The Relationship between Trading Volume and Volatility in Korea's Financial Markets

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Abstract The aim of this study is to identify the relationship between trade volume and volatility in Korea's financial markets, including the KOSPI 200 Index, KOSPI 200 options, and KOSPI 200 futures. With regards to the relationship between the trading volume of the KOSPI 200 Index and the volatility of KOSPI 200 derivatives markets, the trading volume of the underlying index is found to increase the volatilities of KOSPI 200 options and the futures markets. The expected trading volume of the underlying index has a positive relation with VKOSPI, which is the options market volatility measure; further, the unexpected components have a positive relation with the volatility of the futures market. In short, the trading volume of the underlying index is positively related with the volatilities of options and futures markets. Moreover, with regards to the relation between derivatives' trading activities and the underlying index volatility, open interests of call and futures, trading volume of futures, and its expected and unexpected components are positively related with the volatility of the KOSPI 200 Index. On the other hand, open interests of put options and their expected components have a negative relation with the volatility of the KOSPI 200 Index. Our empirical results imply that volume and volatility relations have some cross financial markets effects in both the underlying and derivatives markets; furthermore, the trading volumes and volatilities of the underlying and derivatives markets are deeply interrelated with each other.

Keywords: expected trading volume, unexpected trading volume, volatility, sequential information arrival model (SIAM), mixture of distribution hypothesis (MDH)

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1 Introduction

A large volume of academic papers convey that the trading volume and volatility of stock returns are correlated. Karpoff (1987) documents some "stylized facts" about the price changes and trading volume by surveying many empirical studies on the topic. A particular fact to note is that asset price changes and trading volume are positively related. Most studies focus on the relationship between the absolute value of returns and trading volume, where the absolute value of returns or the squared returns can be considered as a volatility measure.

In terms of the theoretical background on the relationship between price changes and volume, there are two main approaches to explain the relationship between trading volume and returns: the mixture of distribution hypothesis (MDH) model by Clark (1973) and the sequential information arrival model (SIAM) by Copeland (1976, 1977). Both models propose a positive correlation between volatility (the absolute value of returns) and trading volume. However, the empirical evidence on the relationship between volume and volatility (or price changes) shows mixed results and is far from conclusive. In addition, both theories on the relation between price changes and trading volume of the same asset are true for the same asset. However, the theories do not mention the relationship between the volume of one market and the price changes of the other market.

Research on the relationship between trading volume and volatility across different financial markets is relatively rare. Most papers deal with the volatility-volatility relationship of the same financial product or market. Thus, it is natural for researchers to explore the relationship between the trading volume of one market and the volatility of the other market. For example, it is meaningful to figure out the volume-volatility relationship among the underlying stock market and its derivatives markets (options and futures markets) because as the underlying stock market and its derivatives markets deeply integrate, the trading volume of each market may have some effects on the volatilities of the other markets. Kyriacou and Sarno (1999) demonstrate that the omission of any of these two options and futures trading activities may generate a serious misspecification problem, which produces misleading estimation and statistical inference.

Hence, we specifically consider the volume-volatility relationship across Korea's financial markets, including the KOSPI 200 Index, KOSPI 200 options, and KOSPI 200 futures. The following volatility measures are considered as the dependent variables: historical volatility of the underlying KOSPI 200 index market, range-based Garman-Klass (1980) volatility of KOSPI 200 futures, and VKOSPI for KOSPI 200 options. For volatility measures of the underling KOSPI 200 index, the GJR-GARCH model,[1] range-based Garman-Klass volatility, and realized volatility are additionally considered as measures to check the robustness of the empirical results. Key explanatory variables include the trading activities of the underlying KOSPI 200 index, KOSPI 200 futures, and KOSPI 200 options.

The rest of the paper is organized as follows. Section 2 provides some theoretical backgrounds and previous works. Section 3 explains the data set and model specifications for the volume-volatility relationships. Section 4 presents the discussions on the empirical results and section 5 concludes the paper.

2 Theoretical Backgrounds and Previous Works

2.1 Theoretical Background

Two major theoretical approaches have been applied to explain the volume-volatility relationship in the stock markets: the mixture of distribution hypothesis (MDH) model by Clark (1973) and the sequential information arrival model (SIAM) by Copeland (1976, 1977). Both models imply a positive correlation between volume and volatility.

In one of the MDH models, Tauchen and Pitts (1983) derive a joint probability density $f(\Delta P, V)$ of the daily price change ΔP, and the trading volume V contains all of the relevant information regarding the price variability-volume relationship. They also portray that the

[1] Glosten, Jagannathan, and Runkle (1993).

conditional expectation of the squared price change, $E(\Delta P^2|V)$, is increasing in the trading volume, which is in agreement with Clark's (1973) findings. Further, the daily volume and volatility in their model depend on three factors: the average daily rate at which new information flows to the market, the extent to which traders disagree when they respond to new information, and the number of active traders in the market.

In the SIAM by Copeland (1976), there is a positive volume-volatility correlation with high values occurring when traders have unanimous opinions with regards to new information and low values occurring when they disagree. As a special case of the sequential information arrival model, Copeland suggests a simultaneous information arrival model, where there is a negative volume-volatility correlation.

The number of studies on the equilibrium model for the role of financial derivatives is relatively small (Cox, 1976; Brennan and Cao, 1996; Kraus and Smith, 1996). However, many empirical studies exist on this topic. It is known that informed traders utilize derivatives markets, such as futures or options markets. A group of authors have suggested that informed traders use options markets and that options trading volumes have some informational roles (Easley et al., 1998;, Cao et al., 2000; Lee and Rui, 2000; Jayaraman et al., 2001; Pan and Poteshman, 2006; Chakravarty et al., 2004; Ahn et al., 2008; Ni et al., 2008, Chang et al., 2010). For futures markets, there are many empirical studies on the volume-volatility relationship within the futures market (Bessembinder and Seguin, 1993; Daigler and Wiley, 1999; Wang, 2002).

There are several previous works on the volume-volatility relation across financial markets. Most of them are on the relation between options, futures, or both trading activities and the underlying spot volatility. As mentioned in Kyriacou and Saron (1999), it is better to consider both options and futures trading activities simultaneously in order to avoid the misspecification problem from the omitted variable.

2.1.1 The mixture of distribution hypothesis

In Clark's seminal model (1973),[2] the speed of information flow is a latent common factor that influences both the trading volume and return volatility simultaneously. He finds that an obvious measure of the speed of information flow is the trading volume, by empirically demonstrating the positive contemporaneous relationship between the trading volume and volatility.

Epps and Epps (1976) also explain the positive volume-volatility relationship in the context of the MDH model. They derive a simple model of the price-formation process, where the volatility follows a mixture of distributions, with trading volume as the mixing variable. The disequilibrium generated by the new information is described in terms of the discrepancy between market price and the individual's reservation price,[3] where the discrepancy is expressed in terms of individual excess demand or supply. The degree of disagreement between different groups of investors tends to increase with the absolute value of the overall changes in the expectations.[4] Further, their equation of the volatility-volume relationship implies that volatility is positively related to trading volume and that trading volume increases with the degree of disagreement between two investor groups.

Tauchen and Pitts (1983) assume a variance-components model, where price changes are decomposed into two parts, common and specific components. Adding the random number of within-day price changes and volumes offer the daily values of each variable. In addition, a bivariate normal mixture model with a likelihood function is obtained. This joint probability density function of the daily price change and the trading volume contains all of the relevant information regarding the volatility-volume relationship. They reveal the positive relation

[2]In Clark's model, the daily price change is a function of a set of distributions that are characterized by different variances and the sum of a random number of within-day price changes. The variance of the daily price changes is proportional to the mean number of daily transactions, where the daily trading volume is positively related to the number of within-day transactions. Therefore, trading volume and volatility of price changes are positively related.

[3]Epps and Epps call it a "null" price.

[4]In the MDH model of Epps and Epps (1976), all the investors are always divided into two groups, i.e., sellers or buyers. Membership in the groups is not fixed and changes each time.

between volatility and volume by numerically obtaining the conditional expectation of the squared price changes.[5]

Park (2010) extends the bivariate mixture model of Tauchen and Pitts (1983) in order to break the information into three types: non-surprising and signed (positive/negative) surprising information. Even though he does not derive the explicit joint distribution of volatility and volume, he empirically demonstrates a positive relationship for non-surprising information and a negative relationship for positive and negative surprising information, using the 4-minute frequency data of the KRW/USD spot exchange rate. He argues that although the trading volume can be regarded as a proxy for the rate of general information, it is a poor proxy for the arrival rate of surprising information.

The MDH model indicates the volatility-volume relationship in the same financial market. However, it does not inform how the trading volume in one financial market can have an effect on the volatility of the other financial market. The sequential information arrival model conveys how the trading volume in the derivatives markets can have an effect on the underlying stock market.

