Option-Trading Activity and Stock Price Volatility: A Regime-Switching GARCH Model

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Abstract

In this paper, we examine whether greater option-trading activity (volume and open interest) is associated with greater stock market volatility using a regime-switching GARCH model. We first partition KOPSI 200 option volume and open interest into expected, unexpected, and moving average components to highlight how differently stock market volatility is related to forecastable option-trading activity and unexpected (informed) option volume. Next, we classify option-trading activity based on moneyness to study how each class is related to stock market volatility. Further, we partition stock market into volatile and stable regimes to investigate how informed option traders react differently in the option market according to the state of the stock market. Empirical results show that informed traders prefer to highly leveraged option in volatile market, while they prefer to relatively less leveraged options in stable market.

JEL classification: G12; G14; C13; C53

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I. INTRODUCTION

The relation between return volatility and volume of stocks has long attracted the attention of market participants and financial economists both on aggregate level [e.g., Campbell et al. (1993)] and on individual stocks [e.g., Llorente et al. (2002)]. Indeed, volatility of financial returns has been the central parameter for most, if not all, financial decisions ever since finance emerged as a discipline of study, while trading volume has been the most frequently used variable for measuring traders' activity. In general, the recent literature predicts a recognizable relation between the return volatility and trading volume of stock price, suggesting that volume provides valuable information about the behavior of returns.

In addition to active research on the relationship between volume and volatility of stock price, several studies extend the literature into futures market by investigating the relations between trading activity in the futures market and stock price volatility. For example, Bessembinder and Seguin (1992) use volume data as measurement of trading activity in the futures market, then they investigate the relations between futures-trading activity (volume and open interest) and underlying stock price volatility after dividing the volume into unexpected and expected components. The unexpected component of volume is regarded as informed trading because the expected component of volume depends on information of past data which is open to the market. They report that the expected component has negative relation with the volatility, while the unexpected component has positive relation with the volatility. Gulen and Mayhew (2000), targeting such countries as US, UK, and Japan, also study the relations between trading activity in the futures market and stock price volatility. They find that the open interest has negative relation with stock price volatility, while the volume does not have statistically significant relationship.

Several recent studies further extend the literature into option market and report that option market contains information about the future stock market movements. Varson and Selby (1997) examine the lead-lag relations between option prices and equity stock prices of underlying stocks. Fleming et al. (1996) show the option prices lead the stock prices and the futures prices lead the option prices. Further, Easley et al. (1998) and Chan et al. (2002)

investigate whether option trading volume has information about the future stock price movements of underlying stocks. Easley et al. (1998) show significant evidence that the option trading volume has information about the future stock prices. However, Chan et al. (2002) report that net-buy-volume of options has no strong predictive ability for stock quote revisions. In addition, Pan and Poteshman (2006) document that the economic source of option trading volume's predictability about future stock prices is nonpublic information possessed by option traders, after analyzing the relations between the put-call ratio and the future stock price returns,. Similarly, other studies report the relations between the option trading activity and the underlying stock market movements. For example, Stephan and Whaley (1990) investigate the lag-lead relations between option prices and stock prices and option volume and stock volume, respectively. They report that the stock prices lead the option prices, but option market precedes stock market in the case of volume.

The main purpose of this paper is to examine further whether greater option-trading activity (volume and open interest) is associated with greater stock market volatility. In this context, our study contributes to the literature in two ways. First, we extend the methodology Bessembinder and Seguin (1992) applied to the analysis of *futures-trading* activity and stock price volatility into the analysis of option-trading activity and stock price volatility. An important innovation of their study is incorporating a well-established recognition that there are roughly two different investor groups, namely, speculators and hedgers, in futures market. Because most speculators close their position during intraday, Bessembinder and Seguin (1992) regard volume as trading-activity of speculators and open interest as trading activity of hedgers, typically known as uninformed traders. One group (hedgers) trades option to hedge the risk of their underlying assets while the other group (speculators) trades option to seek the higher gain by using the leverage effect. In the current investigation, we first classify option-trading activity into trading volume and open interest. Then, we further classify trading volume into expected and unexpected components. The expected component of option volume is forecastable option-trading activity, based on historical data, while unexpected component is considered to be trading activity based on private information. That is, unexpected component is regarded as informed traders' trading activity.

Second, we investigate the relation between each series (to be defined shortly) of option volume and stock price volatility using a regime-switching generalized auto regressive conditional heteroskedasticity (RS-GARCH) model, in which parameters are different in each regime to account for the possibility that the data generating process undergoes a finite number of changes over the sample period. There are various option series depending on the structure of maturity or exercise price for the same underlying asset. Therefore, for the purpose of our investigation, we define an option series as options of the same class (call or put), strike price, and maturity. Because each series of options has different class, maturity or exercise price for the same underlying asset, trading activity in each series of options may have different information and expectation as to the movement of underlying asset. That is, each series of options would affect stock price volatility differently in each regime. Therefore, we first divide all the options data (to be described in Section III) into several option series according to moneyness, and then analyze how differently each series of options affect the volatility of stock market price using a GARCH model. Finally, to highlight the linkage between the leverage effect of moneyness and regime-changing characteristics of stock price volatility, we apply a RS-GARCH model. The extent that informed traders with private information would prefer deep-out-of-the-money option relative to other categories of moneyness option would be greater in a highly volatile market because of the highest leverage effect. In a stable market, however, informed traders would not be attracted to deep-out-of-the-money option because of low delta (the rate of change of option price with respect to the change in price of underlying asset). Our RS-GARCH model confirms such heterogeneous relations between each component of option-trading activity and stock market volatility based on the states of the economy.

The rest of the paper is organized as follows. In the next section, we provide a description of the empirical methods we use to estimate relations between options-trading activity and equity volatility. In addition, we present a RS-GARCH model and discuss how it fits into the purpose of our investigation. In Section III, we discuss our data and present the descriptive statistics. Then, we present empirical findings in Section IV. Finally, Section V concludes the paper with a summary.

