \approx (1/N) \sum_{i=1}^N \exp((1/2)\beta_{t,i})$ , where  $\beta_{t,i}$  denotes the  $i$ -th random draw of  $\beta_t$  given  $Y_n$ . See Appendix A for the notations. We have Black Monday on October 20, 1987 (October 19, 1987 in the Eastern Standard Time), when the stock price drastically falls down in New York stock market. On Black Monday, the volatility extremely increases, as shown in Figures 2(a)–(c). Since 1990, Japanese stock price drastically starts to decrease (see Figure 1), which represents the bubble-burst phenomenon. However, the volatility increases after the bubble burst. Thus, it is shown in Figures 2(a)–(c) 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. Moreover, Figures 2(a)–(c) are very close to each other. We cannot distinguish them at a glance. However, Models 10 and 12 have more jagged lines than Model 1, because Models 10 and 12 include more exogenous variables than Model 1. Thus, Models 10 and 12 can catch a lot of small movements by including extra effects (i.e., the asymmetry, holiday, U.S. stock price volatility transmission and Tuesday effects) and the structural change into the volatility. From Figures 2(b) and (c), we cannot observe too much difference between Models 10 and 12, but on Black Monday the volatility of Model 12 is less than that of Model 10. In Model 10, the change in the price level is not taken into account, where all the

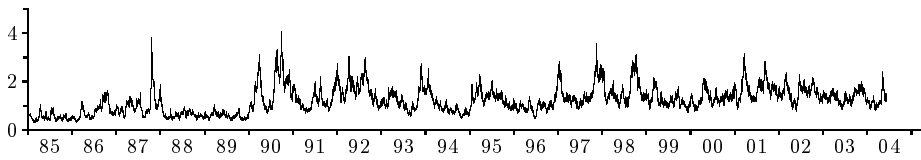
(a) Model 1



(b) Model 10



(c) Model 12

Figure 2. Volatility in Models 1, 10 and 12:  $E(\exp((1/2)\beta_t) | Y_n)$ .

sources of price change are assumed to be due to only the volatility change.

## 5. Concluding remarks

In this paper, assuming that the percent change of the Nikkei stock average depends on a sum of the deterministic part and the irregular component, the volatility of the irregular component is estimated by using the state-space model. Estimation of the unknown parameters and the state variables is performed by Bayes method. We have estimated 12 models. In Models 1–10, we have focused on the volatility in the stock price. Model 1 is the simplest model, where we have no exogenous variable. In Model 2, the asymmetry effect is included. Model 3 examines the holiday effect. In Model 4, the U.S. stock price change effect, which corresponds to the asymmetry effect caused by U.S. stock market, is incorporated. Model 5 represents the volatility transmission effect. Model 6 combines Models 2–5, where the asymmetry, holiday, U.S. stock price change and its volatility transmission effects are formulated. Model 7 represents the day-of-the-week effect. It is difficult to distinguish the holiday effect from the Monday effect, because most of Mondays have the holiday effect. As a counter reaction, we have observed the negative Tuesday effect in the volatility. In Model 8, therefore, the Tuesday effect is added to Model 6. Model 9 has the structural change in the holiday effect with Model 8. In Model 10, the structural change in



the constant term is considered in addition to Model 8. Comparing Models 1–10, we have obtained the result that Model 10 is more plausible than Models 1–9, taking into account significance of each coefficient as well as the log  $f_Y(Y_n)$  criterion. Thus, the structural change in the constant term as well as the asymmetry, holiday, U.S. stock price volatility transmission, Tuesday effects are important for volatility. In Models 11 and 12, we have considered the deterministic component in Japanese stock returns. Japanese stock price change level today does not depend on Japanese stock price change level yesterday, but it is highly affected by the most recent U.S. stock price change level. Moreover, it has been observed that in 1990 we also have the structural change in Japanese stock change level.