2.1.2 The sequential information arrival model

The academic background of the relationship between the underlying return volatility and the trading volume of derivatives is based on studies on price discovery and information flow between the underlying stock market and its derivative markets.

Mougoué and Aggarwal (2011) show that trading volumes and return volatility are negatively correlated in the three major currency futures markets using the generalized method of moments (GMM) for contemporaneous correlation. They argue that their empirical results from the contemporaneous correlation estimates as well as from both linear and nonlinear Granger causality tests support the sequential information arrival model (SIAM). However,

[5] Tauchen and Pitts (1983) further show that the relationship between volatility and volume depends on three factors: 1) the average daily rate at which new information flows to the market, 2) the extent to which traders disagree when they respond to new information, and 3) the number of active traders in the market.

estimates of lagged correlation coefficients of volume and volatility show positive signs, which imply that their results may not support the SIAM.

Easley et al. (1998) examine the informational link between options markets and the underlying equity markets. According to their results, under certain conditions, there exists a pooling equilibrium where some informed traders may choose to trade in the options markets, resulting in particular option trades being informative for the future movement of stock prices. Their empirical tests reveal that stock prices lead options volumes and particular options volumes lead stock price changes. This result implies that options markets are a venue for information-based trading. Easley et al. (1998) suggest that volume is not the outcome of the trading process, but does contain some information.[6]

Chan et al. (2002) analyze the intraday interdependence of order flows and price movements for actively traded NYSE stocks and their CBOE (Chicago Board Options Exchange)-traded options. They find that the stock net trade volume (buyer-initiated volume minus sell-initiated volume) has a strong predictive ability for stock and option quote revisions; yet, the option net trade volume has no incremental predictive ability. They argue that informed traders initiate trades in the stock market, but none in the options market.

Regarding the direction of the information flow between the underlying stock market and its options market, Holowczak, Simaan, and Wu (2006) find that the price discovery on the directional movement of the stock price mainly occurs in the stock market rather than in the options market due to real-time updates on quotes and transactions of U.S. stocks and stock options.[7] Regarding the informativeness of the option quotes, they discover that such informativeness increases as the options trading activity generates a net sell or buy pressure on the underlying stock price.

Using the unique data set of options trading volume, which is subdivided into 16 categories defined by four trade types and four investor classes,[8] Pan and Poteshman (2006) find

[6]Blume et al. (1994) show the information content of volume in the equity markets. Easley et al. (1998) suggest some role of the volume in the option markets.

[7]This is done by automated quote updating algorithms.

[8]The four trade types are "open-buys" which are initiated by a buyer to open a new option position,

that the predictability of options volume for the underlying stock price is increasing in the concentration of informed traders as well as in the leverage of options contracts. However, they find no evidence of informed trading in the index options market, and explain this outcome as a result of informed traders tending to possess firm-specific rather than market-wide information. Although they focus on the information in options volume with regards to the future direction of the underlying stock prices, they suggest an investigation on volatility information in options volume as a future research topic.

2.2 Derivative trading volume and underlying volatility

There have been numerous empirical studies on the relationship between derivative volume and the underlying volatility.

Chatrath, Kamath, Chakornpipat, and Ramchander (1995) investigate the causal relationships between options trading activity and trends in the underlying S&P 100 cash index, and find that options trading has a stabilizing impact on cash markets.

Hagelin (2000) examines the Granger causality relationship between options market activity and cash market volatility on the OMX index in Sweden. He finds unidirectional causality from cash market volatility to call option market activity and a bilateral causality between put option market activity and cash market volatility.

Bessembinder and Seguin (1992) provide empirical evidence on the interrelation between spot-trading volume, future-trading activities (trading volume and open interest), and equity volatility. They find that the unexpected futures-trading volume is positively related to spot volatility, but that the open interest of futures and expected futures-trading volume are negatively related to spot volatility.

Using the 15-minute intraday data of the selected Chicago Board Options Exchange options volume and underlying stock prices, Boluch and Chamberlain (1997) observe the

"open sells" which are initiated by a seller to open a new position, "close-buys" which are initiated by a buyer to close an existing short position, and "close-sells" which are initiated by a seller to close an existing long position. The four investor classes are firm proprietary traders, public customers of discount brokers, public customers of full service brokers, and other public customers.

feedback relationship between options volume and stock price changes, implying that the options market does not show any evidence of being a leading indicator of stock price changes.

The put-call ratio (PCR) in the options market is found to have a significant predictive power in the underlying index markets by Billingsley and Chance (1998), Chance (1990), and Simon and Wiggins (2001). However, Cassano and Han (2008) suggest the strike distribution as a better predictor of both direction and volatility of the exchange rate movements as compared to the put-call ratio. They also criticize that the put-call ratio and the put-call signal are very blunt and imperfect measures of market sentiments.

Bollen and Whaley (2004) investigate the relationship between the net buying pressure from public order flow and the shape of the implied volatility function for index and individual stock options. According to their results, the implied volatility of S&P 500 options is most strongly affected by the buying pressure for index puts, whereas the implied volatility of stock options is dominated by the call option demand.

Ni, Pan, and Poteshman (2008) find that options volume is informative about the future volatility of the underlying stocks by showing that the non-market maker net demand for volatility in the options market is positively related to the subsequent realized volatility of the underlying stocks. That is, they find that options volume has a predictive power of the realized volatility of the underlying stocks. Their findings are consistent with those of Bollen and Whaley (2004).

Bhargava and Malhotra (2007) examine the relationship between volatility and trading activity in four major currency futures markets, using daily trading volume and open interest. They use the bivariate VAR (vector autoregression) model with volume and volatility variables and find that futures trading volume destabilizes the futures market, whereas it is unclear as to whether open interest increases or decreases.

Kyriacou and Sarno (1999) investigate the dynamic relationship between the FTSE 100 index return volatility, futures trading, and options trading in the context of a trivariate simultaneous equations model. They point out the statistical problem when any of the three trading volumes of the underlying index, options, and futures is omitted. They use various volatility measures as dependent variables and find out that contemporaneous relative futures trading activities normalized by open interest are positively related with all of the considered volatility measures; and that contemporaneous relative option trading activities normalized by open interest are negatively correlated with all of the considered volatility measures.

Schlag and Stoll (2005) investigate the relation of index futures price change and signed volume using the five-minute transaction data for options and futures on the German DAX Index.[9] They find that futures traders react more quickly to information about the index; moreover, they, not the options traders, provide a price discovery in the DAX. Regarding the relation between options and futures volume, they discover that the option traders are the followers in price discovery and that neither options nor futures volume predict the underlying price changes at the next interval.

3 Empirical Analysis

3.1 Data

The data set ranges from 6 February 2003 to 29 December 2011 and consists of 2017 daily observations. All of the trading volume variables are re-scaled by the appropriate scalars; we then take the natural logarithms of all variables in order to convert all the trading volume variables into single-digit numbers.[10] All the data used in this research come from the Korea Exchange.[11]

According to the Augmented Dickey-Fuller unit root test, all variables, except futures trading volume, are stationary. Thus, de-trended futures trading volume is used.[12] The

[9]Following Easley et al. (1998), positive option trades are buying a call or selling a put and negative option trades are selling a call or buying a put.

[10]Trading volume variables of stock, options and futures are divided by 10^9 and the number of contracts traded and open interests of options and futures are divided by 10^3. They all are converted into the natural logarithms.

[11]http://www.krx.co.kr.

[12]Futures trading volume is de-trended with the linear and squared time trends.

volatility variables are as follows: HV_{K200}, VGK_{K200}, $VKOSPI$, and VGK_F. HV_{K200} is the historical volatility of the KOSPI 200 index return. The index returns are conventionally defined as $r_t = 100 \times \ln(S_t/S_{t-1})$. HV_{K200} is estimated from a past 23-day sample standard deviation of the KOSPI 200 index return. VGK_{K200} is a type of intra-day price change-based volatility developed by Garman and Klass (1980), and estimated as follows:

$$VGK_{K200,t} = \sqrt{0.5[\ln(S_t^h/S_t^l)]^2 - (2\ln 2 - 1)[\ln(S_t^c/S_t^o)]^2}, \tag{1}$$

where, S_t^h is the highest price of KOSPI 200 at trading day t, S_t^l is the lowest price, S_t^o is the opening price, and S_t^c is the closing price at trading day t. Likewise, VGK_F is defined and estimated in the same way for the futures market of the KOSPI 200 Index. $VKOSPI$ is the volatility index from the KOSPI 200 index options markets. Thus, $VKOSPI$ reflects the implied volatilities of call and put options and has some predictive power of future volatility. The daily trading volume variables are TV_S the trading volume of stocks of KOSPI 200, TV_C trading volume of KOSPI 200 call options, TV_P trading volume of KOSPI 200 put options, and TV_F trading volume of KOSPI 200 futures. The open interests for the derivatives markets are OI_C open interests of KOSPI 200 call options, OI_P open interests of KOSPI 200 put options, and OI_F open interests of KOSPI 200 futures.