II. EMPIRICAL METHODS

We first construct a detrended option-volume series by deducting the 30-day moving average from the original series. We also implement ADF (Augmented Dickey-Fuller) test after removing the trend by using 10-day, 50-day, and 100-day moving average so that whatever period is used for the test, all of the time series are stationary and do not affect the result of main empirical test. Then, we use ARIMA (1, 0, 1) to divide option volume into expected and unexpected components. For the purpose of current study, we further divide option volume into each series of options according to moneyness, then again separate each series of options into expected, unexpected, and moving average components to analyze **how stock price volatility is affected by each component**. In the case of KOSPI 200 option, which is the source of data for the current study, each class of options has four different maturities. Among options that have different maturities, we use first month option for our empirical test. Let first month option denotes a series of options with less than one month of maturity. Next, option series with the same maturity are also divided according to exercise price. The moneyness classification is illustrated in Table 1.

[Insert Table 1 about here.]

A. The GARCH model

We first use a GARCH (1,1) model modified for the purpose of our investigation to find the influence of trading activity on stock price volatility. The model used in this study is as follows:

$$y_t = \mu + \sum_{i=1}^{4} \lambda_i D_{i,t} + \kappa y_{t-1} + \varepsilon_t \qquad \varepsilon_t \sim i.i.d.(0, \sigma^2) \tag{1}$$

$$\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + \alpha\varepsilon_{t-1}^2 + \sum_{k=1}^{6} \gamma_k Vol_{k,t} \tag{2}$$

In the above model, the dependent variable y_t denotes the rate of return at time t; $y_t = \ln(P_t / P_{t-1})$, where P_t is the KOSPI 200 index value at time t. $D_{i,t}$ is the dummy variable used to control day-of-the-week effects, ε_t is the residual with zero mean and σ_t^2 of variance from equation (1), σ_t^2 is the conditional variance, and $Vol_{k,t}$ are the unexpected, expected and moving-average components for both volume and open interest. Thus, coefficients γ_k show the relations between conditional variance and trading activities for each of option series.

B. The Regime-Switching GARCH model

In addition, we estimate the relations between option trading activity and stock price volatility by using RS-GARCH (1,1) model proposed by Gray (1996) to find the presence of informed trading after separating stock price volatility into two states. The model adjusted for our empirical study is as follows:

$$y_t = \mu_{s_t} + \sum_{i=1}^{4} \lambda_{i,s_t} D_{i,t} + \kappa_{s_t} y_{t-1} + \varepsilon_t \qquad \varepsilon_t \sim i.i.d.(0,\sigma^2) \tag{3}$$

$$\sigma_t^2 = \omega_{s_t} + \beta_{s_t} \sigma_{t-1}^2 + \alpha_{s_t} \varepsilon_{t-1}^2 + \sum_{k=1}^{6} \gamma_{k,s_t} Vol_{k,t} \tag{4}$$

$$p_{jt} = \Pr(s_t = j | \Im_{t-1}) = p_{jt}(y_{t-1}^2), \quad j = 1,2,\cdots,n \tag{5}$$

We define for each t an unobserved variable $S_t \in \{1,2,\cdots,n\}$, which selects the model parameters with probability $p_{jt} = \Pr(s_t = j | \Im_{t-1})$ where $\Im_t$ is information set available at time t. The function $p_{jt}(\cdot)$ can be a logistic or exponential link function. This function depends on unknown parameters at this stage and is the cumulative normal distribution function which ensures that the probabilities are positive and sum to unity. In this way, the state probabilities are allowed to be time varying and the dynamics of regimes switching probabilities depend on the level of stock returns. Also, if we assume this model has two possible states at each period (volatile or stable regime), we could obtain two coefficients $\gamma_{k,1}$ and $\gamma_{k,2}$ for each γ_k.

In RS-GARCH model, the conditional variance σ_t^2 depends on state s_t and σ_{t-1}^2, where σ_{t-1}^2 also depends on s_{t-1} and σ_{t-2}^2, and so on. Consequently, the conditional variance at time t depends on the entire sequence of regime up to time t. Therefore, there are n^t possible paths, where n is the number of states. Assuming normality, the model is estimated by using maximum likelihood estimation. To compute the likelihood function for the t-th observation we have to integrate over n^t possible paths. This is really huge size to compute it. That is why previous research, e.g., Cai (1994) and Hamilton and Susmel (1994), develop regime-switching models in which the conditional variance in each regime is characterized by a low-order ARCH process. But, Gray (1996) solves this problem. If conditional normality is assumed within each regime, the conditional variance in each regime is not path-dependent, therefore, it can be used as the lagged conditional variance in constructing $\sigma_{1,t+1}^2$, $\sigma_{2,t+1}^2$, and so on.

There are four possible paths in the current paper since we use two states and a second observation. The subscripts show the paths of the regimes. For example, $\sigma_{t|1,2}^2$, stands for the conditional variance at time t, given that the process was in regime 1 at time $t-1$ and is in regime 2 at time t. The current regime at time t is not dependent on regime of history of the process.

Let $s_t \in \{1,2\}$ denote possible states 1 and 2 at time t. Path 1 is a regime path when $s_t = s_{t-1} = 1$, path 2 is the one when $s_t = 2$ and $s_{t-1} = 1$, path 3 is the one when $s_t = 1$ and $s_{t-1} = 2$, and the last path is the one when $s_t = s_{t-1} = 2$. An illustration of path dependence in a regime-switching GARCH model with two states is presented in Figure 1.

[Insert Figure 1 about here.]

