Cash Stock Volatility and the Option Volume :

Empirical Tests in the Japanese Markets*

Mikiyo Kii Niizeki
(Doshisha University
Fucalty of Economics
Associate Professor)

Abstract : This paper investigates the correlation between the trading activity of the stock index option and the volatility of the underlying stock return using daily data for Japan. In order to investigate this relationship, both an implied volatility regression (IVR) and a nonparametric kernel regression (NKR) models are used to estimate the conditional variance (or volatility) of the cash stock return and its partial derivative with respect to the trading volume of the stock index option.

Two important features are found. First, a positive relationship is found between the conditional variance of the cash stock return and the expected trading volume of the stock index option. Second, the unexpected option trading activity contributes to decrees the volatility of the cash stock return. This is consistent with the contention that the Japasene option market systematically leads to price destabilization in the underlying market.

1 INTRODUCTION

Explaining the movement of an asset's volatility, which induces a changing risk premium of the asset, is one of the most important problems of modern financial theories. In recent years, the role of trading activity for explaining the movement of an asset's volatility has received increasing attention from academic researchers. Several theoretical studies predict a positive relationship between return volatility and trading volume. The most widely used model is the mixture of distributions hypothesis (MDH) developed by Clark (1973). This model posits a joint dependence of volatility and volume on the underlying latent information flow variable and shows that the sequential arrival of new information generates a positive correlation between returns volatility and trading volume (see Epps and Epps (1976)). Under this model, trading activity provides information about the factors that generate return volatility process.

* The financial support of the World Wide Bussiness Center, Doshisha University, is gratefully acknowledged.

On the empirical front, Karpoff (1987) surveys the early literature on price−volume relations in the various financial markets and finds weak positive correlations between trading volumes and price changes per se. More recently, Lamoureux and Lastrapes (1990) use a univariate volatility−volume system such as the autoregressive conditional heteroskedasticity (ARCH) model of Engle (1982) and find that the trading volume provides a significant positive effect on the return volatility. Andersen (1996) estimates a bivariate mixture model with an autocorrelated latent information arrival process and finds that the modified MDH model is supported. This study also shows that the estimated measure of volatility persistence drops significantly relative to univariate specifications for volatility only and doubts the ability of the bivariate mixture model to account for the joint behavior of return volatility and trading volume, especially for the high volatility persistence (see Liesenfeld (2001)). Although the early tests of the implications of the MDH are supported, the more recently studies find negative relationships between return volatilities and trading activities (see Lamoureux and Lastrapes (1994)).

Moreover, the factor generating the process of the spot asset's volatility is not only the spot trading volume but also the trading activity in the derivative market. In general, derivatives markets allow traders to generate larger order flows at lower cost than if spot positions are taken. And traders in the derivative market are able to react more sensitively to the market information about the equilibrium price of the underlying asset due to lower marginal requirements. So the latent information flow variable tends to strongly affect the trading activity of the derivative market than that of the spot market. This article investigates the MDH and the positive volatility−volume relationship with the option volume data as the trading activity factor in the Japanese stock index market.

Several theoretical papers attempt to make clear the relationship between spot price volatility and derivative volume. Stein (1987) argues that futures markets attract uninformed speculative order flow at lower cost and that futures trading by poorly informed speculators can destabilize the spot market and elevate the underlying asset's volatility. In contrast, Danthine (1978) and Grossman (1988) imply that the existence of futures markets improves market depth and the liquidity that stabilize the spot market and reduce the volatility. Empirical evidence on the effect of derivative trading on spot volatility is also inconclusive. Figlewski (1981) finds that the GNMA futures contracts lead to increase the volatilities of the prices. On the other hand, Bessembinder and Seguin (1992) examine the volatility−volume relationship with S&P futures trading and find that the equity volatility is negatively related to the forecastable futures activity. Using the option data at the Chicago Board of Options Exchange in 1991, Park, Switzer and Bedrossian (1999) find a positive relationship between the unexpected option volume and the equity volatility.