The basic statistics of the considered variables and correlation coefficients are summarized in Tables 1 and 2, respectively, and the time-series graphs are shown in Figure 1. The trading volume variables, TV_S, TV_C, TV_P, and TV_F are for the KOSPI 200 Index, call options, put options, and futures, respectively. OI_C, OI_P, and OI_F are open interests of call options, put options, and futures, respectively. The mean of the trading volume of KOSPI 200 futures is 0 because it is demeaned.

As documented in previous studies such as Bessembinder and Seguin (1992, 1993), Daigler and Wiley (1999), and Wang (2002), we partition each trading activity series into expected and unexpected components. Unlike previous models in which univariate time-series models are used to partition the trading volume, in this study, a VAR (vector autoregression) model is used for the deeply-integrated the KOSPI 200 Index and its derivatives markets. All of the trading activity variables (TV_S, TV_C, TV_P, TV_F, OI_C, OI_P, and OI_F) are included in order to estimate the VAR(2) model.[13] The estimated trading activities from the estimation of VAR(2) are the expected components, which are interpreted as forecast parts of the trading activity. The unexpected components are residuals of the estimation of the VAR(2) model, which are interpreted as daily shocks of the trading activity. The expected components of each series are denoted as E_S, E_C, E_P, E_F, E_{OI_C}, E_{OI_P}, and E_{OI_F}, for the KOSPI 200 Index, call options, put options, futures, open interests of call options, open interests of put options, and open interests of futures, respectively. The unexpected components of trading activity are denoted as U_S, U_C, U_P, U_F, U_{OI_C}, U_{OI_P}, and U_{OI_F}, respectively. Table 3 provides the summary statistics on these trading activities. Tables 4 and 5 show the correlation coefficients of these variables.

3.2 Model specification

3.2.1 Bivariate Linear Granger Causality

We run a bivariate regression of the form to test the linear Granger causality relations between two variables volatility Vol and trading activity TA:

$$Vol_t = a_0 + \sum_{i=1}^{N_1} a_{1,i} Vol_{t-i} + \sum_{j=1}^{N_2} a_{2,j} TA_{t-j} + \varepsilon_{Vol,t}, \tag{2}$$

$$TA_t = b_0 + \sum_{l=1}^{N_3} b_{1,l} TA_{t-l} + \sum_{m=1}^{N_4} b_{2,m} Vol_{t-m} + \varepsilon_{TA,t}. \tag{3}$$

The variable TA is said to not to Granger cause Vol if $a_{2,j} = 0$, for any $j = 1, 2, \ldots, N_2$. This means that the past values of TA do not provide any additional information to predict the future values of h. Similarly, Vol does not Granger cause TA if $b_{2,m} = 0$, for any

[13]The optimal lag length is determined as 2 by the Schwarz information criterion.

$m = 1, 2, \ldots, N_4$. The linear causal relations between Vol and TA can be tested by testing the following null hypotheses separately:

$$H_0^1 \quad : \quad a_{2,1} = a_{2,2} = \cdots = a_{2,N_2} = 0, \tag{4}$$

$$H_0^2 \quad : \quad b_{2,1} = b_{2,2} = \cdots = b_{2,N_4} = 0. \tag{5}$$

3.2.2 Volatility-volume Relationship

We use two model specifications to scrutinize the relationship between volatility and volume. A linear regression model and a GARCH (generalized autoregressive conditional heteroskedasticity) model are considered.

In a linear regression specification, contemporaneous expected and unexpected trading activities are used as explanatory variables:

$$Vol_t = c_0 + c_1 Vol_{t-1} + \sum_{i=1}^{N} d_i TA_{i,t} + \epsilon_t, \tag{6}$$

where, Vol_t is the volatility measure such as HV_{K200}, VGK_{K200}, $VKOSPI$, and VGK_F. $TA_{i,t}$ is the trading activity of i at date t. The trading activity $TA_{i,t}$ includes contemporaneous expected and unexpected components of trading activities in the KOSPI 200 Index, options, and futures markets: E_S, E_C, E_P, E_F, E_{OI_C}, E_{OI_P}, E_{OI_F}, U_S, U_C, U_P, U_F, U_{OI_C}, U_{OI_P}, and U_{OI_F}.

It is meaningful to figure out whether trading volume can have any predictive power for the future realized volatility. Therefore, a realized volatility for one month ahead is used as a dependent variable:

$$RV_t \quad = \quad f_0 + f_1 RV_{t-1} + \sum_{i=1}^{N} g_i TA_{i,t} + e_t, \tag{7}$$

where, RV_t is a realized volatility for one month ahead and is defined as $RV_t = HV_{K200,t+23}$. It is known that the volatility index VKOSPI has a predictive power of the realized volatility. Using this specification, we attempt to figure out whether trading activities also have additional explanatory power for the one-month ahead volatility.

Additionally, a linear regression model with one-day lagged unpartitioned trading volumes is used to check the robustness of the linear regression model:

$$Vol_t = j_0 + j_1 Vol_{t-1} + \sum_{i=1}^{N} k_i TA_{i,t-1} + \epsilon_t, \tag{8}$$

where, $TA_{i,t-1}$ the trading activity of i at date $t-1$, including $TV_{S,t-1}$, $TV_{C,t-1}$, $TV_{P,t-1}$, $TV_{F,t-1}$, $OI_{C,t-1}$, $OI_{P,t-1}$, and $OI_{F,t-1}$.

For a conditional heteroskedasticity model, the Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) model is used to capture the asymmetry of the conditional volatility:

$$r_t = \mu_0 + \varepsilon_t, \tag{9}$$

$$\sigma_t^2 = \omega + \alpha\sigma_{t-1}^2 + \beta\varepsilon_{t-1}^2 + \gamma I_{t-1} \cdot \varepsilon_{t-1}^2 + \sum_{i=1}^{N} \delta_i TA_{i,t}, \tag{10}$$

where, $\varepsilon_t = \sigma_t z_t$, $z_t \sim iid(0,1)$, $I_t = 1$ if $\varepsilon_t < 0$ and 0 otherwise. If $\gamma > 0$, bad news increases the volatility and also causes asymmetric volatility. Here, r_t is the underlying KOSPI 200 index return. Further, additionally lagged trading activities $TA_{i,t-1}$ are also used to check the robustness of the model.

3.3 Estimation Results

3.3.1 Bivariate Linear Granger Causality

The results of a linear Granger causality test are summarized in Table 6. The expected components of trading activities in stock, options, and futures markets, such as E_S, E_C, E_P, and E_F, have feedback linear causal relations with both HV_{K200} and VGK_{K200}. Regarding $VKOSPI$, it has a unidirectional causal relation from $VKOSPI$ to most trading activities, feedback linear causal relations with TV_P, E_C, and E_P, and no linear causal relations with

OI_C, U_S, and U_{OI_F}. This is because $VKOSPI$ has predictive information for the one-month ahead volatility and further, $VKOSPI$ is made of prices of call and put options. In particular, the trading activities in the KOSPI 200 put options market have feedback linear causal relations with many volatility measures. The trading volume of puts, TV_P, has feedback linear causal relations with VGK_{K200}, $VKOSPI$, and VGK_F. The expected components of the trading volume of puts, E_P, has feedback linear causal relations with HV_{K200}, VGK_{K200}, $VKOSPI$, and VGK_F. And expected components of open interests of put options have feedback linear causal relations with VGK_{K200}. These imply that the trading activities in put options markets are informative for volatility.

3.3.2 Volatility-volume relationship

The estimation results of the linear regression models are summarized in Tables 7 and 8.

For the underlying historical volatility HV_{K200} and a range-based volatility VGK_{K200}, open interests in options and futures markets, such as $OI_{C,t-1}$, $OI_{P,t-1}$, and $OI_{F,t-1}$, have statistically significant explanatory power. In particular, the expected components of open interests do have such power, whereas the unexpected components of open interests do not. Further, open interests of KOSPI 200 put options (OI_P) and their expected components (E_{OI_P}) have negative estimates. However, none of the trading activities in the options markets, such as $TV_{C,t-1}$, $TV_{P,t-1}$, E_C, E_P, U_C, and U_P, are statistically significant. The trading volume of KOSPI 200 futures (TV_F) and its expected and unexpected components (E_F and U_F) have significant positive estimates. Regarding the underlying index return volatility and trading volume relationships, only the unexpected components of the underlying trading volume (U_S) have a statistically significant negative estimate. Therefore, for the underlying stock volatilities (HV_{K200} and VGK_{K200}), open interests and their expected components ($OI_{C,t-1}$, $OI_{P,t-1}$, $OI_{F,t-1}$, E_{OI_P}, and E_{OI_F}), and trading activities in futures (TV_F, E_F, and U_F), are significant explanatory variables. Open interests of puts ($OI_{P,t-1}$) and their expected component (E_{OI_P}) serve to mitigate the underlying historical volatility

(HV_{K200}) and a range-based volatility (VGK_{K200}).

