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Daily GARCH Effects versus Volume Effects in Nearby and Distant Nikkei Index Futures Markets

By

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1. Introduction

In the Tokyo Stock Exchange (TSE), the highest Nikkei Index value was November 29, 1989, and the highest Nikkei Index futures price was November 27, 1989, while the highest index return was October 2, 1990 and the lowest index return was April 2, 1990.[1] It is interesting to investigate about the Nikkei Index futures which Nikkei Index futures has traded in the Singapore International Monetary Exchange (SIMEX) since September 3, 1986, in the Index and Option Market Division of the Chicago Mercantile Exchange

(CME)[2] since September 1990 as well as in Japan. There are some researches about the Nikkei Index itself and the derivatives, and many authors have discussed respectively a positive relationship between trading volumes and price variabilities in the futures markets.[3] Karpoff (1987) reports a survey about a relationship between price changes (including absolute price changes) and trading volumes in both a lot of spot and futures markets. He mentions the positive relationship between price changes and trading volumes in equity markets, and a positive relationship between absolute price changes and trading volumes in both equity and futures markets. Clark (1973) examines a positive relationship between square values of daily price changes and daily trading volumes in cotton futures markets. Cornell (1991) which analyzes about 17 futures, Tauchen and Pitts (1983) which researches about the Treasury bill futures, and Grammatikos and Saunders (1986) which investigate about the foreign currency futures, report respectively and independently the relationship between price variabilities and trading volumes.

Lamoureux and Lastrapes (1990a) report a positive relationship between daily equities returns and daily trading volumes of 20 activity traded stocks which have their options trading in the Chicago Board of Exchange (CBOE) markets, using Heteroskedastic Mixture Model (HMM). Their model is based on Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model with a mixing variable as a trading volume variable, and their model is proposed on the Sequential Information Arrival Model (SIAM) which the daily number of information arrival is serially correlated.[4] Especially they analyze how stock trading volumes affect on stock price variabilities by which a daily volume variable is contained in GARCH model or not. Then they emphasize that the daily volume variable which is treated as information arrival times is significantly explanationable, and also that GARCH effect (which measures by the total of estimates over the first-order coefficient in unpredictable shock equation) tends to disappear whenever the volume variable is contained in HMM. Proposed HMM, Najand and Yung (1991) analyze a positive relationship between close-close log-relative prices and daily trading volumes of the Treasury bond futures from January 1984 to August 1989. Then they consider about the relationship with two reasons which are the Mixture of Distribution Hypothesis (MDH) as well as the SIAM. The MDH grounds on joint dependence on a common underlying directing variable,[5] which could be interpreted as the rate of information flow into the market.[6] Then they also conclude that daily futures volumes are able to explain significantly unpredictable shock in HMM, similar to the method in Lamoureux and Lastrapes. However Najand and Yung report that GARCH effect tends to be persist permanently even though the volume variable is contained in HMM.

There is few analysis about a relationship between price variabilities and trading volumes of the index futures in Japan's security markets. So it is worth researching about the relationship of Nikkei Index futures. Both Lamoureux and Lastrapes (1990a), and Najand and Yung (1991) evidenced independently the relationship between close-close volatilities and daily trading volumes. However I will provide the empirical evidence of a relationship between daily trading volume and close-open (called as overnight) returns and open-close (called as daytime) log-relative prices as well as a relationship between daily trading volumes and close-close log-relative prices in respectively the nearby and distant Nikkei Index futures markets. Then a log-relative prices time series consists of close-close log-relative prices while an another log-relative prices time series is made mutually from overnight and daytime log-relative prices.[7] Nakagawa (1995) proves that the better model to analyze overnight and daytime log-relative prices time series of the main Nikkei Index futures is AR(1)-GARCH(1,1) model[8] with a dummy variable which takes a value of 1 on the corresponding daytime log-relative prices and a value of 0 on the corresponding overnight log-relative prices.

The remainder of this article proceeds as follows. In the first section, HMM is explained theoretically. Section 3 shows characteristics of basic statistics of both nearby and distant futures log-relative prices and daily trading volumes, and four time series figures. The log-relative prices is called as returns the following. Sample period is from September 4, 1988 to June 12, 1992. I will analyze about both the nearby and distant futures markets in not only sample period called as the full-period, but also two devided subperiods called as the first and second subperiods which are respectively from September 4, 1988 to July 31, 1990 and from August 1, 1990 to June 12, 1992.

In section 4, the analyzing time series are close-close returns and daily trading volumes of both nearby and distant futures. Section 5 is analyzed about an another time series which is made mutually from overnight and daytime log-relative prices. In this section the HMM which contains only one dummy variable for a volume variable is first used on the time series, given nonnegative parametric constraint on unpredictable shock equation. The dummy variable takes a value of 1 on the corresponding daytime returns and a value of 0 on the corresponding overnight returns. Second a new HMM is reestimated with a dummy variable corresponding to all coefficients.

2. Heteroskedastic mixture model

Before explaining the HMM, I will begin to explain the theoritical background of HMM and first take McCurdy and Morgan's (1988) model. Their model is denoted as follows.

$$r_t = E[r_t \mid \psi_{t-1}] + \varepsilon_t, \tag{1}$$

$$\varepsilon_t \mid \psi_{t-1} \sim N(0, h_t), \quad E[\varepsilon_t \varepsilon_{t+1} \mid \psi_{t-1}] = 0 \quad \text{for} \quad i = 1, 2, \cdots,$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} + \sum_{i=1}^{n} \phi_i x_{it}, \tag{2}$$

where

$$\psi_t = \{x_{kt}, x_{kt-1}, \cdots, x_{nt}, \varepsilon_t, \varepsilon_{t-1}, \cdots\}, \quad (k = 1, 2, \cdots, n).$$

r_t denotes the explanation variable, ε_t denotes the disturbance vaiable, x_{it} is the ith explanation variable at time t, and ψ_t denotes the multivariate information set at time t. $E[r_t \mid \psi_{t-1}] = 0$ denotes the conditional expectation of r_t, given the information set ψ_{t-1} at time t–1. α_0 denotes the constant term, and α_i, β_i and ϕ_i denote coefficient terms. $N(0, h_t)$ denotes the normal distribution which the mean is zero and the conditional variance at time t is h_t. As a whole the effect of an unpredictable return shock i periods ago ($i \leq q$ and $i \leq p$) on the current volatility is governed by the parameter α_i and β_i. The HMM first developed by Lamoureux and Lastrapes (1990) is the model which contains x_{1t} as a mixture variable in GARCH(1, 1) model when $E[r_t \mid \psi_{t-1}] = 0$. The x_{1t} in their model denotes the daily trading volume time series for each stock at time t.[9] Najand and Yung (1991) also develop similar to Lamoureux and Lastrapes' model with the Treasury-bond futures returns and the daily futures volumes. However Najand and Yung insist to regard the trading volume variable as an endogenous variable in the Lamoureux and Lastrapes' model, because they assert that the estimating procedure is likely to yield inconsistently parametric estimators in their model when volumes are correlated with disturbances in the stochastic part of their model. Hence Najand and Yung emphasize that Lamoureux and Lastrapes must estimate simultaneously both returns and volume equations in their model, or that x_{1t-1} must be used instead of x_{1t} in eq. (2) if some researchers would not like the simultaneous estimating method.

3. Data and statistics

A time series is made respectively from each nearby or each distant Nikkei Index futures close-close returns. An another time series is made respectively from overnight and daytime returns of each nearby or each distant futures. The percent of close-close returns of futures at time t is defined as follows in Table Ia and Table Ib.