Thus, in this paper, we find that (i) Japanese stock price volatility at time  $t$  depends on the sign of Japanese stock price change at time  $t - 1$ , the number of nontrading days between trading days  $t$  and  $t - 1$ , the movement of U.S. stock price volatility available at time  $t$ , the day-of-the-week (Monday and Tuesday), and the structural change in the constant term after 1990, (ii) we have symmetric volatility transmission from U.S. to Japan, (iii) Japanese stock price volatility increases after the bubble burst in 1990, which is caused by the sudden shift of the other exogenous shocks, rather than the shift of the holiday effect, (iv) a decrease in U.S. stock price change level leads to a decrease in Japanese stock price change level (i.e., Japanese economy falls down if U.S. economy falls down), and (v) in 1990 we have the structural change with respect to both level and volatility in Japanese stock returns, where we have observed low stock returns with unstability after 1990.

### Appendix A: Estimation procedure

Under the setup shown in Section 3, the density function of  $y_t$  given  $\beta_t$ , and that of  $\beta_t$  given  $\beta_{t-1}$  are obtained as  $f_y(y_t | \beta_t)$  and  $f_\beta(\beta_t | \beta_{t-1})$ , which are given by:

$$(A.1) \quad f_y(y_t | \beta_t) = \frac{1}{\sqrt{2\pi \exp(\beta_t)}} \exp\left(-\frac{1}{2 \exp(\beta_t)}(y_t - z_t \alpha)^2\right),$$

$$(A.2) \quad f_\beta(\beta_t | \beta_{t-1}) = \frac{1}{\sqrt{2\pi \sigma^2}} \exp\left(-\frac{1}{2\sigma^2}(\beta_t - x_t \gamma - \delta \beta_{t-1})^2\right).$$

(A.1) is derived from (3.1), and (A.2) comes from (3.2). We estimate the unknown parameters by Bayes method. Therefore, the prior densities are assumed as follows:

(A.3)

$$\alpha \sim N(\tilde{\alpha}, \tilde{\Sigma}_\alpha), \quad \beta_0 \sim N(\tilde{\beta}_0, \tilde{\sigma}_{\beta_0}^2), \quad \begin{pmatrix} \gamma \\ \delta \end{pmatrix} \sim N(\tilde{\gamma}, \tilde{\Sigma}_\gamma), \quad \sigma^2 \sim IG(\tilde{a}_0, \tilde{b}_0),$$

where  $X \sim IG(a, b)$  indicates  $1/X \sim G(a, b)$ . 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  $b$ . We need to give some values to the hyper-parameters  $\tilde{\alpha}$ ,  $\tilde{\Sigma}_\alpha$ ,  $\tilde{\beta}_0$ ,  $\tilde{\sigma}_{\beta_0}^2$ ,  $\tilde{\gamma}$ ,  $\tilde{\Sigma}_\gamma$ ,  $\tilde{a}_0$  and  $\tilde{b}_0$ , which will be discussed at the end of Appendix A.

Let us denote  $B_t = (\beta_0, \beta_1, \dots, \beta_t)$ ,  $B_t^+ = (\beta_t, \beta_{t+1}, \dots, \beta_n)$  and  $\theta = (\alpha', \gamma', \delta, \sigma)$ . In this model,  $B_n$  and  $\theta$  have to be estimated. We consider generating random draws of  $B_n$  and  $\theta$ . Given (A.1)–(A.3), we can derive the following conditional densities:

$$(A.4) \quad f(\beta_t | B_{t-1}, B_{t+1}^+, \theta) \propto \begin{cases} \frac{1}{\sqrt{\exp(\beta_t)}} \exp\left(-\frac{1}{2\exp(\beta_t)}(y_t - z_t\alpha)^2\right) \\ \quad \times \exp\left(-\frac{1}{2\tilde{\sigma}^2}(\beta_{t+1} - x_{t+1}\gamma - \delta\beta_t)^2\right) \\ \quad \times \exp\left(-\frac{1}{2\sigma^2}(\beta_t - x_t\gamma - \delta\beta_{t-1})^2\right), & \text{for } t = 1, 2, \dots, n-1, \\ \frac{1}{\sqrt{\exp(\beta_t)}} \exp\left(-\frac{1}{2\exp(\beta_t)}(y_t - z_t\alpha)^2\right) \\ \quad \times \exp\left(-\frac{1}{2\sigma^2}(\beta_t - x_t\gamma - \delta\beta_{t-1})^2\right), & \text{for } t = n, \end{cases}$$