For the volatility measure of the KOSPI 200 options markets, the volatility index VKOSPI is used as a dependent variable. The trading volume of put options ($TV_{P,t-1}$) has a significant negative estimate, whereas the underlying trading volume ($TV_{S,t-1}$) has a significant positive estimate. When trading activities are decomposed into expected and unexpected parts, more trading activities become statistically significant. For call option trading activities, the expected parts (E_C) have a significant positive estimate, whereas the unexpected ones (U_C) have a significant negative estimate. Put option trading activities, however, show opposite results. That is, the expected parts (E_P) have a significant negative estimate, whereas the unexpected ones (U_P) have a significant positive estimate. Unexpected open interests of call, put, and futures, U_{OI_C}, U_{OI_P}, and U_{OI_F}, are statistically significant and expected open interests of put options, E_{OI_P}, are also statistically significant. Both the expected and unexpected components of open interests of put options (E_{OI_P} and U_{OI_P}) have negative estimates. Most of the unexpected components of trading activities are statistically significant to explain VKOSPI.

For the volatility measure of the KOSPI 200 futures markets, the Garman-Klass range-based volatility VGK_F is chosen. One interesting thing to note is that the trading activities of futures markets ($TV_{F,t-1}$ and $OI_{F,t-1}$) are not statistically significant. Instead, the underlying trading volume ($TV_{S,t-1}$), call option trading volume ($TV_{C,t-1}$), and open interests of calls and puts ($OI_{C,t-1}$ and $OI_{P,t-1}$) are statistically significant. Only the unexpected components of futures trading volume and open interests (U_F and U_{OI_F}) are statistically significant and have positive estimates. Most of the unexpected components of trading activities are statistically significant to explain the volatility of the KOSPI 200 futures markets. Open interests of puts ($OI_{P,t-1}$), their partitioned parts (E_{OI_P} and U_{OI_P}), trading volume of calls ($TV_{C,t-1}$), and their expected parts (E_C) serve to reduce the volatility of futures market (VGK_F).

Regarding the relationship between the trading volume of the KOSPI 200 Index and the volatility of the KOSPI 200 derivatives markets, the trading volume of the underlying index

($TV_{S,t-1}$) is found to increase the volatilities of KOSPI 200 options and futures markets. The expected trading volume of the underlying index (E_S) has a positive relation with VKOSPI the options market volatility measure in Korea, and the unexpected components (U_S) have a positive relation with the volatility of the futures market. In short, the trading volume of the underlying index is positively related with the volatilities of options and futures markets.

Regarding the relation between derivatives' trading activities and the underlying index volatility, open interests of calls and futures ($OI_{C,t-1}$ and $OI_{F,t-1}$), the trading volume of futures ($TV_{F,t-1}$), and its expected and unexpected components (E_F and U_F) have a positive relation with the volatility of the KOSPI 200 Index (HV_{K200} and VGK_{K200}). On the other hand, open interests of put options ($OI_{P,t-1}$) and their expected components (E_{OI_P}) are negatively related with the volatility of the KOSPI 200 Index (HV_{K200} and VGK_{K200}). These results are similar to the results of Kyriacou and Sarno (1999) and are mostly opposite to the results of Bessembinder and Seguin (1992).

For realized volatility RV, all trading volumes of the underlying stock, options, and futures ($TV_{S,t-1}$, $TV_{C,t-1}$, $TV_{P,t-1}$, and $TV_{F,t-1}$), are statistically significant, particularly the expected components of them (E_S, E_C, E_P, and E_F). Further, the trading volumes of put options and futures ($TV_{P,t-1}$ and $TV_{F,t-1}$) and their expected components (E_P and E_F) have negative estimates. Therefore, the trading volumes of the underlying stocks, options, and futures, particularly their expected components, have a predictive power for the underlying realized volatilities. Additionally, open interests of futures $OI_{F,t-1}$ and unexpected trading volume of the underlying stocks (U_S) have significant negative estimates.

For the GJR-GARCH model, the expected and unexpected components of trading activities are separately used as explanatory variables due to perfect linear dependency. The estimation results are summarized in Table 9. The estimate of the indicator function I_t is statistically significant and positive. This means that the KOSPI 200 index return volatility shows asymmetric and negatively skewed patterns. The underlying stock trading volume and its expected components ($TV_{S,t-1}$, E_S) have statistically significant and negative estimates.

The trading volume of futures and its expected and unexpected components ($TV_{F,t-1}$, E_F, and U_F) have statistically significant and positive estimates. These results are consistent with those of the linear regression models of historical volatility (HV_{K200}) and range-based volatility (VGK_{K200}). Open interests of call options ($OI_{C,t-1}$) and expected components of them (E_{OI_C}) have statistically significant and negative estimates. These results are opposite to the linear regression model of historical volatility (HV_{K200}), where they have positive signs.

4 Conclusion

We estimate to figure out the relationship between volatility and volume across Korea's financial markets, including the underlying KOSPI 200 Index, KOSPI 200 options and futures. The volatility measures of the KOSPI 200 Index are a past 23-day sample standard deviation of the index return (HV_{K200}) and a range-based volatility (VGK_{K200}), proposed by Garman and Klass (1980). A volatility measure of KOSPI 200 options market is VKOSPI, which is the volatility index of KOSPI 200 options. For KOSPI 200 futures, the Garman-Klass range-based volatility measure (VGK_F) is used.

According to a bivariate linear Granger causality test, the historical volatility of the underlying KOSPI 200 index is Granger-caused not only by the underlying trading volume but also by the trading volume of derivatives, such as call, put and futures. Garman-Klass range-based volatility of KOSPI 200 (VGK_{K200}) is also Granger-caused by the trading volume of both the underlying and derivatives markets. Volatility index VKOSPI Granger-causes the trading volume of both the underlying and derivatives markets. However, the trading volume of only put options Granger-causes VKOSPI. The volatility of KOSPI 200 futures market (VGK_F) also Granger-causes the trading volume of both the underlying and derivatives markets. Similarly, the trading volume of only put options Granger-causes the volatility of futures market (VGK_F).

The linear regression model specification with the dependent variable of various volatility measures are used to find out the volume-volatility relationship. Additionally, the GJR-GARCH model is used. We partition volume into two parts: expected and unexpected ones. Bessembinder and Seguin (1992) interpret the expected part of volume as the daily activity shock and the expected component of volume as activity that is forecastable, but highly variable across days. When levels of volume are used as explanatory variables, lagged measures are used, whereas when decomposed volume variables are used as explanatory variables, contemporaneous ones are used.

For historical volatility of the KOSPI 200 Index, levels of futures trading volume and open interests of call, put, and futures have the explanatory power. In particular, the estimate of level of futures open interests has a negative sign. All other estimates have a positive sign. When partitioned volume variables are used as explanatory variables, the expected open interests, expected futures trading volume, unexpected underlying index trading volume, and expected futures trading volume are statistically significant. The expected open interest of puts and the unexpected index trading volume have negative estimates.

For the dependent variable of Garman-Klass volatility of the KOSPI 200 Index, futures trading volume, open interests of call, put, and futures have significant estimates. The estimate of futures open interests has a negative sign. When partitioned trading volumes are used as explanatory variables, the expected volumes of the underlying index, futures, open interests of put, open interests of futures, and unexpected futures trading volume have statistically significant estimates. The estimates of the expected underlying index and open interest of put have negative signs.

Therefore, for the underlying stock volatilities (HV_{K200} and VGK_{K200}), open interests and their expected components ($OI_{C,t-1}$, $OI_{P,t-1}$, $OI_{F,t-1}$, E_{OI_P}, and E_{OI_F}), and the trading activities in futures ($TV_{F,t-1}$, E_F, and U_F), are significant explanatory variables. Further, the open interests of puts ($OI_{P,t-1}$) and their expected component (E_{OI_P}) serve to mitigate the underlying historical volatility (HV_{K200}) and the range-based volatility (VGK_{K200}).

For the dependent variable of the Korean volatility index VKOSPI, as implied volatilities from options markets, the trading volumes of the underlying index and puts have statistically significant estimates. The sign of estimate in the trading volume of puts is negative. When decomposed trading volumes are considered as explanatory variables, all but the unexpected trading volume of the underlying index have significant explanatory power.