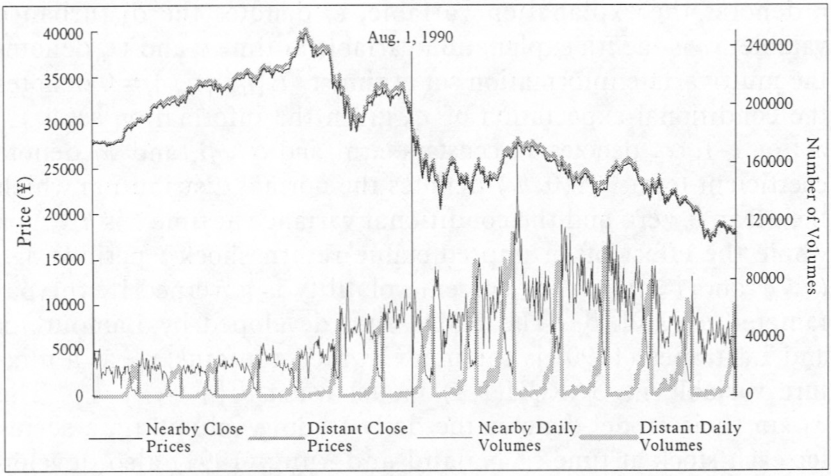

Figure 1. Nearby and distant Nikkei Index futures close prices and daily volumes.
The period is from September 5, 1988 to June 12, 1992. The *black line* is the nearby close prices and the nearby daily volumes. The *gray line* is the distant close prices and the distant daily volumes. It is excluded the nearby Nikkei Index futures log-relative price of October 2, 3, 1990, and January 6, 7, 1992 because of no nearby futures trading at October 2, 1990 and at January 6, 1992. It is excluded the distant Nikkei Index futures log-relative price of September 6, 7, 16, 19, 20, October 5, 6, 13, 14, 17, 18, 19, 20, 1988, March 7, 8, 13, 14, 16, 17, 23, 24, 27, 28, 29, 30, 31, April 3, 4, 5, 6, 7, 11, 12, 13, 14, 19, 20, June 7, 8, 9, 12, 13, 14, 19, 20, 23, 26, 27, 28, July 17, 18, September 7, 8, 12, 13, 18, 19, 20, 21, December 7, 8, 11, 12, 13, 14, 1989, March 8, 9, April 2, 3, June 7, 8, 1990 because of no distant futures trading at September 6, 16, 19, October 5, 13, 17, 19, 1988, March 7, 13, 16, 23, 24, 28, 30, April 3, 5, 6, 11, 12, 13, 19, June 7, 9, 13, 19, 23, 26, 27, July 17, September 7, 12, 18, 19, 20, December 7, 8, 11, 13, 1989, March 8, April 2, June 7, 1990.

$$r_t = 100 \cdot \ln (p_t / p_{t-1}). \tag{3}$$

p_t denotes the present close price at time t, p_{t-1} denotes the previous close price, and r_t denotes the return which is denoted by the percent at time t. An another distiguishable returns series is made mutually from overnight daytime returns, proposed that a day consists of two parts which are an overnight and a daytime.

$$r_{2k-1} = 100 \cdot \ln \left(p_j^{op} \middle/ p_{j-1}^{cl} \right), \quad r_{2k} = 100 \cdot \ln \left(p_j^{cl} \middle/ p_j^{op} \right), \quad k = 1, 2, \cdots. \tag{4}$$

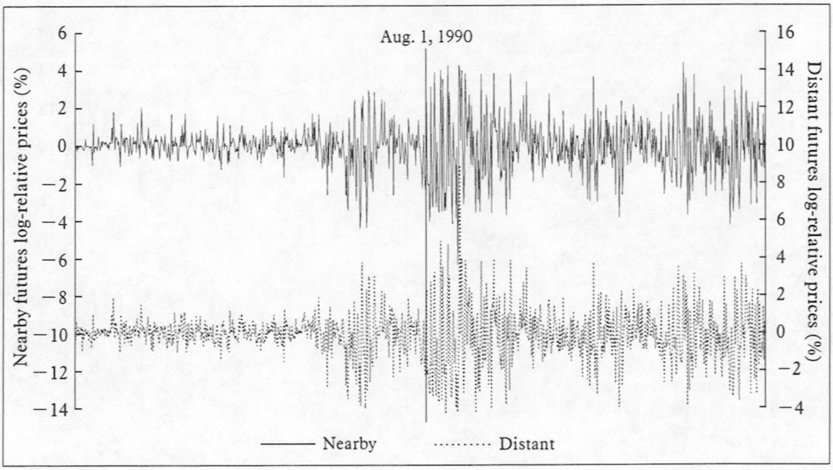

Figure 2. Nikkei Index futures close-close log-relative prices.

The period is from September 5, 1988 to June 12, 1992. The *solid line* is the nearby close-close log-relative prices. The *dashed line* is the distant close-close log-relative prices. It is excluded the nearby Nikkei Index futures log-relative price of October 2, 3, 1990, and January 6, 7, 1992 because of no nearby futures trading at October 2, 1990 and at January 6, 1992. It is excluded the distant Nikkei Index futures log-relative price of September 6, 7, 16, 19, 20, October 5, 6, 13, 14, 17, 18, 19, 20, 1988, March 7, 8, 13, 14, 16, 17, 23, 24, 27, 28, 29, 30, 31, April 3, 4, 5, 6, 7, 11, 12, 13, 14, 19, 20, June 7, 8, 9, 12, 13, 14, 19, 20, 23, 26, 27, 28, July 17, 18, September 7, 8, 12, 13, 18, 19, 20, 21, December 7, 8, 11, 12, 13, 14, 1989, March 8, 9, April 2, 3, June 7, 8, 1990 because of no distant futures trading at September 6, 16, 19, October 5, 13, 17, 19, 1988, March 7, 13, 16, 23, 24, 28, 30, April 3, 5, 6, 11, 12, 13, 19, June 7, 9, 13, 19, 23, 26, 27, July 17, September 7, 12, 18, 19, 20, December 7, 8, 11, 13, 1989, March 8, April 2, June 7, 1990.

$r_t = \{r_{2k-1}, r_{2k}\} p_j^{op}$ denotes the futures open price at the jth date, and p_j^{cl} denotes the futures close price at the jth date. Figure 1 and Figure 2 show respectively the nearby and distant Nikkei futures close-close returns time series and the daily trading volumes time series. In Figure 1 the movement of nearby daily volumes is remarkably different from one of distant daily volumes. The movement of overnight and daytime returns of nearby futures are shown in Figure 3 and one of distant futures are shown in Figure 4. The observated period is from September 3, 1988 which the Nikkei Index

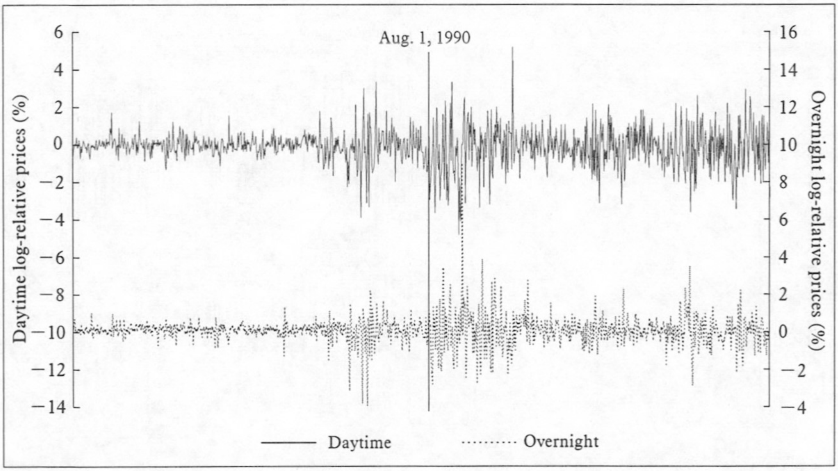

Figure 3. Nearby Nikkei Index futures overnight and daytime log-relative prices. The period is from September 5, 1988 to June 12, 1992. The *solid line* is the nearby daytime log-relative prices. The *dashed line* is the nearby overnight log-relative prices.It is excluded the nearby Nikkei Index futures log-relative price of October 2, 3, 1990, and January 6, 7, 1992 because of no nearby futures trading at October 2, 1990 and at January 6, 1992.

futures market opened in Japan, to June 12, 1992 however the analyzed periods are also divided into two subperiods before and after August 1, 1990 as a boundary. Because the return movement of the former subperiod is different visually from one of the latter in Figure 2, Figure 3, and Figure 4. Notice no futures trading dates are excluded from all figures.[10]

Some summary statistics of close-close, overnight, and daytime returns of both nearby and distant Nikkei Index futures are reported in respectively Table Ia and Table Ib. As a convention, the asymptotic student t values are reported in parenthesis (·). The sample square and absolute averages of returns are contained in their two tables. Because in assuming that the sample average of returns equals zero, the sample square average of returns is equal to the sample variance of returns and also the sample absolute average of returns is equal to the sample volatility (standard deviation) times $\sqrt{\pi / 2}$.