This paper examines the correlation of the option volume with the volatility of the spot asset's return in the Japanese stock index market, using two statistical approaches that are new methods not used in the earlier works. In the first, an implied volatility regression (IVR) model is used to estimate the cash stock volatility (see Poterba and Summers (1986)). In this model, the implied volatility (IV) is obtained by equating the observed option prices to their theoretical values, given the observed option prices and values for several parameters in the option pricing model (see Latane and Rendleman (1976)). This approach is not a time−series one and depends on the particular functional form of the specific pricing system adopted, for example, the Black−Scholes (BS) model. Second, a time−series model such as a nonparametric regression model (a normal kernel regression (NKR) model) is employed to estimate the volatility. A nonparametric method has been developed recently to estimate a regression curve without making strong assumptions about the shape of the true regression function (see Silverman (1986)). Moreover, a nonparametric derivative method is used to examine the relationship between the volatility and the option volume.

The analysis in this paper uses daily data on the Japanese *Nikkei 225* stock index from November 1991 when the option trade is introduced, to December 1999. During the sample period including a period when the Japanese economy and the stock market are in long slumps, there appears to be a positive contemporaneous correlation between the option volume and the underlying equity volatility. In addition, the trading activity is driven into the two parts by ARIMA model： one is the anticipated trading volume and the other is the noise part of the trading activity in the option market. The results show that the expected component of the option volume is positively associated with the cash stock volatility and that there is a strong negative relationship between the unexpected component of the volume and the volatility. It is also found that the conditional variance (volatility) exhibits heteroskedasticity, depending on the option volume linearly, indicating a high degree of integration of the spot and the option markets.

The paper is organized as follows. Section 2 provides details of the two approaches that are used to estimate the volatility of the cash stock return. A description of the data and details of the empirical results are presented in section 3. Finally, section 4 contains a brief conclusion.

2 ESTIMATION METHODS

2. 1 The IVR Model

The volatility of the stock return can be implied from a particular financial pricing model such as the BS model. Black and Scholes (1973) derived an option−pricing model (the BS model), which was extremely useful in catalyzing much research on option−like financial instruments. The pricing formulas for the BS model are

$$c = SN(d_1) - Ke^{-r\tau}N(d_2), \tag{1}$$

$$p = Ke^{-r\tau}N(-d_2) - SN(-d_1) \tag{2}$$

where c is the current call option price, p is the current put option price, S is the current price of the underlying stock, r is the risk−free interest rate, K is the exercise price, τ is the time to maturity of the option, and $N(\bullet)$ is the standard normal cumulative density function. The variables d_1 and d_2 are defined as

$$d_1 = \frac{\ln(S/K) + r\tau}{V^{1/2}\sqrt{\tau}} + \frac{V^{1/2}\sqrt{\tau}}{2},$$

$$d_2 = d_1 - V^{1/2}\sqrt{\tau}$$

where $V^{1/2}$ is the standard deviation of the stock's rate of return (volatility).

In this study, the estimates of IV are computed by applying implied volatility regression. This is a nonlinear least square procedure applied to option prices in the following model (see Latane and Rendleman (1976)),

$$c_{tk} = \Psi_{ctk}(\hat{V}_{ctk}^{1/2};\ S, K, r, \tau) + \eta_{ctk}, \tag{3}$$

$$p_{tk} = \Psi_{ptk}(\hat{V}_{ptk}^{1/2};\ S, K, r, \tau) + \eta_{ptk} \tag{4}$$

where $\Psi_{ctk}(\bullet)$ (or $\Psi_{ptk}(\bullet)$) is the price given in the right hand side of (1) (or (2)), η_{ctk} (or η_{ptk}) is a random disturbance, and $\hat{V}_{ctk}^{1/2}$(or $\hat{V}_{ptk}^{1/2}$) represents the IV for call (c) (or put (p)) options of the k−th monthly maturity at time t, respectively. Estimates of $\hat{V}_{ctk}^{1/2}$ and $\hat{V}_{ptk}^{1/2}$ are obtained by solving the following minimization problem (see Whaley (1981)) :

$$\min_{\hat{V}_t^{1/2}} G_t = \sum_{i=1}^{N_{ctk}} (c_{itk} - \Psi_{ictk}(\bullet))^2 + \sum_{i=1}^{N_{ptk}} (p_{jtk} - \Psi_{jptk}(\bullet))^2 \tag{5}$$

where N_{ctk} (or N_{ptk}) represents the number of call (or put) options, c_{itk} (or p_{jtk}) shows call (or put) options of k months maturity and ith (or jth) exercise price at time t, respectively.
The solution to (5) minimizes the sum of the squared deviations between the observed and calculated option prices.