For the Garman-Klass volatility of KOSPI 200 futures, except for futures trading volume and open interests, other trading volumes have significant explanatory power. The signs of estimates are negative for the trading volume of call and open interests of put. When decomposed trading volumes are considered as explanatory variables, except for the expected trading volume of the underlying index, the expected open interests of futures, and the unexpected open interests of call, all other dependent variables are statistically significant. Parameter estimates for the expected trading volume of call as well as both the expected and unexpected open interests of put have negative signs.

Regarding the relationship between the trading volume of the KOSPI 200 Index and the volatility of KOSPI 200 derivatives markets, the trading volume of the underlying index ($TV_{S,t-1}$) is to increase the volatilities of KOSPI 200 options and the futures markets. The expected trading volume of the underlying index (E_S) has a positive relation with VKOSPI, which is the option market volatility measure, and the unexpected components (U_S) have a positive relation with the volatility of the futures market. In conclusion, the trading volume of the underlying index has a positive relation with volatilities of options and futures markets.

Regarding the relation between derivatives' trading activities and the underlying index volatility, open interests of call and futures ($OI_{C,t-1}$ and $OI_{F,t-1}$), the trading volume of futures ($TV_{F,t-1}$), and its expected and unexpected components (E_F and U_F) are positively related with the volatility of the KOSPI 200 Index (HV_{K200} and VGK_{K200}). On the other hand, open interests of put options ($OI_{P,t-1}$) and their expected components (E_{OI_P}) are negatively related with the volatility of the KOSPI 200 Index (HV_{K200} and VGK_{K200}).

Our empirical results imply that volume-volatility relations have some cross financial markets effects in both the underlying and derivatives markets. Furthermore, the trading volumes and volatilities of the underlying and derivatives markets are deeply interrelated with each other.

References

Ahn, H., J. Kang, and D. Ryu, 2008, "Informed Trading in the Index Option Market: the Case of KOSPI 200 Options," Journal of Futures Markets, Vol. 28, No. 12, pp. 1118–1146.

Bessembinder, H., and P. J. Seguin, 1992, "Futures-trading Activity and Stock Price Volatility," Journal of Finance, Vol. 47, No. 5, pp. 2015–2034.

Bessembinder, H., and P. J. Seguin, 1993, "Price Volatility, Trading Volume, and Market Depth: Evidence from Futures Markets," Journal of Financial and Quantitative Analysis, Vol. 28, Issue 1, pp.21−39.

Bhargava, V., and D. K. Malhotra, 2007, "The Relationship between Futures Trading Activity and Exchange Rate Volatility," Journal of Multinational Financial Management, Vol. 17, Issue 2, pp. 95−111.

Billingsley, R. S., and D. M. Chance, 1988, "Put-Call Ratios and Market Timing Effectiveness," Journal of Portfolio Management, Vol. 15, No. 1, pp. 25−28.

Blume, L., D. Easley, and M. O'Hara, 1994, "Market Statistics and Technical Analysis: the Role of Volume," Journal of Finance, Vol. 49, pp. 153−181.

Bollen, N. P. B., and R. E. Whaley, 2004, "Does Net Buying Pressure Affect the Shape of Implied Volatility Functions?" Journal of Finance, Vol. 59, Issue 2, pp. 711−753.

Boluch, M. J., and T. W. Chamberlain, 1997, "Option Volume and Stock Price Behavior: Some Evidence from the Chicago Board Options Exchange," Atlantic Economic Journal, Vol. 25, No. 4, pp. 358−370.

Brennan, M. J., and H. H. Cao, 1996, "Information, Trade and Derivative Securities," Review of Financial Studies, Vol. 9, pp. 163–208.

Cao, C., Z. Chen, and J. M. Griffin, 2000, The Informational Content of Option Volume Prior to Takeovers, Working paper, Pennsylvania State University.

Cassano, M., and B. Han, 2008, “Option Volume, Strike Distribution, and Foreign Exchange Rate Movements,” Review of Quantitative Finance and Accounting, Vol. 30, No. 1, pp. 49−67.

Chakravarty, S., H. Gulen, and S. Mayhew, 2004, “Informed Trading in Stock and Option Markets,” Journal of Finance, Vol. 59, No. 3, pp. 1235–1258.

Chan, K., Y. P. Chung, and W. M. Fong, 2002, “The Informational Role of Stock and Option Volume,” Review of Financial Studies, Vol. 15, No. 4, pp. 1049−1075.

Chance, D. M., 1990, “Default Risk and the Duration of Zero Coupon Bonds,” Journal of Finance, Vol. 45, Issue 1, pp. 265−274.

Chang, Chuang-Chang, Pei-Fang Hsieh, and Yaw-Huei Wang, 2010, “Information Content of Options Trading Volume for Future Volatility: Evidence from the Taiwan Options Market,” Journal of Banking & Finance, Vol. 34, pp. 174–183.

Chatrath, A, R. Kamath, R. Chakornpipat, and S. Ramchander, 1995, “Lead-lag Associations between Option Trading and Cash Market Volatility,” Applied Financial Economics, Vol. 5 No. 6, pp. 373–381.

Clark, P. K., 1973, “A Subordinated Stochastic Process Model with Finite Variance for Speculative Prices,” Econometrica, Vol. 41, pp. 135−156.

Copeland, T. E., 1976, “A Model of Asset Trading under the Assumption of Sequential Information Arrival,” Journal of Finance, Vol. 31, pp. 1149−1168.

Copeland, T. E., 1977, “A Probability Model of Asset Trading,” Journal of Financial and Quantitative Analysis, Vol. 12, No. 4, pp. 563−578.

Cox, C., 1976, “Futures Trading and Market Information,” Journal of Political Economy, Vol. 84, No. 6, pp. 1215–1237.

Daigler, R. T., and M. K. Wiley, 1999, "The Impact of Trader Type on the Futures Volatility-Volume Relation," Journal of Finance, Vol. 54, Issue 6, pp. 2297−2316.

Easley, D., M. O'Hara, and P. S. Srinivas, 1998, "Option Volume and Stock Prices: Evidence on Where Informed Traders Trade," Journal of Finance, Vol. 53, No.2, pp. 431−465.

Epps, T. W., and M. L. Epps, 1976, "The Stochastic Dependence of Security Price Changes and Transaction Volumes: Implications for Mixture-of-Distribution Hypothesis," Econometrica, Vol. 44, pp. 305−321.

Garman, M. B., and M. J. Klass, 1980, "On the Estimation of Security Price Volatilities from Historical Data," Journal of Business, Vol. 53, No. 1, pp. 67−78.

Glosten, L. R., R. Jagannathan, and D. E. Runkle, 1993, "On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks," Journal of Finance, Vol. 48, Issue 5, pp. 1779−1801.

Hagelin, N., 2000, "Index Option Market Activity and Cash Market Volatility under Different Market Conditions: An Empirical Study from Sweden," Applied Financial Economics, Vol. 10, No. 6, pp. 597–613.

Holowczak, R., Y. E. Simaan, and L. Wu, 2006, "Price Discovery in the U.S. Stock and Stock Options Markets: A Portfolio Approach," Review of Derivatives Research, Vol. 9, No. 1, pp. 37−65.

Jayaraman, N., M. Frye, and S. Sabherwal, 2001, "Informed Trading around Merger Announcements: An Empirical Test Using Transaction Volume and Open Interest in Options Market," Financial Review, Vol. 36, No. 2, pp. 45–74.

Karpoff, J. M., 1987, "The Relation between Price Changes and Trading. Volume: A Survey," Journal of Financial and Quantitative Analysis, Vol. 22, No. 1, pp. 109−206.

Kraus, A., and M. Smith, 1996, "Heterogeneous Beliefs and the Effect of Replicatable Options on Asset Prices," Review of Financial Studies, Vol. 9, pp. 723–756.

Kyriacou, K., and L. Sarno, 1999, "The Temporal Relationship between Derivatives Trading and Spot Market Volatility in the U.K.: Empirical Analysis and Monte Carlo Evidence," Journal of Futures Markets, Vol. 19, No. 3, pp. 245–270.

Lee, C. F., and O. M. Rui, 2000, "Does Trading Volume Contain Information to Predict Stock Returns? Evidence from China's Stock Markets," Review of Quantitative Finance and Accounting, Vol. 14, Issue 4, pp. 341−360.

Mougoué, M., and R. Aggarwal, 2011, "Trading Volume and Exchange Rate Volatility: Evidence for the Sequential Arrival of Information Hypothesis," Journal of Banking and Finance, Vol. 35, Issue 10, pp. 2690−2703.

Ni, S. X., J. Pan, and A. M. Poteshman, 2008, "Volatility Information Trading in the Option Market," Journal of Finance, Vol. 63, No. 3, pp. 1059−1091.

Pan, J., and A. M. Poteshman, 2006, "The Information in Option Volume for Future Stock Prices," Review of Financial Studies, Vol. 19, No. 3, pp. 871−908.