We explain the Bayesian algorithm for a RS-GARCH model with two regimes and normality of the error term u_t. For the case of two regime, the model is given by equation (3) and (4), $s_t = 1$ indicating the volatile regime and $s_t = 2$ for the other regime, and a functional specification of either p_{1t} or p_{2t} (since $p_{2t} = 1 - p_{1t}$). We specify

$$p_{1t} = \left[1 + \exp(\delta_0 + \delta_1 y_{t-1}^2)\right]^{-1} \tag{6}$$

with $\delta_1 < 0$. Thus, p_{1t} tends to 1 as y_{t-1}^2 tends to infinity, as required by assumption $p_{1t}(y_{t-1}^2) > 0$ and $p_{1t}(y_{t-1}^2) \to 1$ as $y_{t-1}^2 \to \infty$ for all t. We assume that the probability that $s_t = 1$ is strictly positive. This implies that regardless of the state the process is in at time $t-1$, there is always a positive probability that it will reach the volatile state at time t. The assumption does not bound p_{1t} from above, so the process can spend its entire time in the volatile regime. Furthermore, it is assumed that the stable process dominates the global process in the sense that the process collapses back to the stable regime when a big shock has occurred.

The model parameters consist of $\delta = (\delta_0, \delta_1)'$, $w = (w_1, w_2)'$, $\theta = (\theta_1, \theta_2)'$ where $w = (w_1, w_2)'$ is $w_k = (\mu_k, \lambda_{1,k}, \lambda_{2,k}, \lambda_{3,k}, \lambda_{4,k}, \kappa_k)'$ and $\theta = (\theta_1, \theta_2)'$ is $\theta_k = (\omega_k, \alpha_k, \beta_k, \gamma_{1,k}, \gamma_{2,k}, \gamma_{3,k}, \gamma_{4,k}, \gamma_{5,k}, \gamma_{6,k})'$ for $k = 1, 2$. We denote by Y_t the vector $(y_1\, y_2 \cdots y_t)$ and likewise $S_t = (s_1\, s_2 \cdots s_t)$. The joint density of y_t and s_t given the past information and the parameters is factorized as

$$f\left(y_t, s_t \middle| \theta, \delta, Y_{t-1}, S_{t-1}\right) = f\left(y_t \middle| s_t, w, \theta, Y_{t-1}, S_{t-1}\right) f\left(s_t \middle| \delta, Y_{t-1}\right) \tag{7}$$

with

$$f\left(y_t \middle| s_t, w, \theta, Y_{t-1}, S_{t-1}\right) = \frac{1}{\sqrt{2\pi\sigma_t^2}} \exp\left(- \frac{\left(y_t - \mu_{s_t} - \sum_1^4 \lambda_{i,s_t} D_{i,t} - \kappa_{s_t} y_{t-1} \right)^2}{2\sigma_t^2} \right) \tag{8}$$

(a normal density, where σ_t^2 is a function of θ through s_t defined by equation (4)), and

$$f\left(s_t \middle| \delta, Y_{t-1}\right) = p_{1t}^{2-s_t} (1 - p_{1t})^{s_t - 1}, \tag{9}$$

(a Bernouilli distribution). The joint density of $y_t = (y_1, y_2, \cdots, y_T)$ and $S_t = (s_1, s_2, \cdots, s_T)$ given the parameters is then obtained by taking the product of the densities in (8) and (9) over all observation:

$$f\left(y, S \middle| w, \theta, \delta\right) \propto \prod_{t=1}^{T} \sigma_t^{-1} \exp\left(-\frac{\left(y_t - \mu_{s_t} - \sum_{1}^{4} \lambda_{i,s_t} D_{i,t} - \kappa_{s_t} y_{t-1} \right)^2}{2\sigma_t^2} \right) p_{1t}^{2-s_t} \left(1 - p_{1t}\right)^{s_t - 1} \tag{10}$$

Since integrating this function with respect to S by summing over all paths of the state variables is numerically too demanding, we implement a Gibbs sampling algorithm that allows us to sample from the full conditional posterior densities of blocks of parameters given by θ, w, δ, and the element of S.

III. DATA DESCRIPTION

Our primary sample consists of all daily data on the KOSPI 200 index and KOSPI 200 option from the Korea Exchange (KRX), and the sample period is from January 4, 1999 to February 28, 2007. Although the KOSPI 200 option was listed in the KRX on July 7, 1997 for the first time, options were not actively traded during the beginning years, and thus we use the data traded from January 1999. Figure 2 is the KOSPI 200 Index returns during the sample period. As can be seen, the movement of stock market varies widely over time. It has been stable for sometimes but also been highly volatile for other times. If the reaction of informed traders on the market movement differs from uninformed traders' at each regime, we should expect such a result from our empirical test using a RS-GARCH model rather than a GARCH model.

Table 2 and Table 3 provide descriptive statistics on the KOSPI 200 index returns and KOSPI 200 option volumes for each of the option series. We use option volume divided by 1,000. In Table 2, we can confirm that our sample data cannot be modeled by normal distribution because Jarque-Bera tests reported in the table reject the normality. Therefore, we expect that the variance in our sample data is not constant. In addition, we find that this distribution has long and fat tail to the left due to negative skewness. Finally, we find that mean and variance of the volumes are much larger than those of the open interests for both call and put options.

[Insert Figure 2 about here.]

Table 3 provides summary statistics on the KOSPI 200 options for each series of call and put option. In the case of call options, we find that the mean and variance of volumes for near-the-money, out-of-the-money, and deep out-of-the money options are much larger than those of the open interest. To the extent that the open interest is regarded as trading activity of hedgers, hedgers trade in-the-money and deep-in-the-money option more actively, while speculators trade near-the-money, out-of-the-money, and deep out-of-the money option more actively. In the case of put options, we observe that in-the-money, out-of-the-money, deep out-of-the-money options are traded more actively in both open interest and volume. That is, near-the-money and deep-in-the-money options are less actively traded relative to other three moneyness categories. In other words, we are likely to find important piece of information, if any, from in-the-money, out-of-the-money, and deep out-of-the-money options. In sum, investors reveal their different preferences for moneyness in their option-trading activity and thus the relations between option-trading activity and stock volatility can be different for each moneyness class of options.

[Insert Table 2 and 3 about here.]

IV. EMPIRICAL RESULTS AND THEIR INTERPRETATION

Table 4 presents the result of GARCH(1,1) test modified for our study. The variables of this table follow equations (1) and (2). In the remaining tables to be discussed, let γ_1, γ_2, γ_3, γ_4, γ_5, and γ_6 denote the unexpected component of volume , the expected component of volume, the moving average component of volume, the unexpected component of open interest, the expected component of open interest, and the moving average component of open interest, respectively.