$$(A.5) \quad \beta_0 | B_1^+, \theta \sim N(\tau b, \tau),$$

where  $\tau^{-1} = \delta^2/\sigma^2 + 1/\tilde{\sigma}_{\beta_0}^2$  and  $b = \delta(\beta_1 - x_1\gamma)/\sigma^2 + \tilde{\beta}_0/\tilde{\sigma}_{\beta_0}^2$ ,

$$(A.6) \quad \begin{pmatrix} \gamma \\ \delta \end{pmatrix} | B_n, \alpha, \sigma^2 \sim N(Pq, P),$$

where  $P^{-1} = \tilde{\Sigma}_{\gamma}^{-1} + \sum_{t=1}^n x_t^* x_t^*/\sigma^2$ ,  $q = \tilde{\Sigma}_{\gamma}^{-1}\tilde{\gamma} + \sum_{t=1}^n x_t^* \beta_t/\sigma^2$  and  $x_t^* = (x_t, \beta_{t-1})$ ,

$$(A.7) \quad \alpha | B_n, \gamma, \delta, \sigma^2 \sim N(Qp, Q),$$

where  $Q^{-1} = \tilde{\Sigma}_{\alpha}^{-1} + \sum_{t=1}^n z_t' z_t e^{-\beta_t}$  and  $p = \tilde{\Sigma}_{\alpha}^{-1}\tilde{\alpha} + \sum_{t=1}^n z_t' y_t e^{-\beta_t}$ ,

$$(A.8) \quad \sigma^2 | B_n, \alpha, \gamma, \delta \sim IG\left(\tilde{a}_0 + \frac{n}{2}, \left(\frac{1}{\tilde{b}_0} + \frac{\sum_{t=1}^n (\beta_t - x_t\gamma - \delta\beta_{t-1})^2}{2}\right)^{-1}\right).$$

Using the above conditional densities (A.4)–(A.8), the Gibbs sampler can be performed to generate random draws of  $B_n$  and  $\theta$ . It is hard to generate the random draws of  $\beta_t$  from (A.4). Therefore, the Metropolis-Hastings algorithm is utilized for random number generation for  $\beta_t$ . See, for example, Chib and Greenberg (1995) and Tierney (1994) for the Metropolis-Hastings algorithm. Also, see Jacquier *et al.* (1994) for Bayesian estimation of the stochastic volatility model. The Metropolis-Hastings algorithm requires the sampling density. Let  $f_*(\beta_t)$  be the sampling density of  $\beta_t$ . We take  $f_*(\beta_t) \propto f_{\beta}(\beta_{t+1} | \beta_t) f_{\beta}(\beta_t | \beta_{t-1})$  for  $t = 1, 2, \dots, n-1$  and  $f_*(\beta_t) = f_{\beta}(\beta_t | \beta_{t-1})$  for  $t = n$ , which leads to a normal distribution. Through the random draws from the sampling density, the random draws of  $\beta_t$  from the target density (A.4) are generated. Let  $\beta_{t,i}$  be the  $i$ -th random draw of  $\beta_t$  given  $Y_n$ ,  $\delta_i$  be the  $i$ -th random draw of  $\delta$  given  $Y_n$ , and  $\sigma_i$