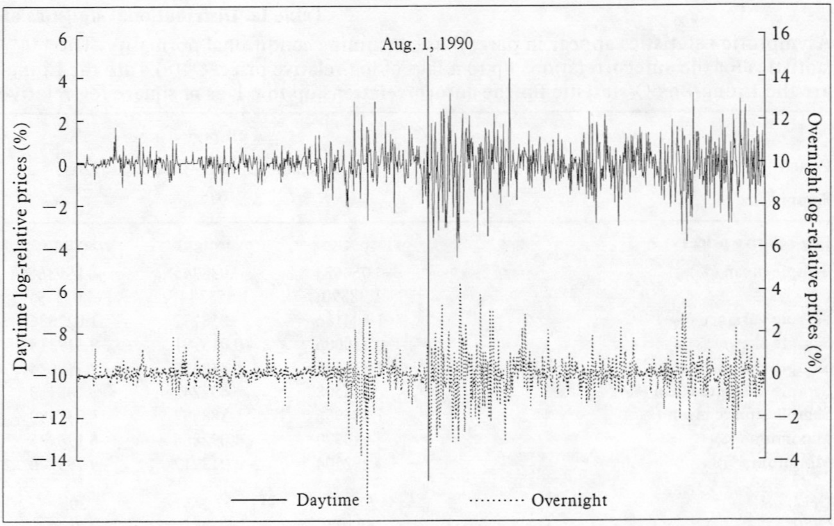

Figure 4. Distant Nikkei Index futures overnight and daytime log-relative prices.
The period is from September 5, 1988 to June 12, 1992. The *solid line* is the distant daytime log-relative prices. The *dashed line* is the distant overnight log-relative prices. It is excluded the distant Nikkei Futures log-relative price of September 6, 7, 16, 19, 20, October 5, 6, 13, 14, 17, 18, 19, 20, 1988, March 7, 8, 13, 14, 16, 17, 23, 24, 27, 28, 29, 30, 31, April 3, 4, 5, 6, 7, 11, 12, 13, 14, 19, 20, June 7, 8, 9, 12, 13, 14, 19, 20, 23, 26, 27, 28, July 17, 18, September 7, 8, 12, 13, 18, 19, 20, 21, December 7, 8, 11, 12, 13, 14, 1989, March 8, 9, April 2, 3, June 7, 8, 1990 because of no distant futures trading at September 6, 16, 19, October 5, 13, 17, 19, 1988, March 7, 13, 16, 23, 24, 28, 30, April 3, 5, 6, 11, 12, 13, 19, June 7, 9, 13, 19, 23, 26, 27, July 17, September 7, 12, 18, 19, 20, December 7, 8, 11, 13, 1989, March 8, April 2, June 7, 1990.

The null hypothesis of autocorrelations up to twelve lags is rejected over the 5 percent level with close-close and overnight returns during both the full-period and the first subperiod in the nearby and distant futures markets. This fact provide that both close-close and overnight returns are different from daytime returns during both two subperiods in the nearby and distant futures markets. Furthermore the movement of returns during the first subperiod may be different from one during the second subperiod in Table Ia, Table Ib, Figure 3, and Figure 4. Especially in both the nearby and distant futures

Table Ia. Distributional statistics of

Asymptotic t statistics appear in parenthesis assuming conditional normality. The ** (*) statistics for the autocorrelations up to n lags of log-relative price. $Q^*(n)$'s are the Ljung- are the Ljung-Box Q-statistic for the autocorrelations up to n lags of square log-relative

		Full-period	
Period		September 5, 1988–June 12, 1992	
Sample size		947	
Log-relative prices	close- close	overnight	daytime
Sample mean (%)	−0.060623	.038745	−0.099368**
	(−1.38890)	(1.555284)	(−3.02379)
Sample variance (%^{2})	1.804186	.058772	1.022686
Sample skewness	−0.110006	−0.015791	−0.319318
Sample excess kurtosis	1.511541	5.330390	2.769624
Sample absolute mean (%)	.948508	.497242	.708313
Sample square mean (%^{2})	1.805956	.588597	1.031480
Maximum (%)	4.910970	4.092866	5.198225
Minimum (%)	−4.292504	−4.013917	−4.793946
$Q(12)$	51.5**	52.2**	20.3
$Q(20)$	68.9**	56.2**	39.4*
$Q^*(3)$	380**	302**	195**
$Q^*(5)$	641**	468**	366**
$Q^{**}(3)$	288**	114**	95**
$Q^{**}(5)$	479**	170**	172**
Daily transaction volumes			
Sample mean		40825**	
		(47.5998)	
Sample standard deviatiov		26393.3	
Sample skewness		.818271	
Sample excess kurtosis		.402145	
Maximum		170293	
Minimum		375	

1) It is excluded the nearby Nikkei Index futures log-relative price of October 2, 3, 1990 6, 1992.

2) The Ljung-Box Q-statistic of the pth-order $Q(p)$ is as follows.

$$Q(p) = T(T+2)\sum_{i=1}^{p} \frac{1}{T-i}\rho_i^2 ,$$

where p denotes the order of the Ljung-Box Q-statistic, T denotes the number of observations,

3) One (Five) percent critical value is 16.2662 (12.8382) under the null of no serial correlation of no serial correlation distributed as $\chi^2(5)$. One (Five) percent critical value is 32.9095 critical value is 45.3147 (37.5662) under the null of no serial correlation distributed as

nearby Nikkei Index futures 1)

denotes that the coefficient is at the 1 (5) percent level. $Q(n)$'s 2) are the Ljung-Box Q-
Box Q-statistic for the autocorrelations up to n lags of absolute log-relative price. $Q^{**}(n)$'s
price. The Ljung-Box Q-statistics distribute asymptotically the chi-square distribution.

First subperiod			Second subperiod		
September 5, 1988–July 31, 1990			August 1, 1990–June 12, 1992		
485			432		
close-close	overnight	daytime	close-close	overnight	daytime
.0026242	.055201*	−0.028959	−0.163815*	.021855	−0.185671**
(.637030)	(2.24992)	(−0.94049)	(−2.03000)	(−0.47304)	(3.06241)
.823022	.291947	.459827	2.813191	.922130	1.587971
−0.642274	−1.754821	−0.232582	.132121	.354928	−0.180612
4.651652	16.14144	6.727388	.222169	2.251025	1.077661
.598650	.326715	.446825	1.315784	.676259	.982819
.822013	.294387	.459717	2.838882	.897453	1.631706
3.783553	2.146773	3.361375	4.910970	4.092866	5.198225
−4.013917	−4.013917	−3.907701	−4.292504	−2.926160	−4.793946
52.1**	44.0*	28.4	30.7	41.3*	14.9
66.0**	57.4**	53.1**	42.9*	48.2**	24.2
176**	115**	63.3**	71.0**	83.4**	21.0**
280**	178**	141**	124**	123**	47.4**
188**	16.5*	32.9**	73.9**	58.9**	20.2*
310**	33.9**	106**	121**	78.1**	35.2**
	24993**			58634**	
	(35.4514)			(47.8232)	
	15526.2			25483.1	
	.947224			.360846	
	.609264			.312573	
	77700			170293	
	375			8724	

and January 6, 7, 1992 because of no nearby futures trading at October 2, 1990 and at January

and ρ_i is the autocorrelation of lag i between residuals. See Ljung and Box (1978).
distributed as $\chi^2(3)$. One (Five) percent critical value is 20.5150 (15.0863) under the null
(26.2170) under the null of no serial correlation distributed as $\chi^2(12)$. One (Five) percent
$\chi^2(20)$.

Table Ib. Distributional statistics of

Asymptotic t statistics appear in parenthesis assuming conditional normality. The ** (*) statistic for the autocorrelations up to n lags of log-relative price. $Q^*(n)$'s are the Ljung-are the Ljung-Box Q-statistic for the autocorrelations up to n lags of square log-relative

		Full-period	
Period		September 5, 1988–June 12, 1992	
Sample size		880	
Log-relative prices	close-close	overnight	daytime
Sample mean (%)	−0.062351	.0203025	−0.082653*
	(−1.33456)	(.7180971)	(−2.44724)
Sample variance ($\%^2$)	1.920828	.703418	1.005868
Sample skewness	−0.144495	−0.017785	−0.283422
Sample excess kurtosis	1.591129	5.196284	2.410794
Sample absolute mean (%)	.981034	.522382	.702145
Sample square mean ($\%^2$)	1.922532	.703031	1.011556
Maximum (%)	4.360964	4.279985	4.895636
Minimum (%)	−6.334927	−3.797925	−4.465977
$Q(12)$	62.8**	72.9**	15.9
$Q(20)$	87.9**	82.5**	32.4**
$Q^*(3)$	36.1**	230**	143**
$Q^*(5)$	59.3**	397**	225**
$Q^{**}(3)$	270**	125**	72.1**
$Q^{**}(5)$	435**	204**	99.7**
Daily transaction volumes			
Sample mean		11679**	
		(16.5166)	
Sample standard deviatiov		20976.4	
Sample skewness		2.404082	
Sample excess kurtosis		5.459984	
Maximum		111423	
Minimum		1	