Park, B. J., 2010, "Surprising Information, the MDH, and the Relationship between Volatility and Trading Volume," Journal of Financial Markets, Vol. 13, pp. 344−366.

Schlag, C., and H. Stoll, 2005, "Price Impacts of Options Volume," Journal of Financial Markets, Vol. 8, Issue 1, pp. 69−87.

Simon, D. P., and R. A. Wiggins, 2001, "S&P Futures Returns and Contrary Sentiment," Journal of Futures Markets, Vol. 21, Issue 5, pp. 447−462.

Tauchen, G. E., and M. Pitts, 1983, "The Price Variability-Volume Relationship on Speculative Markets," Econometrica, Vol. 51, No. 2, pp. 85−505.

Wang, C. Y., 2002, “The Effect of Net Positions by Type of Trader on Volatility in Foreign Currency Futures Markets,” Journal of Futures Markets, Vol. 22, No. 5, pp. 427–450.

Table 1: Summary Statistics of Volatilities and Trading Volumes

Variable	Mean	Median	Max	Min	Std	Skew	Kurt	Obs
HV_{K200}	1.43	1.27	5.54	0.47	0.69	2.32	11.35	2107
VGK_{K200}	0.01	0.01	0.10	0.00	0.01	4.37	38.99	2107
$VKOSPI$	25.53	22.99	89.30	14.15	9.51	2.40	11.34	2107
VGK_F	0.01	0.01	0.11	0.00	0.01	3.86	36.55	2107
TV_S	8.29	8.35	9.51	7.03	0.48	−0.25	2.15	2107
TV_C	6.02	6.00	7.51	4.74	0.48	0.18	2.54	2107
TV_P	6.01	5.98	8.46	4.49	0.56	0.32	2.76	2107
TV_F	0.00	0.01	0.79	−1.12	0.24	−0.28	3.37	2107
OI_C	7.41	7.46	8.41	5.54	0.43	−0.52	3.12	2107
OI_P	7.48	7.55	8.61	5.88	0.43	−0.54	3.01	2107
OI_F	4.55	4.56	4.90	3.60	0.13	−1.26	8.81	2107

Note: HV_{K200} is the historical volatility of the KOSPI 200 index return, VGK_{K200} a Garman-Klass range-based volatility measure of the KOSPI 200 Index, $VKOSPI$ the volatility index from KOSPI 200 options markets, and VGK_F a Garman-Klass range-based volatility measure of KOSPI 200 index futures. Trading volume variables, TV_S, TV_C, TV_P, and TV_F, are for the KOSPI 200 Index, call option, put option, and futures, respectively. OI_C, OI_P, and OI_F are open interests of call options, put options, and futures, respectively. Trading volume variables of stock, options and futures are divided by 10^9 and the number of contracts traded and open interests of options and futures are divided by 10^3. Then, hen they all are converted into natural logarithms. The mean of the trading volume of KOSPI 200 futures is 0 because it is demeaned.

Table 2: Correlation Coefficients of Varialbes

	HV_{K200}	VGK_{K200}	$VKOSPI$	VGK_F	TV_S	TV_C	TV_P	TV_F	OI_C	OI_P
VGK_{K200}	0.64									
$VKOSPI$	0.91	0.69								
VGK_F	0.64	0.69	0.73							
TV_S	0.03	0.10	0.07	0.06						
TV_C	0.24	0.24	0.23	0.26	0.69					
TV_P	0.27	0.29	0.31	0.37	0.64	0.81				
TV_F	0.17	0.31	0.23	0.46	0.24	0.46	0.53			
OI_C	0.13	0.11	0.11	0.08	−0.08	0.29	0.31	0.19		
OI_P	−0.28	−0.20	−0.26	−0.27	0.09	0.23	0.08	0.09	0.65	
OI_F	0.14	0.16	0.16	0.13	0.22	0.23	0.29	0.05	0.10	0.00

Note: HV_{K200} is the historical volatility of the KOSPI 200 index return, VGK_{K200} a Garman-Klass range-based volatility measure of the KOSPI 200 Index, $VKOSPI$ the volatility index from KOSPI 200 options markets, and VGK_F a Garman-Klass range-based volatility measure of KOSPI 200 futures. Trading volume variables, TV_S, TV_C, TV_P, and TV_F, are for the KOSPI 200 Index, call option, put option, and futures, respectively. OI_C, OI_P, and OI_F are open interests of call options, put options, and futures, respectively.

Figure 1: Time-series of All Variables

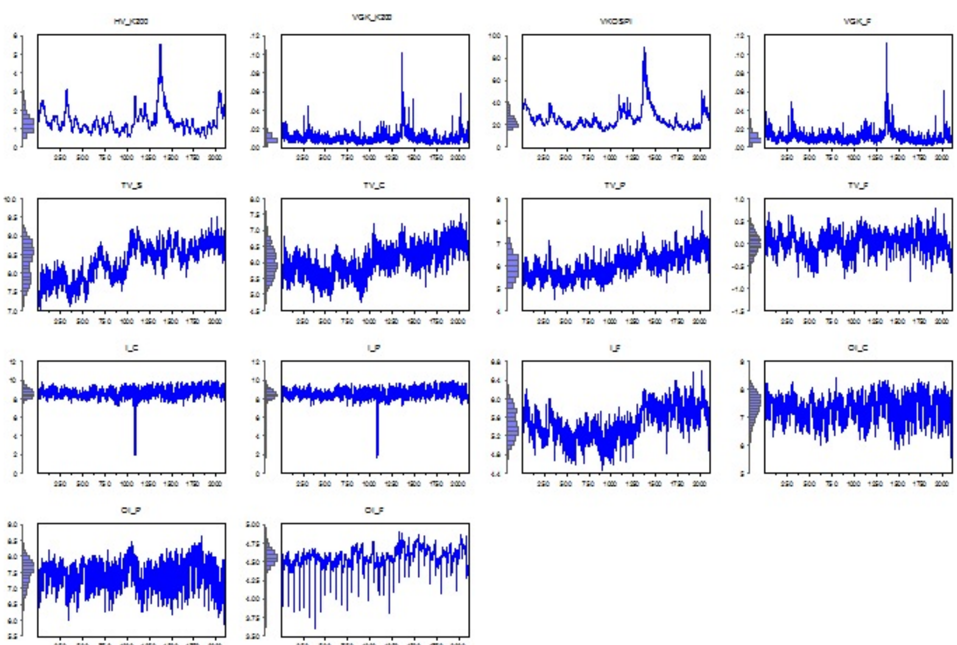

Table 3: Summary Statistics of Partitioned Trading Volumes

Variable	Mean	Median	Max	Min	Std	Skew	Kurt	Obs
E_S	8.29	8.36	9.43	7.13	0.46	−0.25	2.07	2105
E_C	6.02	6.00	7.42	5.05	0.41	0.26	2.42	2105
E_P	6.01	5.99	8.01	4.90	0.48	0.33	2.54	2105
E_F	0.00	0.00	0.50	−0.80	0.17	−0.23	3.38	2105
E_{OI_C}	7.41	7.44	8.20	5.75	0.34	−0.52	3.31	2105
E_{OI_P}	7.48	7.53	8.35	5.95	0.34	−0.59	3.21	2105
E_{OI_F}	4.55	4.55	4.86	3.80	0.11	−1.08	7.95	2105
U_S	0.00	0.00	0.70	−0.52	0.16	0.13	3.30	2105
U_C	0.00	−0.01	0.87	−0.81	0.24	0.10	3.31	2105
U_P	0.00	−0.02	1.16	−0.93	0.28	0.40	3.55	2105
U_F	0.00	0.00	0.60	−0.78	0.17	−0.10	3.45	2105
U_{OI_C}	0.00	0.04	0.73	−2.01	0.27	−3.35	17.66	2105
U_{OI_P}	0.00	0.04	0.58	−1.78	0.26	−3.21	16.20	2105
U_{OI_F}	0.00	0.00	0.72	−0.46	0.07	0.48	23.57	2105

Note: Estimated trading activities from the estimation of VAR(2) are the expected components. Unexpected components are residuals of the estimation of the VAR(2) model. Expected components of each series are denoted as E_S, E_C, E_P, E_F, E_{OI_C}, E_{OI_P}, and E_{OI_F}, for the KOSPI 200 Index, call options, put options, futures, open interests of call options, open interests of put options, and open interests of futures, respectively. Corresponding unexpected components of trading activity are denoted as U_S, U_C, U_P, U_F, U_{OI_C}, U_{OI_P}, and U_{OI_F}, respectively.