As can be seen in Table 4, in the case of call option, we do not find day-of-the-week effects. The first serial correlation is also not statistically significant. In GARCH model, ω means long-term average value, α shows information about volatility during the previous period, and β shows the relations with the fitted variance from the model during the previous period. The result indicates the conditional mean term (ω) is not significantly different from zero, and the conditional variance is statistically positively related to the volatility and fitted variance from the model during the previous period, with $\alpha = 0.1502,\ \beta = 0.6002$. Also, the results for relation between each trading activity and stock price volatility are in keeping with our assumption. That is, to the extent that the unexpected component of volume is regarded as informed trading, the results indicate that the informed trading is positively related to the volatility of stock price. All other components of option trading activities with the exception of moving average of open interest are either negatively related to volatility or do not have statistically significant relations. Estimated coefficients for both of moving average series are significant, again indicating that long term variations in activity are relevant for explaining volatility. Coefficient estimates on the moving average of option volume is negative and open interest is positive. The finding indicates that stock price volatility is negatively related to longer-term shifts in option volume but it is positively related to longer-term shifts in open interest. Also, the unexpected component of open interest gives significant negative coefficients even though open interest is regarded as trading of uninformed traders.

In the case of put option, we find the dummy variable for Monday is negatively significant, and the first serial correlation is not significant. The unexpected component of volume shows positive relation with stock price volatility, while other components either have negative relations with stock price volatility or do not have statistically significant relations. The fact that the unexpected component of volume has positive relation with volatility and the expected component of volume and all of components of open interest have negative relation with volatility agrees with our expectation that trading activity of uninformed traders is negatively related with stock volatility.

[Insert Table 4 about here.]

Our findings so far show the evidence on *whether* informed traders take part in options market or not. However, further tests may be in order to clearly show *where* and *how* they take part in options market. As shown in Table 3, option traders prefer to invest in option differently according to moneyness of options. Accordingly, we divide option volume into each series of options according to moneyness, then estimate each series of options by using a modified GARCH(1,1) model. Table 5 and Table 6 present the results for each series of call and put options, respectively.

Table 5 presents the results of call options after partitioning option volume and open interest according to their moneyness. The results show all of the unexpected components of volume have positive relations with stock price volatility with the exception of out-of-the-money option. To the extent that the unexpected component of volume represents informed trading, the results indicate the evidence of informed traders' activities on the volatility of stock price. In deep-in-the-money option, the moving average component of volume is positively related to stock price volatility. The moving average components of open interest in in-the-money and deep-out-of-the-money options are also positively related to stock price volatility. Unusually, the expected component of open interest in near-the-money option is positively related with the volatility. Other trading activities show either negative relations with volatility or insignificant results. Because we regard the expected components of volume and open interest as uninformed trading, the results are in keeping with our assumption and the findings of previous research (e.g., Bessembinder and Seguin(1992)) that report uninformed trading as having negative or insignificant relation with volatility.

삭제됨: of-

[Insert Table 5 about here.]

The results of test for put options are reported in Table 6. Unlike the case of call options, the results show that all of the unexpected components of volume have positive relations with stock price volatility regardless of the moneyness. In deep-in-the-money option, however, the expected component of volume which is assumed as trading activity of uninformed traders is positively related to stock price volatility. In addition, some of the unexpected and expected components of open interest which are regarded as trading activity of hedgers, also have positive relations with volatility. This is an interesting economic result because these results do not correspond to our initial expectation. In general, the stock index responds to the market more sensitively in downward market than upward market. Because of such an asymmetric property of market volatility (Nelson, 1991), many individual investors tend to prefer put options to call options. Specifically, typical uninformed traders are individual investors who do not have enough money to invest in options and they would prefer deep-out-of-the-money options which have the cheapest option premium when other things are equal. When market volatility increases, these individual investors buy deep-out-of-the-money put options, then sell the options immediately or hold the option not for hedging but for gaining from the option position. The result that the trading activities of open interest are positively related with stock market volatility may be the reflection of trading behavior by these uninformed individual players in options market. Although some of the uninformed trading has positive relations with volatility, most of uninformed trading has negative or insignificant relations with stock price volatility.

[Insert Table 6 about here.]

In sum, both Table 5 and Table 6 show the strong evidence of informed trading in options market. Specifically, in these tables we can find *where* and *how* informed traders take part in options market after dividing trading activity into several moneyness components of informed trading and uninformed trading. As stated earlier, however, the changes in option value respond differently to the movement of underlying stock according to moneyness. Therefore, we further investigate informed traders' trading behavior with respect to option contracts that have greater leverage implications in detail.

If there are informed traders having private information, they will particularly prefer deep-out-of-the-money option due to high leverage effects. Such preference would be more prevalent in a highly volatile market. Deep-out-of-the-money option is sometimes referred to as being options on volatility since deep-out-of-the-money option has the highest leverage effect in a volatile market. In a stable market, however, informed traders would not be attracted to deep-out-of-the-money option because of low delta, which is the rate of change of option price with respect to the price of underlying asset. In other words, although deep-out-of-the-money option can have the highest leverage effects in a volatile market, the change of value of that option is expected to be mostly insensitive to the change of underlying asset's value in a stable market. For these reasons, informed traders would differently behave in the different states of volatility. Thus, we divide the market volatility into two states --- volatile and stable regimes. For example, informed traders may prefer to invest in deep-out-of-the-money options rather than other moneyness options due to leverage effects in a volatile market, while they prefer to invest in relatively higher delta option than deep-out-of-the-money option in a stable market because value of low delta options are not easily changed in a stable market. To capture such preferential differences of informed traders, we use RS-GARCH models for our study. Specifically, if the unexpected component of volume is regarded as informed traders' activity, it will have positive relationship with stock market volatility, since the value of options is high when market volatility is high. Moreover, the positive relationship would be stronger in high leverage options when the volatility of market is very high.