1) It is excluded the distant Nikkei Index futures log-relative price of September 6, 7, 16, 19, 20, 4, 5, 6, 7, 11, 12, 13, 14, 19, 20, June 7, 8, 9, 12, 13, 14, 19, 20, 23, 26, 27, 28, July 17, 18, September 1990 because of no distant futures trading at September 6, 16, 19, October 5, 13, 17, 19, 1988, September 7, 12, 18, 19, 20, December 7, 8, 11, 13, 1989, March 8, April 2, June 7, 1990.
2) The Ljung-Box Q-statistic of the pth-order $Q(p)$ is as follows.

$$Q(p) = T(T+2)\sum_{i=1}^{p} \frac{1}{T-i}\rho_i^2,$$

where p denotes the order of the Ljung-Box Q-statistic, T denotes the number of observations,
3) One (Five) percent critical value is 16.2662 (12.8382) under the null of no serial correlation of no serial correlation distributed as $\chi^2(5)$. One (Five) percent critical value is 32.9095 value is 45.3147 (37.5662) under the null of no serial correlation distributed as $\chi^2(20)$.

distant Nikkei Index futures [1)]

denotes that the coefficient is at the 1 (5) percent level. $Q(n)$'s [2)] are the Ljung-Box Q-Box Q-statistic for the autocorrelations up to n lags of absolute log-relative price. $Q^{**}(n)$'s price. The Ljung-Box Q-statistics distribute asymptotically the chi-square distribution.

First subperiod			Second subperiod		
September 5, 1988–July 31, 1990			August 1, 1990–June 12, 1992		
414			466		
close-close	overnight	daytime	close-close	overnight	daytime
.010391	.028054	−0.017662	−0.126975	.013416	−0.140391*
(.242596)	(1.04632)	(−0.57613)	(−1.59657)	(−0.28058)	(−2.43527)
.788613	.297622	.389114	2.947461	1.065246	1.548713
−0.755634	−1.345197	.121760	.028396	.172760	−0.189963
4.509162	12.83886	5.045960	.261929	2.697872	.878795
.575158	.309929	.420493	1.341619	.711127	.952369
.757840	.297691	.388486	2.957259	1.063140	1.565099
2.966599	2.702867	2.877474	4.360964	4.279985	4.895636
−4.404660	−3.797925	−2.715399	−6.334927	−3.590554	−4.465977
43.4*	48.5**	18.8	39.0*	55.2**	13.8
57.5**	64.4**	35.1*	57.3**	62.7**	20.7
124**	97.8**	29.9**	84.0**	62.4**	14.5
157**	138**	37.1**	149**	118**	23.5**
110**	83.4**	10.2	87.6**	30.8**	13.6
133**	101**	10.6	146**	74.7**	17.0*
	5319**			17329**	
	(10.7088)			(14.4197)	
	10106.6			25943.0	
	2.448742			1.724771	
	6.217680			1.945604	
	53266			111423	
	1			1	

October 5, 6, 13, 14, 17, 18, 19, 20, 1988, March 7, 8, 13, 14, 16, 17, 23, 24, 27, 28, 29, 30, 31, April 3, 7, 8, 12, 13, 18, 19, 20, 21, December 7, 8, 11, 12, 13, 14, 1989, March 8, 9, April 2, 3, June 7, 8, March 7, 13, 16, 23, 24, 28, 30, April 3, 5, 6, 11, 12, 13, 19, June 7, 9, 13, 19, 23, 26, 27, July 17,

and ρ_i is the autocorrelation of lag i between residuals. See Ljung and Box (1978).
distributed as $\chi^2(3)$. One (Five) percent critical value is 20.5150 (15.0863) under the null (26.2170) under the null of no serial correlation distributed as $\chi^2(12)$. One (Five) percent critical

markets, the null hypothesis-of the zero sample mean is significant at the 5 percent level for daytime returns during the full-period and the first subperiod. Also except daytime returns during the second subperiod, close-close and overnight returns have persistent autocorrelations during both the full-period and the first subperiod in both the nearby and distant futures markets, because of the Ljung-Box Q-statistic[11] for the twentieth-order serial correlation for returns. The Ljung-Box Q-statistics distribute asymptotically the chi-square distribution. Moreover characteristics of the unconditional non-normal distribution on two returns series may be leptokurtic (fat tails) as well as skew because each value of skewness and excess kurtosis approaches to normal distribution as each value approaches to zero. Furthermore from the Ljung-Box Q-statistic for the third-order and the fifth-order serial correlations for both square and absolute returns in respectively the nearby and distant futures markets, serial correlations are significant for each futures close-close, overnight and daytime of returns variances. Thus the Ljung-Box Q-statistics of both square and absolute returns suggests strongly the presence of time-varying volatilities. The null hypothesis of autocorrelations up to five lags of the sample absolute and square means of returns are rejected during all periods in both the nearby and distant futures markets, except the daytime sample absolute and square values of returns during both the first and second subperiods. Therefore these results may exist evidently autocorrelations of variance of returns. Hence GARCH model is not only more appropriate than the standard OSL statistical model, but also it was valuable that subperiods to analyze had been divided into two with August 1, 1990.

4. Close-close returns

In this section, a model structure is analogous to the one in Najand and Yung's, and data are the close-close returns time series and the daily trading volumes time series of respectively nearby and distant Nikkei Index futures. Then HMM is developed to investigate a relationship between the GARCH effect and volume effect on close-close returns and daily volumes in each futures markets. A persistence of unpredictable shock can be measured by the GARCH effect which is evaluated by total value of coefficients of both the square value of unpredictable returns (the residuals) and the unpredictable shock at time $t-1$. Hence the current unpredictable shock hold a permanently persistent effect on future unpredictable shocks, therefore on unpredictable shocks of future returns, as the value of $\alpha_1+\beta_1$ approaches 1.[12] The GARCH effect includes respectively in both GARCH model and HMM, while the volume effect can be measured by the coefficient of the trading volume variable which is contained only in HMM. The HMM with AR(1) (called as AR(1)-HMM) is as follows.

$$r_t = c_0 + a_1 r_{t-1} + \varepsilon_t, \tag{5}$$

$$\varepsilon_t \mid \psi_{t-1} \sim N(0, h_t), \quad E[\varepsilon_t \varepsilon_{t+s} \mid \psi_{t-1}] = 0 \quad \text{for} \quad s = 1, 2, \cdots,$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \phi_1 V_{t-1}, \tag{6}$$

where

$$\psi_t = \{V_t, V_{t-1}, \cdots, \varepsilon_t, \varepsilon_{t-1}, \cdots\}. \tag{7}$$

ε_t is the unpredictable return at time t and it is also treated as a collective measure of news at time t. A positive ε_t (an unexpected increase in price) suggests the arrival of good news, while a negative ε_t (an unexpected decrease in price) suggests the arrival of bad news. V_{t-1} denotes the trading volume at time $t-1$. ψ_t denotes the bivariate information set which is constituted daily trading volumes and residuals of expected return past t. h_t denotes the conditional variance of unpredictable return at time t given the bivariate information set ψ_{t-1} at time $t-1$. In a word, h_t is the unpredictable shock at time t. If markets participators buy (sell) more actively therefore trading volumes are larger, it will result in the larger positive (negative) unpredictable shock. This results in that the trading volume variable at time $t-1$ is possible to explain the unpredictable

Table II. GARCH model and HMM of close-close log-relative prices and daily volume of Nikkei Index futures

The parameter space of the conditional variance equation of disturbance term is constrained to be nonnegative, and estimated jointly using numerical technique to maximize the log-likelihood function. The estimating method is based on BHHH.

$$r_t = c_0 + a_1 r_{t-1} + \varepsilon_t, \quad h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \phi_1 V_{t-1}, \quad \varepsilon_t \mid \psi_{t-1} \sim N(0, h_t), \quad E[\varepsilon_t \varepsilon_{t+j} \mid \psi_{t-1}] = 0, \quad (j = 1, 2, \cdots).$$

c_0	a_1	α_0	α_1	β_1	ϕ_1	$\alpha_1 + \beta_1$	Log-likelihood
Panel A : Nearby Nikkei Index futures [1)]							
Full-period : September 5, 1988–June 12, 1992 (Sample size = 947)							
.042491	.052087	.010696**	.130021**	.871601**		1.00712	−1348.89
(1.69432)	(1.47964)	(4.27227)	(6.20856)	(49.1806)			
.044637	.053017	0	.129199**	.853835**	$.759712 \times 10^{-6}$**	.983034	−1345.25
(1.67678)	(1.49811)	(0)	(5.80599)	(40.1471)	(4.25168)		
First subperiod : September 5, 1988–July 31, 1990 (Sample size = 463)							
.064860*	.068150	.022404**	.228131**	.757766**		.985897	−488.987
(2.42069)	(1.29236)	(3.75018)	(5.20286)	(18.7535)			
.065386*	.074643	0	.204106**	.739632**	$.157803 \times 10^{-6}$**	.943738	−486.294
(2.31948)	(1.40748)	(0)	(4.62231)	(15.8618)	(3.58677)		
Second subperiod : August 1, 1990–June 12, 1992 (Sample size = 484)							
−.073981	.026456	.040749	.080601**	.902324**		.982925	−848.902
(−1.09155)	(.531403)	(1.65650)	(2.88772)	(30.0796)			
−.073981	.026456	.040749	.080601**	.902324**	0	.982925	−848.902
(−1.09155)	(.531402)	(1.65650)	(2.88772)	(30.0796)	(0)		