A cross−sectional estimate of IV is obtained for all options using two methods. First, the initial value of $V_t^{1/2}$ can be estimated using the golden section method (GSS), then IV is calculated at the same time using a Gauss search method.[1] Both methods are employed to solve (5), in which the partial derivative of G_t with respect to $V_t^{1/2}$ is set close to zero.

In recent option studies, the IVR model has been the most popular for investigation of not only the implied volatility of stock returns but also implied stock prices (see Manaster and Rendleman (1982)). The V_t is thought to be very important because it is the conditional variance of the underlying asset's return at the equilibrium point. If the derivative price actually depend on the BS model, the V_t can reflect the investors assessments of the equilibrium price, that is, the implied value can sensitively reflect the expected information in the market. As the option value is fixed in the balance with supplied and demanded volumes, the V_t implied from the option premia can be related to the option volumes.

However, this approach depends on the particular functional form of the specific pricing system adopted, that is, the BS model. If the BS model is mis−specified, the volatility estimates may be biased. Next, a time−series model that does not need to specify the particular functional model is used.

2. 2 The NKR Model

In estimating the volatility of cash stock returns, a nonparametric method, which does not need to specify the model parametrically, is also used. This approach will be useful, especially for estimating volatility if the parametric model such as an ARCH model is mis−specified and does not adequately explain either an asymmetric feature or a complex nonlinearity in conditional variance. In this investigation, to avoid making strong assumptions about the shape of the true regression function, the normal kernel regression (NKR) model developed by Rosenblatt (1956) is the nonparametric regression model used to estimate the conditional variance of the cash stock returns.

The MDH implies that the conditional variance of the asset's price change depends on the trading volume. Then, the conditional variance of the cash stock returns at time t can be defined as

$$V_t = E[Y_t^2 \mid X_t = x] - (E[Y_t \mid X_t = x])^2, \tag{6}$$

where Y_t shows the underlying asset's return and X_t shows the option volume, respectively. Estimates of the conditional means, $E[Y_t^2 \mid X_{t-1} = x]$ and $E[Y_t \mid X_{t-1} = x]$, are obtained from the following two nonparametric regressions,

$$Y_t^2 = f_1(X_t) + \nu_{1t},$$

$$Y_t = f_2(X_t) + \nu_{2t}$$

where ν_{1t} and ν_{2t} are disturbances.

The standard nonparametric regression model is

$$Y_t = f(X_t) + \nu_t, \quad t = 1, \ldots, T \tag{7}$$

where Y_t is the dependent variable, X_t is a vector of regressors, and ν_t is assumed to be *iid* with mean zero and finite variance. The aim is to obtain nonparametric estimates of $f(X_t)$ at a point x which implies the estimation of $E[Y_t \mid X_t = x]$. Estimates of $f(X_t)$ are given as

$$\hat{f}(x) = \sum_{t=1}^{T} W_t(x) Y_t \tag{8}$$

where $W_t(x)$ is a weight function. To estimate the regression function, a normal kernel function is used, that is, $W_t(x)$ is given by

$$W_t(x) = K(w_t) / \sum_{t=1}^{T} K(w_t), \tag{9}$$

$$w_t = (X_t - x)/h \tag{10}$$

where $K(w_t)$ and h represent the kernel function and the bandwidth, respectively.

In this study, the normal kernel function is used for $K(w_t)$ which is given as

$$K(w_t)=\frac{1}{\sqrt{2\pi}}\exp\left(-\frac{w_t^2}{2}\right), \tag{11}$$
$$K(x)\geq 0 \quad \forall x,$$
$$\int K(x)dx=1,$$
$$\int xK(x)dx=0,$$
$$\int x^2K(x)dx=1$$

Furthermore, the choice of h which minimizes the mean squared error is proportional to $T^{-\frac{1}{4+p}}$ where T denotes the sample size and p is the number of the regressors (see Silverman (1986)). It is important to note that the kernel estimator will be consistent and asymptotically normal. In addition, as can be seen from (8), the regression at each x is a weighted average of linear functions. Hence, an advantage of the nonparametric regression is that the statistical properties of the estimator can be worked out with standard techniques.