Table 7 and Table 8 present the results obtained by using RS-GARCH(1,1) model for call option and put option series, respectively. In the remaining tables to be discussed, let $\gamma_{1,1}$, $\gamma_{2,1}$, $\gamma_{3,1}$, $\gamma_{4,1}$, $\gamma_{5,1}$, and $\gamma_{6,1}$ denote the unexpected component of volume, the expected component of volume, the moving-average component of volume, the unexpected component of open interest, the expected component of open interest, and the moving-average component of open interest, at a volatile state, respectively. And, let $\gamma_{1,2}$, $\gamma_{2,2}$, $\gamma_{3,2}$, $\gamma_{4,2}$, $\gamma_{5,2}$, and $\gamma_{6,2}$ denote the unexpected component of volume, the expected component of volume, the moving-average component of volume, the unexpected component of open interest, the expected component of open interest, and the moving-average component of open interest, at a stable state, respectively. And let P_{12} and P_{21} denote the transition probabilities. That is, P_{12} defines the probability that index return will change from state 1 in period $t-1$ to state 2 in period t, and P_{21} defines the probability that index return will change from state 2 in period $t-1$ to state 1 in period t.

Table 7 presents results for call option series that are classified by the moneyness and incorporates the regime-switching effect of stock price volatility over our sample period. In the volatile state, the unexpected component of deep-out-of-the money option shows statistically significant positive coefficients. The unexpected components of near-the-money and out-of-the-money options also give statistically significant positive coefficients in the stable state. When we consider the unexpected component of volume as informed traders' activities, the results indicate that informed traders actively trade deep-out-of-the money option in volatile markets, and prefer to trade near-the-money and out-of-the money option in stable markets. These are interesting results. Although deep-out-of-the-money option can have very high leverage effects, the value of that option does not get changed much in the stable market because deep-out-of-the-money option has very low delta which is the rate of change of option price with respect to changes in the price of underlying asset. Therefore, it is possible for informed traders to trade out-of-the-money or near-the-money option, whose value is changed more quickly than deep-out-of-the-money options, more actively rather than deep-out-of-the-money option in the stable market. Informed traders, however, may prefer deep-out-of-the-money option in the volatile market even if the delta of the option is very low because potentially high leverage effects on the value of option can be expected in the volatile market. The result also shows that all the components of volume and open interest excluding the expected component of volume are positively related with stock market volatility in a volatile market for deep-out-of-the money option. In contrast, for the same deep-out-of-the money option, all the components of volume and open interest except the expected component of volume are negatively related with stock market volatility or have statistically zero coefficients in a stable market. This means that in volatile markets, deep-out-of-the-money option is actively traded thanks to high leverage effects and low premium without much reference to information which investors have. The results obtained from the RS-GARCH model also show most of the uninformed trading have statistically negative or insignificant relations with stock price volatility. Only deep-in-the-money option of the expected component of volume reports significantly positive relation with stock price volatility. As stated earlier, moving average series indicate that long term variations in activity are relevant for explaining volatility. In volatile markets, moving-average components of deep-out-of-the-money option of volume and open interest have positive relations with stock price volatility. This means that stock price volatility is positively related to longer-term shifts in option volume. Other moving-average components are negatively related to stock price volatility. In addition, most of the transition probabilities are below 1%, so we know the volatility of states are seldom changed. This is in keeping with studies of previous research (e.g., Bollerslev et al. (1992) and Lo (1991)) that volatility of stock price is clustering.

[Insert Table 7 about here.]

Table 8 reports results for put option series that are classified by their moneyness. The results obtained from the test of put option are almost similar to the test results of call option. In the volatile state, the unexpected component of deep-out-of-the-money option volumes has statistically significant positive relations with stock price volatility. In the stable state, in contrast, the unexpected component of near-the-money option volumes has statistically significant positive relations to stock price volatility. These results also show that informed traders move differently in volatile and stable markets. Results obtained from the tests of call and put option indicate that informed traders prefer high leverage option in volatile markets, while they prefer relatively high delta option in stable markets. Uninformed trading activity found in the expected components of volume and open interest shows negative or statistically insignificant relations with stock price volatility. We can interpret the informed trader's behavior in the option market in detail using RS-GARCH model which separates the market volatility into stable and volatile states. Results of empirical tests show the informed traders react differently to the different states of market volatility and invest differently in the option market according to the state of the market.

[Insert Table 8 about here.]

In sum, in all of moneyness options except the out-of-the-money call option, unexpected components of volume representing informed traders are positively related to stock market volatility before dividing the regimes of different volatility. After dividing the volatility into two regimes, however, evidence of informed traders' trading activities is strongly detected in deep-out-of-the-money option in volatile markets and similar evidence is also found near-the-money and out-of-the-money call options and near-the-money put options in stable markets.

V. CONCLUSION

In this paper, we examine the relation between option volume and stock market volatility using RS-GARCH model. The rationale behind the use of this model stems from the fact that the relationship between option volatility and stock market volatility may be better characterized by regime shifts, which, in turn, suggest that trading activities in each of the option volume may respond differently between the volatile and stable markets. Because the higher volatility is one of the key determinants of the higher option value, we can expect a strong interrelation between option trading volume and stock market volatilities. In addition, if informed traders are attracted more to options market than stock market due to lower transactions cost and beneficial leverage effects, option trading volume may precede future stock price volatility. To facilitate the investigation, we first divide option volume in terms of moneyness to examine how each option volume affects stock market volatility. We further divide the option volume into unexpected, expected and moving average components.

Empirical results obtained from GARCH(1,1) models show the evidence of informed traders' behavior in most of option series. To obtain more detailed evidence of informed traders' behavior, after dividing stock price volatility into volatile and stable states, we empirically test further using RS-GARCH(1,1) models. Findings from empirical test indicate that both cases of call and put options contain informational significance in high leverage options such as deep-out-of-the-money option in volatile states. But informed traders invest in high leverage options no longer in stable markets. When the market does not move actively, informed traders invest in relatively high delta option such as near-the-money or out-of-the-money options.