Panel B : Distant Nikkei Index futures 2)

Full-period : September 5, 1988–June 12, 1992 (Sample size = 880)							
.028644	.085563*	.011617**	.115239**	.884712**		.999951	−1275.80
(.978184)	(2.29744)	(4.67965)	(5.50589)	(49.3491)			
.028567	.085506*	.011554**	.115157**	.884833**	0	1.00090	−1275.80
(.976079)	(2.29651)	(4.70007)	(5.51099)	(49.4548)	(0)		
First subperiod : September 5, 1988–July 31, 1990 (Sample size = 414)							
.054331	.100822	.023978**	.227036**	.763794**		.990830	−427.742
(1.75239)	(1.76164)	(4.17223)	(4.89148)	(19.1026)			
.055309	.100857	.024759**	.236629**	.755394**	0	.992023	−427.745
(1.78351)	(1.75457)	(4.20091)	(4.95227)	(18.6370)	(0)		
Second subperiod : August 1, 1990–June 12, 1992 (Sample size = 466)							
−.065669	.067281	.046718	.071388**	.907271**		.978669	−836.472
(−.941808)	(1.26153)	(1.66571)	(2.57544)	(29.4581)			
−.065643	.067295	.046743	.071393**	.907265**	0	.978658	−836.472
(−.941300)	(1.26164)	(1.66578)	(2.57481)	(29.4492)	(0)		

1) It is excluded the nearby Nikkei Index futures log-relative price of October 2, 3, 1990, and January 6, 7, 1992 because of no nearby futures trading at October 2, 1990 and at January 6, 1992.

2) It is excluded the distant Nikkei Index futures log-relative price of September 6, 7, 16, 19, 20, October 5, 6, 13, 14, 17, 18, 19, 20, 1988, March 7, 8, 13, 14, 16, 17, 23, 24, 27, 28, 29, 30, 31, April 3, 4, 5, 6, 7, 11, 12, 13, 14, 19, 20, June 7, 8, 9, 12, 13, 14, 19, 20, 23, 26, 27, 28, July 17, 18, September 7, 8, 12, 13, 18, 19, 20, 21, December 7, 8, 11, 12, 13, 14, 1989, March 8, 9, April 2, 3, June 7, 8, 1990 because of no distant futures trading at September 6, 16, 19, October 5, 13, 17, 19, 1988, March 7, 13, 16, 23, 24, 28, 30, April 3, 5, 6, 11, 12, 13, 19, June 7, 9, 13, 19, 23, 26, 27, July 17, September 7, 12, 18, 19, 20, December 7, 8, 11, 13, 1989, March 8, April 2, June 7, 1990.

3) Asymptotic t statistics appear in parenthesis assuming conditional normality. The ** (*) denotes that the coefficient is at the 1 (5) percent level.

shock at time t. $N(0, h_t)$ denotes the normal distribution that the mean is zero and the conditional variance is h_t at time t. c_0 and α_0 denote the constant terms. α_1, β_1 and ϕ_1 denote coefficient terms. The parameter space of eq. (5) and eq. (6) which is constrained to be nonnegative, and estimated jointly using numerical technique to maximize the log-likelihood function which the estimating method is Berndt, Hall, Hall, and Hausman (BHHH) (1974).[13]

Table II shows estimates of HMM as well as AR(1)-GARCH(1, 1) in the close-close returns time series and the daily volumes time series of respectively nearby and distant Nikkei Index futures. From estimating result of nearby futures in Table II, the coefficients (c_0 and a_1) of AR(1) are not significant in every periods. In the nearby futures markets, the present unpredictable shock (at time t) influences significantly from the previous trading volume (at time t–1) during both the full-period and the first subperiod, given nonnegative estimating constraint on the unpredictable shock equation (6). Also the GARCH effect still persists even though the trading volume variable is contained in the unpredictable shock equation. Lamoureux and Lastrapes (1990a) report that volume effects are significant but the GARCH effects don't have persistent variances in their HMM, in analyzing twenty actively traded stocks in US. However in analyzing with the Treasury-bond futures prices data, Najand and Yung (1991) find that not only a trading volume variable has an significant effect but also the GARCH effect still remains significant in their HMM. The result of nearby futures in Table II is consistent with the result of Najand and Yung. This fact is in the nearby futures markets that the GARCH effect has still a persistent power when the mixing variable as the trading volume variable is included in HMM. However in the distant futures time series, the volume variable has no significant effect on the current unpredictable shock at time t during all periods. Therefore GARCH model may be better than HMM in the distant futures markets.

5. Overnight and daytime returns

To utilize more information it is worth analyzing about a distiguishable another time series which overnight and daytime returns are made with open prices as well as close prices in respectively the nearby and distant Nikkei Index futures. It is proposed that a day consists of an overnight and a daytime. Hence the time series of overnight and daytime futures returns was first reestimated, not reprted, to analyze about a relationship between GARCH effect and volume effect, with $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + (\phi_0 + \phi_1 D_t) V_{t-1}$ instead of eq. (6). D_t denotes the dummy variable which takes a value of 1 on daytime returns and a value of 0 on overnight returns. V_{t-1} denotes the trading volume at time t–1. Whenever the time t is an overnight, the time t–1 denotes the last daytime and then V_{t-1} denotes the just last daytime volume. While V_{t-1} will denote yesterday's daytime volume if the time t is a daytime and therefore the time t–1 is the last overnight. Since daily volume exists only during daytime. The parameter space of the unpredictable shock equation is constrained to be nonnegative, and estimated jointly using numerical technique to maximize the log-likelihood function which the estimating method is BHHH. Then in both the nearby and distant futures markets, however ϕ_0 and ϕ_1 have no significant during all periods. This evidence proposes that the better model might be identified with GARCH model. Hence $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + (\phi_0 (1 - D_t) + \phi_1 D_t) V_{t-1}$ instead of eq. (6) is adopted and reestimated because which GARCH model or HMM may be selected by the analyzing period and each of two futures time series. The estimates of AR(1)-HMM summarizes in Additional Table. Then it is proved evidently during all periods in nearby futures that the previous daily volume influences significantly on the present daytime unpredictable shocks, while the present daily volume does not influence significantly on the next overnight unpredictable shocks,

Table III. ARCH model and HMM of the overnight and daytime log-relative prices and daily volume of Nikkei Index futures
The parameter space of the conditional variance equation of disturbance term is constrained to be unconditional or nonnegative, and estimated jointly using numerical technique to maximize the log-likelihood function. The estimating method is based on BHHH. Asymptotic t statistics appear in parenthesis assuming conditional normality. The ** (*) denotes that the coefficient is at the 1 (5) percent level.