Given X_t is assumed to be strictly stationary and strong mixing to obtain the appropriate asymptotic properties, $f_1(X_t)$ and $f_2(X_t)$ can be estimated with the nonparametric estimates given as (8). That is, (6) can be estimated using

$$\hat{V}_t=\frac{\sum_{t=2}^{T}(X_t)^2K(w_t)}{\sum_{t=2}^{T}K(w_t)}-\left(\frac{\sum_{t=2}^{T}X_tK(w_t)}{\sum_{t=2}^{T}K(w_t)}\right)^2 \tag{12}$$

where $K(w_t)$ is the normal kernel function (11).

3 EMPIRICAL TESTS

3. 1 Data

The Japanese *Nikkei 225* index is used to define the one−period natural log return on a stock as $R_t\equiv \ln S_t - \ln S_{t-1}$, where S_t is the daily stock price measured at the end of period, t. For trading date volumes in the option market are summed across contracts with various strike prices and maturity days for call and put options, which is denoted X_t. In estimating the IV in the IVR model, measures of the kth monthly maturity and ith (or jth) exercise price of *Nikkei 225* index options (c_{tki}, p_{tkj}), and the yield of *CD gensaki* (r_t) are used. All of the data are daily closing values and are taken from the *Nikkei Quick Data.* The data run from the option introduction date in 1 November 1991 to 10 December 1999. The period being investigated includes a dramatic decline of the *Nikkei 225* stock index when the stock prices have been skewed negatively and the daily standard deviations have changed very rapidly.

First, in order to avoid a day of the week effect, the stock returns (Y_t) is defined as

$$R_t=\sum_{i=1}^{5}d_{it}\gamma_i+Y_t \tag{13}$$

Table 1 Sumarry Statistics

Variables	Mean	S.D.	Min	Max	Skew	Kurto
Y	−0.00015803	0.0010966	−0.0018800	0.00086000	−0.55562	−1.45637
X	23324.85549	11650.58622	5740.00000	95078.00000	1.75224	4.36343
IVR	0.019422	0.025380	1.00000 D−10	0.13966	2.01918	3.81403
NKR	0.014350	0.0023787	0.010572	0.024878	0.79342	0.44344

Note : The daily data on the Japanese *Nikkei 225* index return (*Y*) obtained in (13) run from 1 November 1991 through to 10 December 1999. The variable *X* represents the aggregated trading volumes in the stock index option market. The *IVR* or the *NKR* shows the estimated volatility in the IVR model or the NKR model, respectively. Mean and S.D. denote the sample mean and the standard deviation of the variables. And Min and Max are the minimum and maximum values of the data. Skew shows the skewness coefficient and the Kurto represents the excess kurtosis of the variables series, respectively.

Table 2 Correlation Coefficients

	Y
X	0.072899
EX	0.022344
NX	0.12005

Note : See the *Note* in Table 1.

where R_t is the stock return, d_{it} denotes a day of the week dummy variable taking value 1 when t is the ith day of the week and 0 otherwise, which is used to exclude the expiration day effect. Second, the trading activity series in the option market are decomposed into two parts : the expected components (EX_t) and the unexpected components (NX_t) with ARIMA (0, 1, 5) model[2]. In order to assess whether the relationship between the volatility and the volume differs for forecastable versus surprise components of the volume, the factors of the stock return volatility are adopted by the three activities series, that is *X*, *EX*, and *NX*. The *EX* reflects activity that is forecastable but highly variable across days and the *NX*, the difference between the actual volume and the *EX*, is interpreted as the daily activity shock in the option market.

Table 1 presents some summary statistics for the variables and the estimates of the conditional variance of the stock return. Five features are observed. First, the kurtosis of the stock return data is larger than that of the volume data. Second the stock return data is skewed to the left, while the volume data is skewed to the right. Third, the volatility estimated by the NKR model is much smaller than the estimate of the IV. Fourth, the relationship between the stock return and the option volume measured by correlation coefficients is very small (see Table 2). Fifth, the movement of the IV is not similar to that of the volatility estimated with the NKR model especially at the end of the sample period (see Figure 1 and Figure 2).

3. 2 Equity Volatility and Option Volume

In order to evaluate relations between the trading activity in the option market and the volatility estimated in the IVR or the NKR model, this study applies two tests : a nonparametric derivative method and a linear parametric method.