be the  $i$ -th random draw of  $\sigma$  given  $Y_n$ , where  $Y_n$  denotes all the observed data, i.e.,  $Y_n = \{y_1, y_2, \dots, y_n\}$ . Because  $z_t$  and  $x_t$  are assumed to be nonstochastic, it is not in  $Y_n$ . Let us denote  $B_{t,i} = (\beta_{0,i}, \beta_{1,i}, \dots, \beta_{t,i})$ ,  $B_{t,i}^+ = (\beta_{t,i}, \beta_{t+1,i}, \dots, \beta_{n,i})$  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  $\theta$  as  $B_{n,-M}$  and  $\theta_{-M}$ .
- (ii) The Metropolis-Hastings algorithm is performed to generate random draws of  $\beta_t$ ,  $t = 1, 2, \dots, n$ , from (A.4), which is shown in (a)–(c).
  - (a) Generate a random draw of  $\beta_t$  from the sampling density  $f_*(\beta_t)$ , denoted by  $\beta_t^*$ , and compute  $\omega(\beta_{t,i-1}, \beta_t^*) = \min\{f_y(y_t | \beta_t^*)/f_y(y_t | \beta_{t,i-1}), 1\}$ .
  - (b) Set  $\beta_{t,i} = \beta_t^*$  with probability  $\omega(\beta_{t,i-1}, \beta_t^*)$  and  $\beta_{t,i} = \beta_{t,i-1}$  otherwise.
  - (c) Repeat Steps (a) and (b) for  $t = 1, 2, \dots, n$ .
- (iii) Generate  $\beta_{0,i}$  from (A.5),  $(\gamma'_i, \delta_i)'$  from (A.6),  $\alpha_i$  from (A.7), and  $\sigma_i$  from (A.8).

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

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  $\theta$ . 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) tests. The CD proposed by Geweke (1992) is utilized in this paper, and 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 *et al.* (1992), Carter and Kohn (1994, 1996), Chib and Greenberg (1996), Geweke and Tanizaki (1999) and Tanizaki (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  $\beta_0, \beta_1, \dots, \beta_n$  are highly correlated with each other. There are various more efficient procedures for precision of generated random draws, e.g., Kim *et al.* (1998), Shephard and Pitt (1997) and 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  $N = 10^6$ ).

We have to set the hyper-parameters shown in (A.3). The following two-step approach is taken. In the first step, we choose the noninformative priors, where  $\tilde{\alpha} = 0$ ,  $\tilde{\Sigma}_\alpha = \infty$ ,  $\tilde{\beta}_0 = 0$ ,  $\tilde{\sigma}_{\beta_0}^2 = \infty$ ,  $\tilde{\gamma} = 0$ ,  $\tilde{\Sigma}_\gamma = \infty$ ,  $\tilde{a}_0 = 0$  and  $\tilde{b}_0 = \infty$  are set (i.e., all the terms related to the hyper-parameters are erased from (A.4)–(A.8)). From Steps (i)–(iv), we can obtain AVE's and STD's as in Table 2. See Appendix C for AVE and STD. AVE and  $(100 \times \text{STD})^2$  are utilized for each

of  $(\tilde{\alpha}, \tilde{\Sigma}_\alpha)$ ,  $(\tilde{\beta}_0, \tilde{\sigma}_{\beta_0}^2)$ , and  $(\tilde{\gamma}, \tilde{\Sigma}_\gamma)$ , where  $\tilde{\Sigma}_\alpha$  and  $\tilde{\Sigma}_\gamma$  are set to be diagonal. For  $\tilde{a}_0$  and  $\tilde{b}_0$ , compute AVE and STD of  $1/\sigma^2$  and obtain the  $a_0$  and  $b_0$  which satisfy  $a_0 b_0 = \text{AVE}$  and  $a_0 b_0^2 = (100 \times \text{STD})^2$ , i.e.,  $a_0 = \text{AVE}^2 / (100 \times \text{STD})^2$  and  $b_0 = (100 \times \text{STD})^2 / \text{AVE}$ . Remember that the Gamma random variable with  $G(a, b)$  has mean  $ab$  and variance  $ab^2$ . I prefer the prior distributions which are as little informative as possible. Therefore, we assume that each prior density has the same mean as the posterior density obtained in the first step and 100 times as large standard deviation as the posterior density in the first step. In the second step, given the prior densities shown above, Steps (i)–(iv) are implemented to generate  $B_{n,i}$  and  $\theta_i$ , again, and Tables 2 and 3 are constructed.