$$r_t = c_0 + c_1 D_t + (a_0 + a_1 D_t) r_{t-1} + \varepsilon_t, \quad \varepsilon_t \mid \psi_{t-1} \sim N(0, h_t), \quad E[\varepsilon_t \varepsilon_{t+j} \mid \psi_{t-1}] = 0, \quad (j = 1, 2, \cdots),$$
$$h_t = \alpha_0 + \alpha_1 D_t + (\beta_0 + \beta_1 D_t)\varepsilon_{t-1}^2 + (\phi_0 (1 - D_t) + \phi_1 D_t) V_{t-1},$$
$$D_t = \begin{cases} 1 & if \ \text{daytime returns}, \\ 0 & if \ \text{overnight returns}. \end{cases}$$

c_0	c_1	a_1	a_1	α_0	α_1	β_0	β_1	ϕ_0	ϕ_1	Log-likelihood
Panel A : Nearby Nikkei Index futures 1)										
Full-period : September 5, 1988–June 12, 1992 (Sample size = 1894)										
nonnegative parametric constranint on h_t equation										
.041459*	–.117619**	.301191**	–.197269**	.233144**	.445642**	.336487**	.933976**			–2243.87
(2.43078)	(–4.26951)	(20.6520)	(–6.73304)	(24.6170)	(13.6887)	(11.7647)	(7.50757)			
.037871	–.132315**	.336442**	–.250000**	$.622084\times10^{-4}$	$.73344\times10^{-4}$	.080857**	1.15597**	$.129085\times10^{-4}$**	$.946633\times10^{-5}$**	–2187.29
(1.50004)	(–2.77050)	(17.7930)	(–3.15970)	($.318252\times10^{-4}$)	($.140007\times10^{-4}$)	(3.63019)	(8.45226)	(10.9453)	(3.32488)	
unconditional parametric constranint										
.051446**	–.077783**	.303300**	–.445896**	–.029059**	–.098552**	.230927**	1.34590**	$.695503\times10^{-5}$**	$.109096\times10^{-4}$**	–2092.61
(3.76621)	(–2.93904)	(23.7480)	(–15.5777)	(–4.47532)	(–6.20772)	(8.35973)	(10.0301)	(19.1999)	(11.7775)	
First subperiod : September 5, 1988–July 31, 1990 (Sample size = 926)										
nonnegative parametric constranint on h_t equation										
.068545**	–.047962*	.262082**	–5.76806**	.069236**	.165465**	.300702**	2.18319**			–678.460
(6.98983)	(–2.02583)	(19.6993)	(–12.2983)	(15.9760)	(7.78397)	(8.58298)	(8.23845)			
.022816	$–.598414\times10^{-2}$	.257887**	–.454369**	.0214013	$.348384\times10^{-4}$	.306590	–.293718	$.459623\times10^{-5}$**	$.366932\times10^{-4}$**	–746.767
(.872145)	(–.101112)	(3.78609)	(–4.69235)	(.253124)	($.20711\times10^{-5}$)	(.306590)	(–1.12070)	(3.81826)	(4.15947)	
unconditional parametric constranint										
.059510**	–.039139	.198409**	–.468376**	.021150*	–.115155**	.254315**	.341771	$.220713\times10^{-5}$**	$.133062\times10^{-4}$**	–610.116
(3.77949)	(–1.43919)	(4.69473)	(6.91942)	(2.20973)	(–7.20088)	(7.95885)	(1.85913)	(4.77460)	(13.0981)	
Second subperiod : August 1, 1990–June 12, 1992 (Sample size = 968)										
nonnegative parametric constranint on h_t equation										
$–.462591\times10^{-2}$	–.154599*	.264644**	–.078788	.620864**	.849179**	.091793**	.396932*			–1356.71
(–.114225)	(–2.11188)	(8.94603)	(–.836951)	(14.4609)	(6.01361)	(2.64882)	(2.33226)			
.011444	–.294852*	.195659**	–.058160	1.11589**	.584832	.108651	.237657	$.193903\times10^{-8}$	$.133946\times10^{-4}$	–1417.74
(.160650)	(–2.43864)	(3.28451)	(–.415363)	(3.29700)	(1.48132)	(.992907)	(.794012)	($.323285\times10^{-8}$)	(.014029)	
unconditional parametric constranint										
.013344	–.145378*	.181364**	.017617	1.11038**	1.41743**	.056521	–.091357	$–.714765\times10^{-5}$**	$–.562797\times10^{-5}$**	–1334.37
(.358658)	(–2.11098)	(5.92682)	(.220826)	(10.5514)	(7.99037)	(1.86156)	(–.966540)	(–5.25354)	(–3.01735)	

Panel B : Distant Nikkei Index futures 2)

Full-period : September 5, 1988–June 12, 1992 (Sample size = 1760)										
nonnegative parametric constranint on h_t's equation										
.010719	–.113357**	.279269**	$.120075\times10^{-2}$	.378679**	.441253**	.340688**	.055444			–2193.05
(.428342)	(–3.07070)	(9.50349)	(.036587)	(25.0030)	(11.0144)	(9.08423)	(.574562)			
$.387140\times10^{-2}$	–.105860**	.278853**	$.869994\times10^{-2}$	.356573**	.334765**	.352556**	.081217*	$.195771\times10^{-5}$*	$.955379\times10^{-5}$**	–2269.65
(.147368)	(–2.87715)	(10.1322)	(.278920)	(21.7870)	(8.68738)	(9.35078)	(.826739)	(2.17351)	(3.04473)	
unconditional parametric constranint										
$.387140\times10^{-2}$	–.105860**	.278853**	$.869994\times10^{-2}$	.356573**	.334765**	.352556**	.081217*	$.195771\times10^{-5}$*	$.955379\times10^{-5}$**	–2269.65
(.147368)	(–2.87715)	(10.1322)	(.278920)	(21.7870)	(8.68738)	(9.35078)	(.826739)	(2.17351)	(3.04473)	
First subperiod : September 5, 1988–July 31, 1990 (Sample size = 828)										
nonnegative parametric constranint on h_t's equation										
.039124	$-.435660\times10^{-2}$	.094003	–.447234**	.111087**	.217486**	.358663**	.219474			–638.354
(1.66096)	(–.133806)	(1.80653)	(–6.51943)	(19.3962)	(12.0613)	(8.05839)	(1.25834)			
.015032	$.207416\times10^{-2}$	.143006*	–.324442**	.181599**	.201562**	.288134**	$.121225\times10^{-5}$	$.127097\times10^{-6}$	$.140712\times10^{-4}$	–650.099
(.460728)	(.047345)	(1.98471)	(–3.53181)	(17.7404)	(8.07894)	(6.15211)	($.134948\times10^{-7}$)	($.457747\times10^{-4}$)	(.0182732)	
unconditional parametric constranint										
.032473	$-.225631\times10^{-3}$	.107157	–.437223**	.117860**	.188928**	.359384**	.045209	$-.855117\times10^{-6}$	$.831409\times10^{-5}$**	–634.505
(1.31861)	($-.672964\times10^{-2}$)	(1.84602)	(–5.99384)	(18.4560)	(11.4826)	(7.72452)	(.257620)	(–1.26799)	(2.89580)	
Second subperiod : August 1, 1990–June 12, 1992 (Sample size = 932)										
nonnegative parametric constranint on h_t's equation										
–.20987	–.137378	.238167**	.021529	.829566**	.688976**	.132178**	$.514518\times10^{-5}$			–1361.47
(–.426133)	(–1.77499)	(5.09887)	(.282056)	(16.2248)	(5.83012)	(3.97402)	($.215865\times10^{-8}$)			
$.400037\times10^{-2}$	–.159899	.229956**	–.012186	.893529**	.721177**	.111446*	$.352076\times10^{-7}$	$.102627\times10^{-7}$	$.129184\times10^{-5}$	–1364.48
(.075031)	(–1.92129)	(4.82776)	(–.45866)	(14.6887)	(4.79377)	(2.4467)	($.121040\times10^{-9}$)	($.848087\times10^{-6}$)	($.50116\times10^{-3}$)	
unconditional parametric constranint										
$.878621\times10^{-2}$	–.154751*	.214833**	$.147525\times10^{-2}$	.851620**	.712974**	.125535*	–.139348*	$.355232\times10^{-5}$*	$.269927\times10^{-5}$	–1359.98
(.179944)	(–2.09576)	(4.74093)	(.021770)	(15.5462)	(5.61416)	(4.404509)	(–2.46524)	(2.42131)	(.621028)	

1) It is excluded the nearby Nikkei Index futures log-relative price of October 2, 3, 1990, and January 6, 7, 1992 because of no nearby futures trading at October 2, 1990 and at January 6, 1992.
2) It is excluded the distant Nikkei Index futures log-relative price of September 6, 7, 16, 19, 20, October 5, 6, 13, 14, 17, 18, 19, 20, 1988, March 7, 8, 13, 14, 16, 17, 23, 24, 27, 28, 29, 30, 31, April 3, 4, 5, 6, 7, 11, 12, 13, 14, 19, 20, June 7, 8, 9, 12, 13, 14, 19, 20, 23, 26, 27, 28, July 17, 18, September 7, 8, 12, 13, 18, 19, 20, 21, December 7, 8, 11, 12, 13, 14, 1989, March 8, 9, April 2, 3, June 7, 8, 1990 because of no distant futures trading at September 6, 16, 19, October 5, 13, 17, 19, 1988, March 7, 13, 16, 23, 24, 28, 30, April 3, 5, 6, 11, 12, 13, 19, June 7, 9, 13, 19, 23, 26, 27, July 17, September 7, 12, 18, 19, 20, December 7, 8, 11, 13, 1989, March 8, April 2, June 7, 1990.
3) Asymptotic t statistics appear in parenthesis assuming conditional normality. The ** (*) denotes that the coefficient is at the 1 (5) percent level.

that is, the next open price. However the evident result is not able to accept reasonably because the previous daily volume influences significantly on the present open price but the present daily volume does not influence on the present close prices at all.