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삭제됨:

FIGURE 1: Path Dependence in a RS-GARCH Model with Two States

Path 1: $\sigma^2_{t|1,1} = \omega_1 + \beta_1 \sigma^2_{t-1|1} + \alpha_1 \varepsilon^2_{t-1} + \sum_{j=1}^{n} \gamma_{j,1} Vol_{j,t}$

Path 2: $\sigma^2_{t|1,2} = \omega_2 + \beta_1 \sigma^2_{t-1|1} + \alpha_1 \varepsilon^2_{t-1} + \sum_{j=1}^{n} \gamma_{j,2} Vol_{j,t}$

Path 3: $\sigma^2_{t|2,1} = \omega_1 + \beta_2 \sigma^2_{t-1|2} + \alpha_2 \varepsilon^2_{t-1} + \sum_{j=1}^{n} \gamma_{j,1} Vol_{j,t}$

Path 4: $\sigma^2_{t|2,2} = \omega_2 + \beta_2 \sigma^2_{t-1|2} + \alpha_2 \varepsilon^2_{t-1} + \sum_{j=1}^{n} \gamma_{j,2} Vol_{j,t}$

FIGURE 2: KOSPI 200 Index Return in Percent

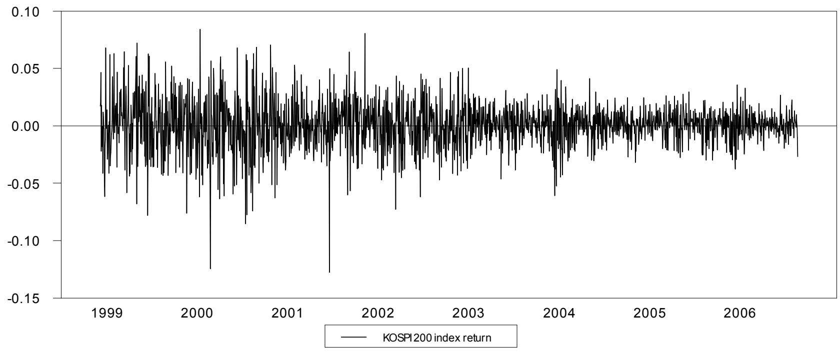

TABLE 1: The Classification of Moneyness

Criterion	Moneyness of Option	
	call	**put**
$K/S > (1+6\%)$	deep out-of-the-money	deep-in-the-money
$(1+2\%) < K/S \leq (1+6\%)$	out-of-the-money	in-the-money
$(1-2\%) \leq K/S < (1+2\%)$	near-the-money	near-the-money
$(1-6\%) \leq K/S < (1-2\%)$	in-the-money	out-of-the-money
$K/S < (1-6\%)$	deep-in-the-money	deep out-of-the-money

S is the price of underlying asset, and K is the exercise price of options. If we classify option volume according to moneyness, we can get 10 different option series for one option class (call option or put option for the same underlying asset).

삭제됨:

TABLE 2: Descriptive Statistics of KOSPI 200 Index Return and Call Option and Put Option for Total Option Volume

삭제됨: .

	KOSPI200 index return	Open interest for call option	Volume for call option	Open interest for put option	Volume for put option
Mean	0.0005**	1326.2**	3,578.10**	1,292.5**	3,246.1**
Std. Dev.	0.0004**	840.6**	2,819.00**	827.5**	2,691.6**
Skewness	-0.3066**	0.2513**	0.7063**	0.1238**	0.9095**
Kurtosis	2.9256**	-0.5667**	0.4099**	-1.096**	0.8071**
Jarque-Bera	749.07**	48.13**	181.45**	105.88**	332.14**

The symbols * and ** denote significance at the 5% and 1% levels, respectively.
Each option volume is divided by 1,000.

TABLE 3: Descriptive Statistics of KOSPI 200 Each Series of Call and Put Option

	DITM	ITM	NTM	OTM	DOTM
call open interest					
Mean	29.8**	40.8**	135.9**	323.3**	681.9**
Std. Dev.	39.4**	44.8**	133.5**	278.9**	602.2**
Skewness	4.2015**	2.0025**	1.4560**	0.7676**	1.0562**
Kurtosis	36.6838**	6.3385**	2.1531**	0.1618**	0.8188**
Jarque-Bera	118,793.03**	4,715.24**	1,100.11**	199.88**	430.50**
call volume					
	DITM	ITM	NTM	OTM	DOTM
Mean	5.0**	42.9**	905.7**	1,506.6**	1,062.9**
Std. Dev.	10.3**	180.2**	1668.0**	1571.0**	1288.9**
Skewness	10.2809**	13.7373**	2.9702**	1.2414**	1.6160**
Kurtosis	179.9601**	243.4889**	9.8330**	1.7580**	2.5006**
Jarque-Bera	2,751,807.79**	5,035,998.85**	11,069.51**	776.24**	1,400.68**
put open interest					
	DITM	ITM	NTM	OTM	DOTM
Mean	23.1**	786.4**	36.3**	107.4**	203.3**
Std. Dev.	40.3**	521.7**	40.1**	102.6**	183.5**
Skewness	7.0179**	0.2248**	2.3945**	1.4698**	0.9958**
Kurtosis	83.9840**	-0.8881**	7.1772**	2.2708**	0.3657**
Jarque-Bera	608,119.97**	83.11**	6,244.18**	1,157.27**	343.92**
put volume					
	DITM	ITM	NTM	OTM	DOTM
Mean	3.8**	1,321.7**	37.0**	716.2**	1,112.9**
Std. Dev.	10**	1,236.4**	150.3**	1,436.6**	1,283.5**
Skewness	11.6508**	1.0031**	11.7559**	3.2668**	1.6369**
Kurtosis	218.7548**	0.7787**	173.5728**	12.5471**	3.3241**
Jarque-Bera	4,057,252**	388.43**	2,484,245**	16,784.97**	1,825.71**

DITM: deep-in-the-money; ITM: in-the–money; NTM: near-the-money; OTM: out-of-the-money; DOTM: deep-out-of-the-money.