At first, to enhance the specificity of the evidence that the levels of option−trading activity can

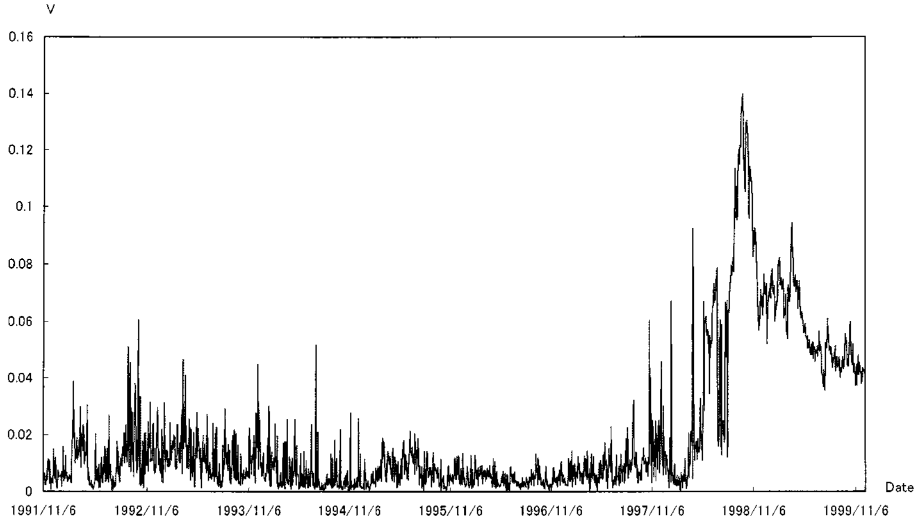

Figure 1
Estimate of the Volatiltiy :
The IVR Model

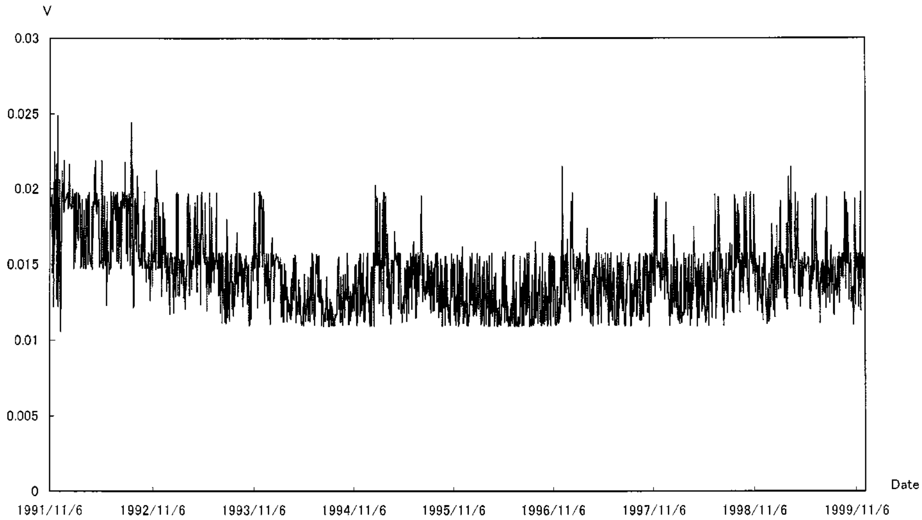

Figure 2
Estimate of the Volatility :
The NKR Model

be factors in the data generated process of the conditional variance of the cash stock returns, a nonparametric derivative procedure with the kernel model is applied to estimate the first order derivative of the conditional variance (V_t in (12)) with respect to the option volume (X_t). As the regression function at each x is easily defined as an expectation and density function involving weighted sums in the kernel method, the nonparametric regression formula is available for estimating not only the conditional variance but also the partial derivatives of the regression function with respect to the regressors.

Using the NKR model, the first order derivative of V_t with respect to X_t can be estimated. For

$\partial V_t / \partial X_t$, the estimator ($\hat{\beta}_t$) is

$$\hat{\beta}_t(x) = \sum_{t=1}^{T} (1-2B) AY_t^2,$$

$$A = \left(\frac{w_t \sum_{t=1}^{T} K(w_t) - \sum_{t=1}^{T} w_t K(w_t)}{h (\sum_{t=1}^{T} K(w_t))^2} \right) K(w_t),$$

$$B = \frac{K(w_t)}{\sum_{t=1}^{T} K(w_t)} \tag{14}$$

where w_t is given by (10).

In addition, the average derivatives can be calculated as

$$\hat{\beta}_v = \frac{1}{T} \sum_{t=1}^{T} \hat{\beta}_t(x), \tag{15}$$

which is consistent and asymptotically normal, which means that this value can be used in the same way as the estimated coefficient of the parametric regression model (see Rilstone (1991)).