Table 4: Correlation Coefficients of Expected and Unexpected Components of Variables

	HV_{K200}	VGK_{K200}	$VKOSPI$	VGK_F	E_S	E_C	E_P	E_F
VGK_{K200}	0.64							
$VKOSPI$	0.91	0.69						
VGK_F	0.64	0.69	0.73					
E_S	0.04	0.09	0.07	0.02				
E_C	0.24	0.23	0.23	0.16	0.76			
E_P	0.29	0.29	0.29	0.24	0.75	0.96		
E_F	0.19	0.34	0.23	0.26	0.27	0.41	0.44	
E_{OI_C}	0.18	0.13	0.15	0.13	−0.09	0.37	0.35	0.27
E_{OI_P}	−0.32	−0.24	−0.29	−0.27	0.12	0.23	0.08	0.14
E_{OI_F}	0.17	0.19	0.18	0.11	0.29	0.35	0.42	0.10
U_S	0.00	0.05	0.02	0.14	0.00	0.00	0.00	0.00
U_C	0.06	0.08	0.06	0.26	0.00	0.00	0.00	0.00
U_P	0.05	0.08	0.11	0.34	0.00	0.00	0.00	0.00
U_F	0.06	0.11	0.10	0.39	0.00	0.00	0.00	0.00
U_{OI_C}	−0.02	0.01	−0.02	−0.05	0.00	0.00	0.00	0.00
U_{OI_P}	−0.04	−0.01	−0.05	−0.09	0.00	0.00	0.00	0.00
U_{OI_F}	0.00	0.02	0.01	0.07	0.00	0.00	0.00	0.00

Note: HV_{K200} is the historical volatility of the KOSPI 200 index return, VGK_{K200} a Garman-Klass range-based volatility measure of the KOSPI 200 Index, $VKOSPI$ the volatility index from KOSPI 200 options markets, and VGK_F a Garman-Klass range-based volatility measure of KOSPI 200 futures. Expected trading activities are denoted as E_S, E_C, E_P, E_F, E_{OI_C}, E_{OI_P}, and E_{OI_F}, for the KOSPI 200 Index, call options, put options, futures, open interests of call options, open interests of put options, and open interests of futures, respectively. Corresponding unexpected components of trading activity are denoted as U_S, U_C, U_P, U_F, U_{OI_C}, U_{OI_P}, and U_{OI_F}, respectively.

Table 5: Correlation Coefficients of Expected and Unexpected Components of Variables (2)

	E_{OI_C}	E_{OI_P}	E_{OI_F}	U_S	U_C	U_P	U_F	U_{OI_C}	U_{OI_P}
E_{OI_P}	0.50								
E_{OI_F}	0.29	0.14							
U_S	0.00	0.00	0.00						
U_C	0.00	0.00	0.00	0.43					
U_P	0.00	0.00	0.00	0.18	0.38				
U_F	0.00	0.00	0.00	0.27	0.57	0.75			
U_{OI_C}	0.00	0.00	0.00	−0.05	0.15	0.24	0.10		
U_{OI_P}	0.00	0.00	0.00	0.00	0.21	0.09	0.03	0.91	
U_{OI_F}	0.00	0.00	0.00	−0.05	−0.08	−0.05	−0.01	−0.26	−0.28

Table 6: Estimation Results of a Bivariate Linear Granger Causality Test

TV_S	$\Leftrightarrow$	HV_{K200}	TV_S	$\Leftrightarrow$	VGK_{K200}	TV_S	$\Leftarrow$	$VKOSPI$	TV_S	$\Leftarrow$	VGK_F
TV_C	$\Rightarrow$	HV_{K200}	TV_C	$\Rightarrow$	VGK_{K200}	TV_C	$\Leftarrow$	$VKOSPI$	TV_C	$\Rightarrow$	VGK_F
TV_P	$\Rightarrow$	HV_{K200}	TV_P	$\Leftrightarrow$	VGK_{K200}	TV_P	$\Leftrightarrow$	$VKOSPI$	TV_P	$\Leftrightarrow$	VGK_F
TV_F	$\Rightarrow$	HV_{K200}	TV_F	$\Rightarrow$	VGK_{K200}	TV_F	$\Leftarrow$	$VKOSPI$	TV_F	$\Leftarrow$	VGK_F
OI_C	$\Rightarrow$	HV_{K200}	OI_C	$\Leftarrow$	VGK_{K200}	OI_C	$\nLeftrightarrow$	$VKOSPI$	OI_C	$\nLeftrightarrow$	VGK_F
OI_P	$\Leftarrow$	HV_{K200}	OI_P	$\Leftrightarrow$	VGK_{K200}	OI_P	$\Leftarrow$	$VKOSPI$	OI_P	$\Leftarrow$	VGK_F
OI_F	$\Rightarrow$	HV_{K200}	OI_F	$\Rightarrow$	VGK_{K200}	OI_F	$\Leftarrow$	$VKOSPI$	OI_F	$\Rightarrow$	VGK_F
E_S	$\Leftrightarrow$	HV_{K200}	E_S	$\Leftrightarrow$	VGK_{K200}	E_S	$\Leftarrow$	$VKOSPI$	E_S	$\Leftarrow$	VGK_F
E_C	$\Leftrightarrow$	HV_{K200}	E_C	$\Leftrightarrow$	VGK_{K200}	E_C	$\Leftrightarrow$	$VKOSPI$	E_C	$\Leftarrow$	VGK_F
E_P	$\Leftrightarrow$	HV_{K200}	E_P	$\Leftrightarrow$	VGK_{K200}	E_P	$\Leftrightarrow$	$VKOSPI$	E_P	$\Leftrightarrow$	VGK_F
E_F	$\Leftrightarrow$	HV_{K200}	E_F	$\Leftrightarrow$	VGK_{K200}	E_F	$\Leftarrow$	$VKOSPI$	E_F	$\Leftarrow$	VGK_F
E_{OI_C}	$\Leftrightarrow$	HV_{K200}	E_{OI_C}	$\Leftarrow$	VGK_{K200}	E_{OI_C}	$\Leftarrow$	$VKOSPI$	E_{OI_C}	$\Leftarrow$	VGK_F
E_{OI_P}	$\Leftarrow$	HV_{K200}	E_{OI_P}	$\Leftrightarrow$	VGK_{K200}	E_{OI_P}	$\Leftarrow$	$VKOSPI$	E_{OI_P}	$\Leftarrow$	VGK_F
E_{OI_F}	$\Rightarrow$	HV_{K200}	E_{OI_F}	$\Rightarrow$	VGK_{K200}	E_{OI_F}	$\Leftarrow$	$VKOSPI$	E_{OI_F}	$\Leftarrow$	VGK_F
U_S	$\Rightarrow$	HV_{K200}	U_S	$\Rightarrow$	VGK_{K200}	U_S	$\nLeftrightarrow$	$VKOSPI$	U_S	$\nLeftrightarrow$	VGK_F
U_C	$\Leftarrow$	HV_{K200}	U_C	$\Rightarrow$	VGK_{K200}	U_C	$\Leftarrow$	$VKOSPI$	U_C	$\Rightarrow$	VGK_F
U_P	$\Rightarrow$	HV_{K200}	U_P	$\Rightarrow$	VGK_{K200}	U_P	$\Leftarrow$	$VKOSPI$	U_P	$\Rightarrow$	VGK_F
U_F	$\Leftrightarrow$	HV_{K200}	U_F	$\Rightarrow$	VGK_{K200}	U_F	$\Leftarrow$	$VKOSPI$	U_F	$\Rightarrow$	VGK_F
U_{OI_C}	$\nLeftrightarrow$	HV_{K200}	U_{OI_C}	$\nLeftrightarrow$	VGK_{K200}	U_{OI_C}	$\Leftarrow$	$VKOSPI$	U_{OI_C}	$\nLeftrightarrow$	VGK_F
U_{OI_P}	$\Leftarrow$	HV_{K200}	U_{OI_P}	$\Rightarrow$	VGK_{K200}	U_{OI_P}	$\Leftarrow$	$VKOSPI$	U_{OI_P}	$\nLeftrightarrow$	VGK_F
U_{OI_F}	$\nLeftrightarrow$	HV_{K200}	U_{OI_F}	$\Rightarrow$	VGK_{K200}	U_{OI_F}	$\nLeftrightarrow$	$VKOSPI$	U_{OI_F}	$\Rightarrow$	VGK_F

Note: Estimation results are from a bivariate linear Granger causality relations between two variables volatility (Vol) and trading activity (TA):

$$
\begin{aligned}
Vol_t &= a_0 + \sum_{i=1}^{N_1} a_{1,i} Vol_{t-i} + \sum_{j=1}^{N_2} a_{2,j} TA_{t-j} + \varepsilon_{Vol,t}, \\
TA_t &= b_0 + \sum_{l=1}^{N_3} b_{1,l} TA_{t-l} + \sum_{m=1}^{N_4} b_{2,m} Vol_{t-m} + \varepsilon_{TA,t}.
\end{aligned}
$$

Optimal lag lengths are determined by Schwarz information criterion. $A \Leftarrow B$ means that A does not Granger cause B. $A \Rightarrow B$ means that B does not Granger cause A. $A \Leftrightarrow B$ means that A and B have a feedback linear causal relation. $A \nLeftrightarrow B$ means that A and B do not have any linear causal relation. HV_{K200} is the historical volatility of the KOSPI 200 Index return, VGK_{K200} a Garman-Klass range-based volatility measure of the KOSPI 200 Index, $VKOSPI$ the volatility index from KOSPI 200 options markets, and VGK_F a Garman-Klass range-based volatility measure of KOSPI 200 futures. Trading volume variables, TV_S, TV_C, TV_P, and TV_F, are for the KOSPI 200 Index, call option, put option, and futures, respectively. Expected trading activities are denoted as E_S, E_C, E_P, E_F, E_{OI_C}, E_{OI_P}, and E_{OI_F}, for KOSPI 200 index, call options, put options, futures, open interests of call options, open interests of put options, and open interests of futures, respectively. Corresponding unexpected components of trading activity are denoted as U_S, U_C, U_P, U_F, U_{OI_C}, U_{OI_P}, and U_{OI_F}, respectively.