The symbols * and ** denote significance at the 5% and 1% levels, respectively.
Each option volume is divided by 1,000.

TABLE 4. Results of GARCH (1,1) Test for Total Call and Put Option

삭제됨: .

	Call Option	Put Option
Variable	Coeff.	Coeff.
μ	0.000017* (0.0471)	0.000016* (0.0350)
λ_1 (Monday)	-0.000018 (0.1172)	-0.000022* (0.0333)
λ_2 (Tuesday)	-0.000005 (0.6836)	-0.000002 (0.9002)
λ_3 (Wednesday)	-0.000011 (0.3514)	-0.000011 (0.3040)
λ_4 (Thursday)	-0.000008 (0.4790)	-0.000009 (0.3838)
κ	0.0404 (0.1224)	0.0404 (0.1022)
ω	0.0004 (0.0625)	0.0002** (0.0000)
α	0.1502** (0.0000)	0.1500** (0.0000)
β	0.6002** (0.0000)	0.6000** (0.0000)
$\gamma_1 (\times 10^4)$	0.0001* (0.0473)	0.0002** (0.0001)
$\gamma_2 (\times 10^4)$	-0.0034 (0.0842)	-0.0008 (0.7985)
$\gamma_3 (\times 10^4)$	-0.0002** (0.0000)	-0.0001** (0.0037)
$\gamma_4 (\times 10^4)$	-0.0006* (0.0148)	-0.0012** (0.0000)
$\gamma_5 (\times 10^4)$	-0.3560 (0.1932)	-0.1360** (0.0000)
$\gamma_6 (\times 10^4)$	0.0001* (0.0325)	-0.0001* (0.0492)

The symbols * and ** denote significance at the 5% and 1% levels, respectively.
Each option volume is divided by 1,000.

TABLE 5: Results of GARCH (1,1) Test for Call Option Series Classified by Moneyness

	Moneyness				
Variable	DITM	ITM	NTM	OTM	DOTM
$\gamma_1(\times 10^4)$	0.0468** (0.0000)	0.0005** (0.0064)	0.0001** (0.0000)	-0.0001 (0.3746)	0.0008** (0.0000)
$\gamma_2(\times 10^4)$	-0.0632 (0.1107)	-0.0008 (0.1724)	-0.0030** (0.0000)	-0.0014 (0.3688)	-0.0149 (0.4475)
$\gamma_3(\times 10^4)$	0.0348* (0.0205)	0.0005 (0.2313)	-0.0001* (0.0311)	-0.0003* (0.0230)	-0.0002** (0.0000)
$\gamma_4(\times 10^4)$	-0.0068** (0.0064)	-0.0054** (0.0000)	-0.0020** (0.0000)	-0.0015* (0.0472)	-0.0005* (0.0168)
$\gamma_5(\times 10^4)$	-12.5300* (0.0111)	-0.0165** (0.0007)	0.0233** (0.0001)	-0.1680 (0.3479)	-0.6290** (0.0013)
$\gamma_6(\times 10^4)$	-0.0035** (0.0050)	0.0027** (0.0000)	-0.0019** (0.0000)	-0.0013* (0.0424)	0.0003** (0.0000)

DITM: deep-in-the-money; ITM: in-the–money; NTM: near-the-money; OTM: out-of-the-money; DOTM: deep-out-of-the-money.

The symbols * and ** denote significance at the 5% and 1% levels, respectively.
Each option volume is divided by 1,000.

TABLE 6: Results of GARCH (1,1) Test for Put Option Series Classified by Moneyness

	Moneyness				
Variable	DITM	ITM	NTM	OTM	DOTM
$\gamma_1 (\times 10^4)$	0.0463** (0.0000)	0.0002** (0.0000)	0.0038** (0.0002)	0.0002** (0.0014)	0.0004* (0.0411)
$\gamma_2 (\times 10^4)$	0.0417** (0.0000)	0.0000 (0.9669)	-0.0370** (0.0072)	-0.0013 (0.3462)	-0.0076** (0.0000)
$\gamma_3 (\times 10^4)$	-0.0895** (0.0000)	-0.0001** (0.0000)	-0.0123** (0.0000)	-0.0004** (0.0000)	0.0001** (0.0000)
$\gamma_4 (\times 10^4)$	0.0042 (0.2664)	-0.0009** (0.0000)	-0.0152** (0.0000)	-0.0046** (0.0000)	0.0067** (0.0000)
$\gamma_5 (\times 10^4)$	-0.0361 (0.5257)	-0.0455** (0.0000)	-0.9400 (0.4584)	-0.0092 (0.7792)	0.0418** (0.0006)
$\gamma_6 (\times 10^4)$	-0.0013 (0.1314)	0.0001** (0.0000)	-0.0097** (0.0015)	-0.0038* (0.0127)	0.0021* (0.0163)

DITM: deep-in-the-money; ITM: in-the–money; NTM: near-the-money; OTM: out-of-the-money; DOTM: deep-out-of-the-money.

The symbols * and ** denote significance at the 5% and 1% levels, respectively.
Each option volume is divided by 1,000.