### Appendix B: Marginal likelihood

In order to compare Models 1–12 in Section 3, integrating out  $B_n$  and  $\theta$  we consider deriving the density of  $Y_n$ , denoted by  $f_Y(Y_n)$ . Let us denote  $f_Y(Y_n | B_n, \theta) = \prod_{t=1}^n f_y(y_t | \beta_t)$  using (A.1). To evaluate the marginal likelihood  $f_Y(Y_n)$ , Newton and Raftery (1994) proposed the following computation:

$$(B.1) \quad f_Y(Y_n) = \left( \frac{1}{N} \sum_{i=1}^N \frac{1}{f_Y(Y_n | B_{n,i}, \theta_i)} \right)^{-1},$$

which can be easily derived from Bayes' formula (also, see Gelfand and Dey (1994) and Omori (2001) for the marginal likelihood shown above).  $B_{n,i}$  and  $\theta_i$  represent the  $i$ -th random draws of  $B_n$  and  $\theta$  given  $Y_n$ . Chib (1995) also proposed another computational procedure of the marginal likelihood, which is more computer-intensive than (B.1). Therefore, for evaluation of the marginal log-likelihood function, we use the computation shown in Newton and Raftery (1994).

### Appendix C: AVE, STD, skewness, kurtosis and CD in Table 2

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

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

where  $g(\cdot)$  is any continuous function, which is typically specified as  $g(x) = x^m$ ,  $m = 1, 2, 3, 4$ . Thus,  $(1/N) \sum_{i=1}^N x_i^m$  is a consistent estimate of  $\text{E}(X^m)$ , 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  $\theta$  in this paper. In Table 2, AVE, STD, Skewness and Kurtosis are defined as  $\bar{x} = (1/N) \sum_{i=1}^N x_i$ ,  $s = \{(1/N) \sum_{i=1}^N (x_i - \bar{x})^2\}^{1/2}$ ,  $(1/N) \sum_{i=1}^N (x_i - \bar{x})^3 / s^{3/2}$  and  $(1/N) \sum_{i=1}^N (x_i - \bar{x})^4 / s^2$ , which are consistent estimates of  $\mu = \text{E}(X)$ ,  $\sigma = (\text{E}(X - \mu)^2)^{1/2}$ ,  $\text{E}(X - \mu)^3 / \sigma^{3/2}$  and  $\text{E}(X - \mu)^4 / \sigma^2$  even in the case where  $x_1, x_2, \dots, x_N$  are serially correlated. Note that AVE, STD, Skewness and Kurtosis in Table 2 represent a shape of each posterior density. That is, STD is not the standard deviation of AVE.

0.005, 0.025, 0.050, 0.500, 0.950, 0.975 and 0.995 are given by 0.5%, 2.5%, 5%, 50%, 95%, 97.5% and 99.5% point values by sorting the  $N$  random draws in order of size for each element of  $\theta$ .

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

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

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

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

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

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

which are based on Newey and West (1987). The sample autocovariances  $\Gamma_a^{(j)}$  and  $\Gamma_b^{(j)}$  are given by  $\Gamma_a^{(j)} = (1/N_a) \sum_{i=j+1}^{N_a} (x_i - \bar{x}_a)(x_{i-j} - \bar{x}_a)$  and  $\Gamma_b^{(j)} = (1/N_b) \sum_{i=N-N_b+j+1}^N (x_i - \bar{x}_b)(x_{i-j} - \bar{x}_b)$ , for  $j = 0, 1, \dots, L$ . 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 and acceptance probability