The MDH predicts that a high volatility appears at a high level of trading activity and that the volatility of the cash stock return is positively correlated with the option volume. The hypothesis can be formally tested with the hypothesis that $\partial V_t / \partial X_t > 0$. Table 3 includes an estimate of the average first order derivative using the NKR model. The value of $\partial V_t / \partial X_t$ is positive and the hypothesis that $\partial V_t / \partial X_t = 0$ can be rejected at the 5% level. This result means that the volatility is heteroskedastic and depends positively on the trading activity in the Japanese option market.

In addition, to examine how the stock return volatility is correlated with the option volume and the nature of the nonlinearity in the conditional variance, an average second order derivative of the nonparametric regression is estimated. The second order derivative of $V_t(x)$ with respect to X_t can be obtained using the NKR model (see McMillan, Ullah and Vinod (1989)). That is, for $\partial^2 V_t(x) / \partial X_t^2$, the estimator ($\hat{\beta}_t^2$) is

$$\hat{\beta}_t^2(x) = \sum_{t=1}^{T} (C - 2B - 2A^2) Y_{2t},$$

$$C = \left(\frac{w_t^2 \sum_{t=1}^{T} K(w_t) - 2 w_t \sum_{t=1}^{T} w_t K(w_t) - \sum_{t=1}^{T} w_t^2 K(w_t)}{h^2 (\sum_{t=1}^{T} K(w_t))^2} + \frac{2(\sum_{t=1}^{T} w_t K(w_t))^2}{h^2 (\sum_{t=1}^{T} K(w_t))^3} \right) K(w_t), \tag{16}$$

where A and B are again given by (14).

Also the average second derivative can be calculated as

$$\hat{\beta}_v^2 = \frac{1}{T} \sum_{t=1}^{T} \hat{\beta}_t^2(x), \tag{17}$$

A estimate of the average second order derivative in (17) using the nonparametric method is also presented in Table 3 for the sample period. The null hypothesis that $\partial^2 V_t / \partial X_t^2 = 0$ cannot be rejected at the 5% level. This result suggests that a complex nonlinearity does not exist in the conditional variance of the Japanese stock return, which permits to use the linear regression model in the next examination.

At second, the following simple regression model that is most used in the previous investigations is estimated to examine the volatility−volume relationship in order to compare with the past studies

Table 3　Derivatives of the Nonparametric Regressions

	estimate	χ^2
$\partial V_t / \partial X_t$	0.127278 E−06	8.54396*
$\partial^2 V_t / \partial X_t^2$	−0.289500 E−12	0.000191513

Note : The χ^2 value is a test of the null hypothesis that the mean of the partial derivative is equal to 0. The 5% critical value for the χ^2 (1) statistics is 3.84 and a superscript * indicates that the null hypothesis that the derivative is zero can be rejected at the 5 percent significance level.

(for examples, Bessembinder and Seguin (1992)). This model is a linear parametric model and is developed to take account of the day of the week and of ‘leverage effects’ in the stock returns (see Christie (1982)).[3]

$$V_t = \sum_{i=1}^{5} D_{it}\beta_i + aY_{t-1} + b|Y_{t-1}| + cV_{t-1} + dEX_t + eNX_t + u_t \qquad (18)$$

where V_t is the conditional variance estimated using the IVR model (5) or the NKR model (12), D_{it} denotes a day of the week dummy variable, Y_{t-1} is defined as in (13), EX_t represents the anticipated value of the option volume, NX_t shows the noise component of the option activity, and u_t is a disturbance.

Ordinary least squares (OLS) estimates and the absolute values of the appropriate t statistics for the equation (18) are presented in Table 4.[4] The coefficient estimates for unexpected option volume are negative and the null hypothesis that $e=0$ can be rejected at the 5 percent level with the estimated volatilities in both the IVR and the NKR models, indicating decreased equity volatility when the unanticipated option volume is high. In addition, the absolute magnitudes of the coefficient estimates on the NX are substantially larger than these on the EX. Unlike the result for the unexpected option volume, the coefficient estimates for the expected option volume (d) are positive and significant for the estimated volatility in the NKR model. The results show that the expected trading activity in the option market coincides with high volatility of the underlying equity return. However, the absolute magnitude of the coefficient estimate on the EX with the IV is smaller than the case with the es-