TABLE 7: Results of RS-GARCH (1,1) Test for Call Option Series Classified by Moneyness

		Moneyness				
	Variable	DITM	ITM	NTM	OTM	DOTM
State 1: volatile regime	$\gamma_{1,1}(\times 10^4)$	-0.0027 (0.7328)	0.0000 (0.9863)	0.0000 (0.8714)	0.0000 (0.9925)	0.0001** (0.0023)
	$\gamma_{2,1}(\times 10^4)$	-1.1904** (0.0000)	-0.1122** (0.0000)	-0.0019* (0.0440)	-0.0071** (0.0000)	-0.6264** (0.0000)
	$\gamma_{3,1}(\times 10^4)$	0.0855** (0.0000)	-0.0002 (0.9194)	-0.0003 (0.1289)	0.0002 (0.3798)	0.0004** (0.0000)
	$\gamma_{4,1}(\times 10^4)$	-0.0014 (0.7015)	-0.0034 (0.2207)	-0.0045* (0.0395)	-0.0014 (0.1688)	0.0002* (0.0230)
	$\gamma_{5,1}(\times 10^4)$	-10.4830 (0.3574)	0.1467** (0.0000)	0.0408** (0.0043)	0.5504 (0.2560)	0.4035** (0.0000)
	$\gamma_{6,1}(\times 10^4)$	-0.0013 (0.6955)	-0.0139** (0.0000)	-0.0113** (0.0000)	-0.0059** (0.0000)	0.0010** (0.0000)
	$P_{2,1}$	0.0025 (0.2356)	0.0054** (0.0071)	0.0086** (0.0008)	0.0114** (0.0000)	0.0063** (0.0000)
State 2: stable regime	$\gamma_{1,2}(\times 10^4)$	0.0022 (0.4112)	0.0000 (0.9951)	0.0000** (0.0050)	0.0000* (0.0479)	-0.0002* (0.0472)
	$\gamma_{2,2}(\times 10^4)$	0.5166 (0.0000)	0.0362** (0.0000)	-0.0055 (0.0000)	-0.0049** (0.0000)	0.8312** (0.0013)
	$\gamma_{3,2}(\times 10^4)$	0.0182* (0.0132)	-0.0008 (0.2581)	0.0001** (0.0000)	0.0004** (0.0000)	-0.0007** (0.0000)
	$\gamma_{4,2}(\times 10^4)$	-0.0010 (0.2123)	-0.0012* (0.0365)	-0.0013** (0.0000)	-0.0010** (0.0000)	-0.0002 (0.5674)
	$\gamma_{5,2}(\times 10^4)$	0.0865 (0.9710)	-0.3949** (0.0000)	-0.0702** (0.0000)	0.7973** (0.0000)	0.1395 (0.5421)
	$\gamma_{6,2}(\times 10^4)$	-0.0022 (0.0070)	0.0035** (0.0000)	-0.0016** (0.0001)	-0.0053** (0.0000)	-0.0001 (0.7219)
	$P_{1,2}$	0.0026 (0.0685)	0.0057* (0.0140)	0.0207** (0.0009)	0.0228** (0.0002)	0.0050* (0.0245)

DITM: deep-in-the-money; ITM: in-the–money; NTM: near-the-money; OTM: out-of-the money; DOTM: deep-out-of-the-money.

The symbols * and ** denote significance at the 5% and 1% levels, respectively.
Each option volume is divided by 1,000.

TABLE 8: Results of RS-GARCH (1,1) Test for Put Option Series Classified by Moneyness

		Moneyness				
	Variable	DITM	ITM	NTM	OTM	DOTM
State 1: volatile regime	$\gamma_{1,1}(\times 10^4)$	-0.0293** (0.0044)	-0.0001 (0.4505)	-0.0003 (0.4129)	0.0002 (0.1479)	0.0000* (0.0406)
	$\gamma_{2,1}(\times 10^4)$	-0.6288** (0.0000)	0.0579** (0.0006)	-0.1463** (0.0000)	-0.0052** (0.0000)	-0.0037** (0.0000)
	$\gamma_{3,1}(\times 10^4)$	0.1549** (0.0000)	-0.0004** (0.0025)	0.0060** (0.0032)	0.0003** (0.1154)	0.0003** (0.0000)
	$\gamma_{4,1}(\times 10^4)$	0.0060 (0.1487)	-0.0004 (0.3571)	-0.0061 (0.0574)	-0.0079** (0.0007)	-0.0011** (0.0000)
	$\gamma_{5,1}(\times 10^4)$	4.8483 (0.0990)	1.0272** (0.0066)	-57.5610** (0.0041)	0.0764** (0.0010)	-0.0569** (0.0000)
	$\gamma_{6,1}(\times 10^4)$	-0.0093* (0.0202)	-0.0025** (0.0000)	0.0174 (0.1003)	-0.0221** (0.0000)	-0.0009** (0.0077)
	$P_{2,1}$	0.0070** (0.0023)	0.0026 (0.1142)	0.0223** (0.0000)	0.0120** (0.0002)	0.0126** (0.0008)
State 2: stable regime	$\gamma_{1,2}(\times 10^4)$	-0.0008 (0.3256)	0.0000 (0.7746)	0.0003* (0.0107)	0.0000 (0.1876)	0.0001 (0.4149)
	$\gamma_{2,2}(\times 10^4)$	0.4549** (0.0000)	-0.0486** (0.0000)	-0.1287** (0.0000)	-0.0083** (0.0000)	-0.0102** (0.0000)
	$\gamma_{3,2}(\times 10^4)$	0.1344** (0.0000)	0.0005** (0.0000)	0.0128** (0.0000)	0.0001** (0.0023)	0.0010** (0.0000)
	$\gamma_{4,2}(\times 10^4)$	0.0026* (0.0032)	-0.0002 (0.0951)	0.0001 (0.9304)	-0.0010** (0.0025)	-0.0055** (0.0001)
	$\gamma_{5,2}(\times 10^4)$	-36.4030** (0.0000)	0.2079* (0.0176)	1.5192** (0.0023)	0.0163** (0.0003)	0.0847** (0.0000)
	$\gamma_{6,2}(\times 10^4)$	0.0385** (0.0000)	-0.0005** (0.0000)	0.0007 (0.5901)	-0.0027** (0.0000)	-0.0196** (0.0000)
	$P_{1,2}$	0.0080** (0.0045)	0.0030 (0.0720)	0.0146** (0.0002)	0.0205** (0.0008)	0.0104** (0.0025)

DITM: deep-in-the-money; ITM: in-the–money; NTM: near-the-money; OTM: out-of-the-money; DOTM: deep-out-of-the-money.

The symbols * and ** denote significance at the 5% and 1% levels, respectively.
Each option volume is divided by 1,000.