In each model of Table 2, CD represents the convergence diagnostic test based on each element of  $\theta$ . The number of parameters included in (3.1) and (3.2) is given by  $(n+1) + (k_1 + k_2 + 2)$ , i.e., the dimension of  $B_n$  is  $n+1$  and that of  $\theta$  is  $k_1 + k_2 + 2$ . It is not easy to evaluate all the CD's at the same time. Therefore, in this appendix we consider the overall convergence diagnostic test for each model. The  $i$ -th random draw of  $\log f_Y(Y_n | B_n, \theta)$  is given by  $\log f_Y(Y_n | B_{n,i}, \theta_i)$ . As shown in Appendix B, the marginal likelihood  $f_Y(Y_n)$  is constructed from  $\log f_Y(Y_n | B_{n,i}, \theta_i)$ . Therefore, it might be plausible for overall convergence to check convergence of  $\log f_Y(Y_n | B_{n,i}, \theta_i)$ . In Table 3, all the CD's are less than 1.96 in absolute value. Therefore, we can conclude that the Gibbs sequence  $\{\log f_Y(Y_n | B_{n,i}, \theta_i)\}_{i=1}^N$  converges at significance level 5%. For comparison, the marginal likelihood  $\log f_Y(Y_n)$  is shown in Table 3, which is equal to the corresponding value in Table 1.

Table 2. Basic statistics on  $\log f_Y(Y_n | B_n, \theta)$ .

Model	1	2	3	4	5	6	7	8	9	10	11	12
AVE	-7495	-7474	-7471	-7493	-7483	-7442	-7492	-7441	-7428	-7424	-7229	-7208
STD	19.92	18.97	20.23	19.98	20.66	19.38	19.66	19.47	20.44	20.74	21.73	21.99
Skewness	0.02	0.02	0.01	0.02	0.02	0.00	-0.01	0.01	0.02	0.03	0.03	0.04
Kurtosis	2.99	3.05	2.97	3.01	2.95	3.02	3.03	3.05	3.02	3.06	2.95	2.98
0.005	-7546	-7522	-7523	-7544	-7536	-7492	-7543	-7491	-7481	-7477	-7284	-7263
0.025	-7534	-7511	-7510	-7532	-7523	-7480	-7531	-7479	-7468	-7464	-7271	-7251
0.050	-7528	-7505	-7504	-7526	-7517	-7474	-7525	-7473	-7462	-7458	-7264	-7244
0.500	-7495	-7474	-7471	-7493	-7483	-7442	-7492	-7441	-7428	-7424	-7229	-7208
0.950	-7462	-7442	-7438	-7460	-7449	-7410	-7460	-7409	-7395	-7389	-7193	-7172
0.975	-7456	-7436	-7431	-7454	-7443	-7404	-7454	-7402	-7388	-7383	-7186	-7164
0.995	-7444	-7424	-7419	-7441	-7430	-7392	-7442	-7390	-7375	-7369	-7172	-7151
CD	0.999	-0.348	-0.101	-0.097	-0.155	0.073	-0.030	1.271	0.751	1.134	-1.037	0.655
$\log f_Y(Y_n)$	-7576	-7546	-7556	-7573	-7565	-7522	-7573	-7515	-7508	-7504	-7309	-7298
AP	0.962	0.962	0.959	0.962	0.960	0.958	0.963	0.959	0.954	0.952	0.953	0.951
	(4)	(3)	(5)	(4)	(4)	(1)	(3)	(1)	(3)	(5)	(4)	(7)

In Table 3, AP denotes the acceptance probability in average. The acceptance probability at time  $t$  is given by  $(1/N) \sum_{i=1}^N I_{(\beta_{t,i} \neq \beta_{t,i-1})}$ , and it corresponds to the probability in which 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  $t = 1, 2, \dots, n$ . AP represents the arithmetic average from the  $n$  acceptance probabilities. Each value in the parentheses under AP indicates the number of the acceptance rates less than 0.6 out of the  $n$  acceptance rates. Taking an example of Model 1, only 4 cases out of  $n = 4914$  are less than 0.6. Especially, for Models 1–10, the minimum acceptance rates are given by 0.399–0.467 on October 20, 1987, which corresponds to Black Monday, i.e., a drastic drop in U.S. stock price. The minimum acceptance rate in Model 11 is 0.583 on January 6, 1988 and the rate in Model 12 is 0.568 on July 29, 1993. The outliers shown in Figure 1(b) result in relatively small acceptance probabilities. In practice, however, the acceptance probability between 0.399 and 0.583 is not too low.

Thus, the CD's in Tables 2 and 3 and the AP's in Table 3 show that the MCMC procedure taken in Models 1–12 works well.

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