Table 4　OLS Estimates of the Parametric Regressions

	a	b	c	d	e
IVR	0.834040	3.94601	0.947203	0.440989 E−08	−0.103160 E−06
	(1.20734)	(2.42289)*	(131.934)*	(0.270158)	(2.11340)*
NKR	−0.015447	−0.344193	0.381448	0.594671 E−07	−0.149911 E−06
	(0.128821)	(1.14462)	(22.7630)*	(16.9020)*	(16.2768)*

Note : This table presents the OLS estimates in the parametric regression model (18) including both the implied volatility in the IVR model (IVR) and the estimated volatility in the NKR model (NKR) for the dependent variables. The absolute value of the t statistics of the parameters are reported in parentheses. The 5% critical values for the t statistics are 1.64 and a superscript * indicates that the parameter is statistically different from zero at the 5% level.

timated volatility in the NKR model and is not significant at the 5% level.

To sum up these empirical results, the equity volatility is positively related to the contemporaneous option−trading activity. This evidence suggests that the MDH in which stochastic changes in the latent number of daily information arrivals generate a positive relationship between return volatility and trading activity is supported in the Japanese stock index markets. Also the significance of the option volume on the equity volatility provides evidence of the integration between the spot stock market and the option market. However, the effect of the noise component of the option volume on the equity volatility is significant, negative, and larger than one of the forecastable component of the option volume. This result indicates that the underlying asset market is stabilized when the background level of the derivative activity is unusually high. In addition, this finding contrasts with the many previous studies documenting uniformly positive correlations between return volatility and trading volume and with the results in Bessembinder and Seguin (1992) using the S & P 500 Index and the S & P 500 futures contract.

These empirical results are important in the debate regarding the role of the derivative market. The findings in this study can give evidence for that belief that trading activity in equity derivative market can elevate volatility in spot equity market, discussed among regulatory authorities and market critics and support introductions of some regulations in the derivative market (for example, 'circuit−breakers'). On the other hand, the theory that derivative trading can improve depth and liquidity provision, leading to stabilize spot equity market, is supported when the greater number of the uninformed noise traders flows into the already existing market, which is inconsistent with the large number of the previous suggestions.

4 CONCLUSION

In this paper, the relationships between the equity volatilities estimated by the two methods and the option volumes divided into the expected and unexpected components are investigated using data for Japan.

This paper has three important conclusions. First, the trading activity in the stock index option market found to be a factor of the conditional variance of the underlying stocks, indicating a high degree of the integration of the spot and the option markets. Secondly, a positive relationship between the spot volatility and the option−trading activity, especially the predictable activity is found in the Japanese stock market. This finding provides an apparent support for the MDH or the theory that derivatives trading lead to prices destabilizations. Thirdly, the noise component of the option volume is found to be negatively associated with the spot volatility. This evidence is consistent with the suggestions that additional uniformed traders tend to entry due to the low cost of the option trading and that the equity volatility is reduced in the resulting deeper market.

These findings have obvious policy implications about the role of the Japanese derivatives markets, suggesting that whether the derivatives contracts stabilize or destabilize the spot market are concerned with the kinds of the derivatives activities : the expected activities and the unexpected activities. However, this paper does not examine the relationship between the spot market volume and the derivative trading because it is difficult to identify the component of the spot volume caused by the derivative trading. It is possible that increased option trading leads to increased spot market volume, causing increases in spot volatility. This problem is left for a future study.

Note

1 The each tolerance criterion of the method is 1.0×10^{-8}.

2 In the data sample, no trend is found. This procedure is as same as Bessembinder and Seguin (1992) or Park, Switzer and Bedrossian (1999). Several sensitivity tests are conducted to investigate alternate volume decompositions, including the use of a 10th order moving average. The conclusions are uniformly unaltered.

3 In the above nonparametric derivative methods, the weekday effect (or the expiration day effect) is excluded in using (13) and the leverage effect does not need to be considered because the nonparametric method depends only on the original feature of the data.

4 This estimation procedure suffers from a 'generated regressor problem' of Pagan (1986) because the estimated values of volatilities are used as the regressors in (18).

References

[1] Andersen, G. T., (1996) "Return Volatility and Trading Volume : An Information Flow Interpretation of Stochastic Volatility," *Journal of Finance,* Vol. 51, pp. 169−204.