Hence a new HMM is reestimated with a dummy variable corresponding to all coefficients. This model also corresponds to both ARCH model and HMM.

$$r_t = c_0 + c_1 D_t + (a_0 + a_1 D_t) r_{t-1} + \varepsilon_t , \tag{8}$$

$$\varepsilon_t \mid \psi_{t-1} \sim N(0, h_t), \quad E[\varepsilon_t \varepsilon_{t+s} \mid \psi_{t-1}] = 0 \quad \text{for} \quad s = 1, 2, \cdots,$$

$$h_t = \alpha_0 + \alpha_1 D_t + (\beta_0 + \beta_1 D_t)\varepsilon_{t-1}^2 + (\phi_0(1 - D_t) + \phi_1 D_t) V_{t-1} . \tag{9}$$

$$D_t = \begin{cases} 1 & \textit{if} \quad \text{daytime returns} \\ 0 & \textit{if} \quad \text{overnight returns} \end{cases} \tag{10}$$

where

$$\psi_t = \{V_t, V_{t-1}, \cdots, \varepsilon_t, \varepsilon_{t-1}, \cdots\} . \tag{11}$$

c_0, c_1, α_0, and α_1 denote the constant terms. β_0, β_1, ϕ_0 and ϕ_1 denote the coefficient terms. The parameter space of eq. (9) is constrained to be unconditional or be nonnegative constraint and estimated jointly using numerical technique to maximize the log-likelihood function which the estimating method is BHHH.

Table III shows estimates of both the ARCH(1) model given nonnegative parametric constraint, and HMM given unconditional parametric constraint or nonnegative parametric constraint on the unpredictable shock equation. From estimates of the ARCH model given the nonnegative parametric constraint on the unpredictable shock equation during all periods, α_0 and α_1 are both significant, and both β_0 and β_1 are significant in the nearby futures markets while β_0 is only significant in distant futures. This fact implies in the nearby futures markets that the daytime ARCH effect is different significantly from the overnight ARCH effect, however in the distant futures markets that the daytime ARCH effect may not be different significantly from the overnight ARCH effect. Especially the previous daytime unpredictable shock influences on the present unpredictable shock in the distant futures markets.

In the case of HMM during the full-period and the first subperiod of nearby futures it is proved evidently that both overnight and daytime unpredictable shocks influence significantly from the previous daily volume. Especially during the first subperiod, the estimates of both overnight and daytime volumes in the HMM are significant instead of the significant estimate of the previous daytime unpredictable shock in the ARCH model. However ARCH model or GARCH model may be better than HMM during the second subperiod, in considering negatively the minus significant estimates on the unpredictable shock equation and the log-likelihoods.

In the distant futures markets, ARCH model may be likely better than HMM during the full-period because the log-likelihood of ARCH model is larger than one of HMM. However comparing the log-likelihood of HMM to one of ARCH model, the daytime volume effect has a significant effect on unpredictable shock during the first subperiod in the HMM which may be better identifiable than ARCH model. While the present unpredictable shock influence significantly from the previous volumes during the second subperiod.

6. Conclusion

In using close-close or overnight and daytime returns and daily trading volumes of nearby and distant Nikkei Index futures in Japan, this article is to evidence which volume effects are significant and which ARCH effects persist significantly and permanently in Heteroskedastic Mixture model (HMM), or not. Lamoureux and Lastrapes report that volume effects are significant in HMM but GARCH effects are much smaller in HMM than in GARCH model, in analyzing twenty actively traded stocks in US. However Najand and Yung find that the GARCH effect still remains significantly even when volume variable is included in HMM, in analyzing with the Treasury-bond futures prices data.

From estimating HMM of nearby futures, the present unpredictable shock influences significantly from the previous trading volume during both the full-period and the first subperiod. Also the GARCH effect still persists even though the trading volume variable is contained in the HMM. The fact is consistent with the result of Najand and Yung. However in the distant futures time series, the volume variable has no significant effect on the current unpredictable shock at time *t* during all periods. Therefore GARCH model may be better than HMM in the distant futures markets.

Moreover an another time series is analyzed to utilize more information. The time series is the overnight and daytime returns time series which is made with open prices as well as close prices of both nearby and distant futures. Then autoregressive conditional heteroskedastic estimates in the unpredictable shock equation are significant during all periods of nearby futures. This evidence implies that the daytime ARCH effect is different significantly from the overnight ARCH effect in ARCH model. In HMM both overnight and daytime unpredictable shocks influence significantly from the previous daily volume during the full-period and the first subperiod of nearby futures. However ARCH model or GARCH model may be better than HMM during the second subperiod, in considering negatively the negative significant estimates on the unpredictable shock equation and the log-likelihoods.

In the distant futures markets, ARCH model is likely better than HMM during the full-period in comparing the log-likelihood of HMM to one of ARCH model. However during the first subperiod in HMM, the daytime volume effect has a significant effect on unpredictable shock. While the present unpredictable shock influences significantly from the previous volumes during the second subperiod .

Additional table. Heteroskedastic mixture model of the overnight and daytime log-relative prices and daily volume of Nikkei Index futures

The parameter space of the conditional variance equation of disturbance term is constrained to be nonnegative, and estimated jointly using numerical technique to maximize the log-likelihood function. The estimating method is based on BHHH. Asymptotic t statistics appear in parenthesis assuming conditional normality. The ** (*) denotes that the coefficient is at the 1 (5) percent level.

$$r_t = c_0 + a_0 r_{t-1} + \varepsilon_t, \quad \varepsilon_t \mid \psi_{t-1} \sim N(0, h_t), \quad E[\varepsilon_t \, \varepsilon_{t+j} \mid \psi_{t-1}] = 0, \quad (j = 1, 2, \cdots),$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + (\phi_0 (1 - D_t) + \phi_1 D_t) V_{t-1},$$

$$D_t = \begin{cases} 1 & \textit{if} \quad \text{daytime returns,} \\ 0 & \textit{if} \quad \text{overnight returns.} \end{cases}$$

c_0	a_0	α_0	α_1	β_1	ϕ_0	ϕ_1	$\alpha_0 + \beta_1$	Log-likelihood
Panel A : Nearby Nikkei Index futures 1)								
Full-period : September 5, 1988–June 12, 1992 (Sample size = 1894)								
.018977	.144438**	0	.081883**	.906706**	$.431367 \times 10^{-6}$**	0	.988589	−1958.04
(1.55944)	(5.24088)	(0)	(10.4672)	(115.568)	(6.17029)	(0)		
First subperiod : September 5, 1988–July 31, 1990 (Sample size = 926)								
.033226*	.141628**	0	.264865**	.268701**	$.101234 \times 10^{-4}$**	0	.433566	−621.170
(2.51947)	(3.68428)	(0)	(8.03426)	(12.0916)	(18.1252)	(0)		
Second subperiod : August 1, 1990–June 12, 1992 (Sample size = 968)								
−.037017	.221019**	.686548**	.080315*	0	$.167229 \times 10^{-4}$**	0	.080315	−1373.39
(−1.04237)	(6.79375)	(14.3152)	(2.39829)	(0)	(12.8443)	(0)		
Panel B : Distant Nikkei Index futures 2)								
Full-period : September 5, 1988–June 12, 1992 (Sample size = 1760)								
.014456	.121339**	$.269494 \times 10^{-2}$**	.070958**	.927740**	$.230967 \times 10^{-6}$	0	.998698	−1873.88
(1.13663)	(4.59111)	(6.78436)	(10.2109)	(149.756)	(1.17560)	(0)		
First subperiod : September 5, 1988–July 31, 1990 (Sample size = 828)								
.031586*		$.366062 \times 10^{-2}$**	.086969**	.903911**	$.364363 \times 10^{-6}$	0	.990880	−547.311
(2.25569)		(5.67278)	(7.90847)	(88.4800)	(1.24998)	(0)		
Second subperiod : August 1, 1990–June 12, 1992 (Sample size = 932)								
−.037749	.168283**	.010057*	.046068**	.944113**	0	0	.990181	−1306.14
(−1.18196)	(4.37216)	(2.35875)	(5.19863)	(99.1446)	(0)	(0)		

1) It is excluded the nearby Nikkei Index futures log-relative price of October 2, 3, 1990, and January 6, 7, 1992 because of no nearby futures trading at October 2, 1990 and at January 6, 1992.