Table 7: Estimation Results of Linear Regression: Contemporaneous Expected and Unexpected Components of Trading Activities

Variable	HV_{K200}		VGK_{K200}		$VKOSPI$		VGK_F		RV	
constant	−0.212	*	0.007		−3.821	*	0.014	*	−0.098	
Lag1	0.977	**	0.535	**	0.978	**	0.536	**	0.998	**
E_S	0.000		−0.001		0.334	*	0.000		0.032	**
E_C	0.037		0.002		0.994	*	−0.003	**	0.069	**
E_P	−0.021		0.000		−1.134	**	0.003	**	−0.083	**
E_F	0.068	**	0.006	**	0.410		0.001		−0.038	**
E_{OI_C}	0.028	**	0.001		0.308		0.002	**	0.020	
E_{OI_P}	−0.041	**	−0.003	**	−0.360	*	−0.003	**	−0.011	
E_{OI_F}	0.055	**	0.004	**	0.622		−0.001		−0.034	
U_S	−0.030	**	0.001		−0.196		0.002	**	−0.028	*
U_C	0.018		0.001		−0.418	*	0.002	**	−0.007	
U_P	−0.010		0.000		4.186	**	0.004	**	−0.020	
U_F	0.051	**	0.002	*	−2.433	**	0.009	**	0.032	
U_{OI_C}	0.017		0.001		1.331	**	0.000		−0.005	
U_{OI_P}	−0.012		−0.001		−1.452	**	−0.002	**	0.007	
U_{OI_F}	−0.013		0.001		1.296	**	0.005	**	−0.020	
Adj-R^2	0.98		0.50		0.97		0.60		0.98	

Note: Estimation results are from the following linear regression specification:

$$Vol_t = c_0 + c_1 Vol_{t-1} + \sum_{i=1}^{N} d_i TA_{i,t} + \epsilon_t,$$

where, Vol_t is a volatility measure, such as HV_{K200}, VGK_{K200}, $VKOSPI$, VGK_F, and RV. $TA_{i,t}$ is the trading activity of i at date t. The trading activity $TA_{i,t}$ includes contemporaneous expected and unexpected components of trading activities in the KOSPI 200 Index, options, and futures markets: E_S, E_C, E_P, E_F, E_{OI_C}, E_{OI_P}, E_{OI_F}, U_S, U_C, U_P, U_F, U_{OI_C}, U_{OI_P}, and U_{OI_F}. Expected trading activities E_S, E_C, E_P, E_F, E_{OI_C}, E_{OI_P}, and E_{OI_F}, are for the KOSPI 200 Index, call options, put options, futures, open interests of call options, open interests of put options, and open interests of futures, respectively. Corresponding unexpected components of trading activity are U_S, U_C, U_P, U_F, U_{OI_C}, U_{OI_P}, and U_{OI_F}, respectively.

Table 8: Estimation Results of Linear Regression: Lagged Unpartitioned Trading Activities

Variable	HV_{K200}		VGK_{K200}		$VKOSPI$		VGK_F		RV	
constant	−0.221	**	0.001		−2.803		0.005		−0.008	
Lag1	0.979	**	0.568	**	0.979	**	0.580	**	0.997	**
$TV_{S,t-1}$	0.005		0.000		0.298	*	0.001	*	0.018	**
$TV_{C,t-1}$	0.012		0.001		0.249		−0.001	**	0.021	**
$TV_{P,t-1}$	−0.004		0.000		−0.475	**	0.001		−0.031	**
$TV_{F,t-1}$	0.045	**	0.002	**	0.295		−0.001		−0.024	*
$OI_{C,t-1}$	0.030	**	0.002	**	0.285		0.003	**	0.008	
$OI_{P,t-1}$	−0.032	**	−0.003	**	−0.178		−0.003	**	0.002	
$OI_{F,t-1}$	0.040	**	0.002	*	0.313		−0.001		−0.032	*
Adj-R^2	0.98		0.47		0.96		0.43		0.98	

Note: Estimation results are from the following linear regression model with explanatory variables of one-day lagged unpartitioned trading volumes:

$$Vol_t = j_0 + j_1 Vol_{t-1} + \sum_{i=1}^{N} k_i TA_{i,t-1} + \epsilon_t,$$

where, Vol_t is a volatility measure such as HV_{K200}, VGK_{K200}, $VKOSPI$, VGK_F, and RV. $TA_{i,t-1}$ is the trading activity of i at date $t-1$. $TV_{S,t-1}$ is one-day lagged trading volume of the KOSPI 200 Index, $TV_{C,t-1}$ is one-day lagged trading volume of KOSPI 200 call options, $TV_{P,t-1}$ is one-day lagged trading volume of KOSPI 200 put options, $TV_{F,t-1}$ is one-day lagged trading volume of KOSPI 200 futures, $OI_{C,t-1}$ is one-day lagged open interests of call options, $OI_{P,t-1}$ is one-day lagged open interests of put options, and $OI_{F,t-1}$ is one-day lagged open interests of futures.

Table 9: Estimation Results of GJR-GARCH

Variable	Estimate		Variable	Estimate		Variable	Estimate	
μ_0	1.177	**	μ_0	1.570	**	μ_0	1.544	**
ε^2_{t-1}	−0.010		ε^2_{t-1}	−0.012		ε^2_{t-1}	0.068	**
I_t	0.181	**	I_t	0.180	**	I_t	0.071	**
σ^2_{t-1}	0.855	**	σ^2_{t-1}	0.861	**	σ^2_{t-1}	0.462	**
$TV_{S,t-1}$	−0.099	**	E_S	−0.136	**	U_S	0.689	
$TV_{C,t-1}$	0.003		E_C	−0.031		U_C	0.900	
$TV_{P,t-1}$	0.100	*	E_P	0.160		U_P	1.035	
$TV_{F,t-1}$	0.193	**	E_F	0.255	**	U_F	1.905	**
$OI_{C,t-1}$	−0.092	*	E_{OI_C}	−0.141	**	U_{OI_C}	−0.102	
$OI_{P,t-1}$	0.018		E_{OI_P}	0.032		U_{OI_P}	−0.540	
$OI_{F,t-1}$	−0.066		E_{OI_F}	−0.064		U_{OI_F}	1.449	

Note: For a conditional heteroskedasticity model, the GJR-GARCH model is used:

$$r_t = \mu_0 + \varepsilon_t,$$

$$\sigma^2_t = \omega + \alpha\sigma^2_{t-1} + \beta\varepsilon^2_{t-1} + \gamma I_{t-1} \cdot \varepsilon^2_{t-1} + \sum_{i=1}^{N} \delta_i TA_{i,t},$$

where, $\varepsilon_t = \sigma_t z_t$, $z_t \sim iid(0,1)$, $I_t = 1$ if $\varepsilon_t < 0$ and 0 otherwise. Expected trading activities E_S, E_C, E_P, E_F, E_{OI_C}, E_{OI_P}, and E_{OI_F}, are for the KOSPI 200 Index, call options, put options, futures, open interests of call options, open interests of put options, and open interests of futures, respectively. Corresponding unexpected components of trading activity are U_S, U_C, U_P, U_F, U_{OI_C}, U_{OI_P}, and U_{OI_F}, respectively. Additionally one-day lagged trading activities ($TA_{i,t-1}$) are also used: $TV_{S,t-1}$ is the trading volume of the KOSPI 200 Index, $TV_{C,t-1}$ is the trading volume of KOSPI 200 call options, $TV_{P,t-1}$ trading volume of KOSPI 200 put options, $TV_{F,t-1}$ is the trading volume of KOSPI 200 futures, $OI_{C,t-1}$ is open interests of call options, $OI_{P,t-1}$ is open interests of put options, and $OI_{F,t-1}$ is open interests of futures.