[2] Black, F. and M. Scholes, (1973) "The Pricing of Options and Corporate Liabilities," *Journal of Political Economy,* Vol. 81, pp. 637−659.

[3] Bessembinder, H. and P. J. Seguin, (1992) "Futures−trading Activity and Stock Price Volatility," *Journal of Finance,* Vol. 47, pp. 2015−2034.

[4] Christie, A. A., (1982) "The Stochastic Behavior of Common Stock Variances," *Journal of Financial Economics,* Vol. 10, pp. 407−432.

[5] Clark, J. K., (1973) "A Subordinated Stochastic Process Model with Finite Variance for Speculative Prices," *Econometrica,* Vol. 41, pp. 135−155.

[6] Danthine, J., (1978) "Information, Futures Prices, and Stabilizing Speculation," *Journal of Economic Theory,* Vol. 17, pp. 79−98.

[7] Engle, R. F., (1982) "Autoregressive Conditional Heteroskedasticity with Estimates of Variance of United Kingdom Inflation," *Econometrica,* Vol. 50, pp. 987−1007.

[8] Epps, T. W. and M. L. Epps, (1976) "The Stochastic Dependence of Security Price Changes and Transaction Volumes : Implications for the Mixture−of−Distributions Hypothesis," *Econometrica,* Vol. 44, pp. 305−321.

[9] Figlewski, S., (1981) "Futures Trading and Volatility in the GNMA market," *Journal of Finance,* Vol. 36, pp. 445−456.

[10] Grossman, S. J., (1988) "An Analysis of the Implications for Stock and Futures Price Volatility of Program Trading and Dynamic Hedging Strategies," *Journal of Business,* Vol. 61, pp. 275−298.

[11] Karpoff, J., (1987) "The Relation between Price Changes and Trading Volume : A Survey," *Journal of Fi-*

nancial and Quantitative Analysis, Vol. 22, pp. 109−126.

[12] Lamoureux, C. and W. Lastrapes, (1990) “Heteroskedasticity in Stock Return Data : Volume versus GARCH Effects,” *Journal of Finance,* Vol. 45, pp. 221−230.

[13] ―――――, (1994) “Endogenous Trading Volume and Momentum in Stock Return Volatility,” *Journal of Bussiness Economic Statistic,* Vol. 12, pp. 253−260.

[14] Liesenfeld, R., (2001) “A Generalized Bivariate Mixture Model for Stock Price Volatility and Trading Volume,” *Journal of Econometrics,* Vol. 104, pp. 141−178.

[15] Latane, H. A. and R. J. Rendleman, (1976) “Standard Deviations of Stock Price Ratios Implied in Options Prices,” *Journal of Finance,* Vol. 31, pp. 369−381.

[16] Manaster, S. and R. J. Rendleman, (1982) “Option Prices as Predictors of Equilibrium Stock Prices,” *Journal of Finance,* Vol. 39, pp. 1043−1057.

[17] Pagan, A. R., (1986) “Two Stage and Related Estimators and their Applications,” *Review of Economic Studies,* Vol. 53, pp. 517−538.

[18] Park, H., N. Switzer and R. Bedrossian, (1999) “The Interactions between Trading Volume and Volatility : Evidence from the Equity Options Markets,” *Applied Financial Economics,* Vol. 9, pp. 627−637.

[19] Poterba, J. M. and L. H. Summers, (1986) “The Persistence of Volatility and Stock Market Fluctuations,” *American Economic Review,* Vol. 76, pp. 1142−1151.

[20] Rilstone, P., (1991) “Nonparametric Hypothesis Testing with Parametric Rates of Convergence,” *International Economic Review,* Vol. 32, pp. 209−227.

[21] Rosenblatt, M., (1956) “Remarks on Some Nonparametric Estimates of A Density Function,” *Annals of Mathematical Statistics,* Vol. 27, pp. 832−835.

[22] Silverman, B. W., (1986) *Density Estimation for Statistics and Data Analysis*, Chapman and Hall, New York.

[23] Stein, J. C., (1987) “Informational Externalities and Welfare−reducing Speculation,” *Journal of Political Economy,* Vol. 95, pp. 1123−1145.

[24] Whaley, R. E., (1981) “Valuation of American Options Dividend−Paying Stocks : Empirical Tests,” *Journal of Finacial Economics,* Vol. 10, pp. 29−58.