2) It is excluded the distant Nikkei Index futures log-relative price of September 6, 7, 16, 19, 20, October 5, 6, 13, 14, 17, 18, 19, 20, 1988, March 7, 8, 13, 14, 16, 17, 23, 24, 27, 28, 29, 30, 31, April 3, 4, 5, 6, 7, 11, 12, 13, 14, 19, 20, June 7, 8, 9, 12, 13, 14, 19, 20, 23, 26, 27, 28, July 17, 18, September 7, 8, 12, 13, 18, 19, 20, 21, December 7, 8, 11, 12, 13, 14, 1989, March 8, 9, April 2, 3, June 7, 8, 1990 because of no distant futures trading at September 6, 16, 19, October 5, 13, 17, 19, 1988, March 7, 13, 16, 23, 24, 28, 30, April 3, 5, 6, 11, 12, 13, 19, June 7, 9, 13, 19, 23, 26, 27, July 17, September 7, 12, 18, 19, 20, December 7, 8, 11, 13, 1989, March 8, April 2, June 7, 1990.

3) Asymptotic t statistics appear in parenthesis assuming conditional normality. The ** (*) denotes that the coefficient is at the 1 (5) percent level.

Notes

[1] The Nikkei Index value increased in 12.43 percent during October 2, 1990 and it decreased in 6.83 percent during April 2, 1990, during a day on the TSE. The stock indices in Japan are Nikkei Index which is first introduced in the Osaka Stock Exchange market, and TOPIX which is introduced in the TSE. Their derivatives are respectively Nikkei Index futures and options, and TOPIX futures.

The Nikkei Index is computed as an arithmetic average of 225 stocks in the First Section of the TSE, by arranging a divisor because of stock splits, right isuues, devidend payment, and so on after a total of 225 stocks prices. The index is announced at one-minute intervals during trading hours (from 9:01 to 11:00 and from 13:01 to 15:15 in Japanese time). While the close time of the derivatives has changed twice in Nikkei Index Futures and Options markets on the TSE. Before Octorber 2, 1990, the trading time was from 9:00 to 11:15 and from 13:00 to 15:15. After then the close time before lunch time was changed from 11:15 to 11:00 and the open time after lunch time was changed from 13:00 to 13:10 before February 6, 1992, and then the trading close time has been changed from 15:10 to 15:00 since February 6, 1992.

[2] The CME opens from 8:00 to 15:15 on the central time in US.

[3] The some researchers about the Nikkei Index or the derivatives on the SIMEX are Bailey (1989), Brenner, Subrahmanyam, and Uno (1989), Lee and Ohk (1992). Bailey (1989) analyzes about mispricing and no arbitrage conditions of the index futures. Lee and Ohk (1992) report how the index structure changes before or after introducing the futures trading, in investigating time-varying volatilities of the index return. Becker, Finnerty, and Gupta (1990) report that daily returns of S & P 500 have a high correlation with daily returns of the Nikkei Index.

[4] Lamoureux and Lastrapes (1990a) use daily futures trading volumes as a mixture variable and in detail explain about the theoritical background of the HMM which is applicable to the SIAM. The SIAM is discussed by Copeland (1976). Then Jennings, Starks, and Fellingham (1981) modify the Copeland's model with a margin requirement as a restriction given short sales, and they analyze in Mossin's (1973) equilibrium.

The SIAM is assumed that only one trader first observes an information, after then he revises his beliefs, and he trades till he arrives at a new optimal position. The consequent of such as events series results in trading volumes and then a new equilibrium price. The next market participant becomes informed after arriving at the new equilibrium, and a second temporary equilibrium is achieved after a similar sequence of events. This process continues until all traders are informed, and the market reaches a final equilibrium when the last trader informed.

5 The directing variable of Harris' (1987) is treated as the rate of information flow over the fixed period. Then market participants trade gradually as they revise their expectations for the ture (equilibrium) price when a new and unexpected information arrives. This implies with the distribution of a directing variable that the unconditional joint distribution of daily price variabilities and volumes is a mixed normal distribution of information arrival.

6 Tauchen and Pitts (1983) report that price variability is independent from trading volume level, however Epps (1975) rejects Tauchen and Pitts' opinion. Harris (1987) as well as they recognizes a positive relationship between daily squared price changes and daily volumes increases in the daily variance of the rate of information flow. Moreover Jennings, Starks, and Fellingham (1981) explain evidently the positive relationship between absolute price changes and trading volumes. Clark (1973) argues that daily return variance is a random variable with a propotional mean to daily trading volume and therefore trading volume has a positive relationship between the variabilities and returns. Epps and Epps (1976) argue theoritically and evidently that the extent of traders' disagreement about actual stock price connects positively with the absolute price changes whenever they revise their belief to their hopeful prices. Then see Smirlock and Starks (1985), and Grammatikos and Saunders (1986) which analyzed about foreign currency futures price variability and the trading volume. Bessembinder and Seguin (1993) report that there is an asynmetric relationship between trading volumes and returns volatilities of commodity and financial futures, and also the negative unexpected volume shocks is bigger than the positive one.

7 The trading period of one Nikkei Index futures survives over 1 year and 3 months. In any time there are four futures which maturities dates are different. However most market participate trade actually the nearby futures in their futures.

8 The nth autoregressive serial correlation model called as AR(n) model is as follows.

$$y_t = c_0 + \sum_{i=1}^{n} c_i \, y_{t-i} + \varepsilon_t ,$$

where y_t denotes the explanation variable at time t, and ε_t denotes the error variable at time t. c_0 denotes a constant term, and $c_i\,(i=1,2,\cdots,n)$ denotes coefficient terms. GARCH(p, q) model is as follows.

$$\varepsilon_t \mid \psi_{t-1} \sim N(0, h_t),$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \, h_{t-i} ,$$

where

$$\psi_t = \{\varepsilon_t, \varepsilon_{t-1}, \cdots\}.$$

α_0 denotes a constsnt term, α_i and β_i denote coefficient terms. ψ_t denotes the univariate information set which is residuals.

[9] They estimate with $E[r_t \mid \psi_{t-1}]=0$ because they report the first-order autoregressive serial correlation in returns had no effect on any of their results. Then they emphasize that trading volume is weakly exogenous in the sense of Engle, Hendry, and Richard (1983), given the assumption that volume is a mixing variable.

[10] In the nearby futures log-relative prices time series, log-relative prices of October 2, 3, 1990, and January 6, 7, 1992 are excluded because of no trading at October 2, 1990 and at January 6, 1992. In the distant futures log-relative prices time series, log-relative prices of September 6, 7, 16, 19, 20, October 5, 6, 13, 14, 17, 18, 19, 20, 1988, March 7, 8, 13, 14, 16, 17, 23, 24, 27, 28, 29, 30, 31, April 3, 4, 5, 6, 7, 11, 12, 13, 14, 19, 20, June 7, 8, 9, 12, 13, 14, 19, 20, 23, 26, 27, 28, July 17, 18, September 7, 8, 12, 13, 18, 19, 20, 21, December 7, 8, 11, 12, 13, 14, 1989, March 8, 9, April 2, 3, June 7, 8, 1990 are excluded because of no trading at September 6, 16, 19, October 5, 13, 17, 19, 1988, March 7, 13, 16, 23, 24, 28, 30, April 3, 5, 6, 11, 12, 13, 19, June 7, 9, 13, 19, 23, 26, 27, July 17, September 7, 12, 18, 19, 20, December 7, 8, 11, 13, 1989, March 8, April 2, June 7, 1990.

[11] The Ljung-Box Q-statistic of the pth-order $Q(p)$ is as follows.

$$Q(p) = T(T+2)\sum_{i=1}^{p}\frac{1}{T-i}\rho_i^2,$$

where p denotes the order of the Ljung-Box Q-statistic, T denotes the number of observations, and ρ_i is the autocorrelation of lag i between residuals. See Ljung and Box (1978).

[12] According to Engle and Bollerslev (1986a, b), it is called as Integrated GARCH (IGARCH) whenever a value of $\alpha_1+\beta_1$ in GARCH(1, 1) model equals 1.

$$\lim_{s\to\infty} \mathrm{Var}(\varepsilon_{t+s} \mid \psi_t) = \frac{\alpha_0}{1-(\alpha_1+\beta_1)} = \infty \quad \text{as} \quad \alpha_1+\beta_1 = 1.$$

Also Nakagawa (1993) argues in details when overnight and daytime log-relative prices reveal mutually in a time series.

[13] The estimating method of BHHH is discussed in detail by Berndt, Hall, Hall, and Hausman (1974).

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