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Volatility information trading in the index options market: An intraday analysis

Heejin Yang[a], Ali M. Kutan[b], Doojin Ryu[c,*]

[a] *Department of Global Economics and Commerce, College of Management and Economics, Dongguk University Gyeongju Campus, Gyeongsangbuk-do, Korea*

[b] *School of Business, Southern Illinois University Edwardsville, USA*

[c] *College of Economics, Sungkyunkwan University, 25-2, Sungkyunkwan-ro, Jongno-gu, Seoul 03063, Korea*

**Corresponding Author (D. Ryu). E-mail: sharpjin@skku.edu*

Abstract

By analyzing intraday volatility information trading according to the demand for options, we determine the types of investors that are informed about future spot market volatility and conduct volatility information trading in a highly liquid options market. Although the overall aggregate options demand does not predict intraday market volatility, the vega-weighted net demand of foreign investment firms conveys significant information about future volatility dynamics. By tracking the positions of all options market participants according to option moneyness, we find that foreign investment firms conduct volatility trading using highly levered options and that their intraday volatility information superiority is more prominent when they close their existing positions.

Keywords: Foreign investment firm; Market microstructure; Implied volatility; Intraday volatility; Volatility information.

JEL classification: G10, G14

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Abstract

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1. Introduction

Many studies in financial economics have analyzed the return predictability of information embedded in options trades. These studies examine, in various settings, whether options trades predict spot market returns and, consequently, whether options investors have directional information. Although most empirical studies provide evidence supportive of directional informed trading in global options markets (Cao, Chen, & Griffin, 2005; Chang, Hsieh, & Lai, 2013; Easley, O'Hara, & Srinivas, 1998; Ge, Lin, & Pearson, 2016; Hu, 2014; Johnson & So, 2012; Lin, Tsai, Zheng, & Qiao, 2018; Pan & Poteshman, 2006; Roll, Schwartz, & Subrahmanyam, 2010; Ryu & Yang, 2018), a significant number of studies reach the opposite conclusion (Chan, Chung, & Fong, 2002; Fahlenbrach & Sandås, 2010; Ryu, 2015; Schlag & Stoll, 2005). Thus, the information role of options trading remains an empirical question and merits further analysis from a different perspective.

Investors with superior information about the dynamics of market volatility may benefit from options trading more than investors with directional information. By predicting underlying asset price movements, the "directional informed traders" can profit from both equity and options trading. However, the "volatility informed traders" would profit only from trading nonlinear derivative securities, such as options, rather than stocks or futures contracts with linear payoff structures. Furthermore, options investors often delta-hedge their exposures using the underlying assets and hedge their exposure to directional movements of the underlying assets. These hedging activities might have a confounding effect when the directional information content of options trading is measured.

As such, several recent options market studies have focused on the options demands of investors with volatility information and analyzed the resulting volatility information trading in options markets. For example, a series of studies on the US options market (Bollen & Whaley, 2004; Gharghori, Maberly, & Nguyen, 2017; Holowczak, Hu, & Wu, 2014; Lai, 2017; Le & Zurbruegg, 2016; Ni, Pan, & Poteshman, 2008) and Asian markets (Chang, Hsieh, & Wang, 2010; Chen, Chung, & Yuan, 2014) show that net demand for volatility partly predicts the underlying assets' future volatilities, whereas other studies find contrasting results (Chiang, Chung, & Louis, 2017). Rourke (2014) finds that vega-informed near-the-money options trading is more commonplace than delta-informed near-the-money options trading in the US options market. However, the literature on volatility information in the options market is relatively scarce. Furthermore, previous studies focus on specific options trading strategies and fail to address the characteristics of volatility information trading systematically. Because market volatility characteristics are essential determinants of option price dynamics and the trading motives of option market participants, volatility information trading should be further examined using high-quality and high-frequency data.

Thus, we examine whether intraday options trades provide information beyond directional movements, especially volatility information, and enable sophisticated trading based on this information. We use a microstructure dataset from the KOSPI200 index options to conduct a detailed analysis. The KOSPI200 options market is highly liquid with little friction and low transaction costs, and its underlying spot market is more volatile than those in developed markets.[1] As such, volatility informed investors have a strong incentive to use options contracts as their trading vehicle. Further, previous studies detect volatility information in options trades under restrictive conditions (e.g., specific volatility strategies, such as straddle and opening trades), because they use data with a lower frequency, such as daily trades. However, in highly speculative and informationally efficient index options markets, informed investors could not consistently outperform others over the time horizon of a day (Chung, Park, & Ryu, 2016; Ryu, 2011). Thus, we analyze the intraday, high-quality dataset of KOSPI200 options, the use of which enables the exact classification of each buy/sell order, which is necessary to construct the net volatility demand measure. Furthermore, the detailed information in the trade and quote data, such as the full identification of investors and their real-time options positions, allows us to examine aspects that previous studies fail to uncover.

Our study contributes to the volatility information trading literature by exploiting a high-quality, informative dataset. The identification of options market participants and their options

[1] The detailed characteristics of the KOSPI200 options market and the properties of options trading are explained in the next section.

positions per order and trade allow us to determine who in the options market has volatility information and, by examining their net demand for options, how superior investors act on volatility information. We calculate intraday options demand for volatility and investigate whether net options demand predicts intraday market volatility. Most previous studies, including Bae and Dixon (2018), Chang, Hsieh, and Wang (2010), Ni, Pan, and Poteshman (2008), and Ryu and Yang (2019) consider only daily net demand and volatility. Professional investors can be informed by processing market-wide and/or public information faster than their index derivative competitors (Ahn, Kang, & Ryu, 2008; Ryu, 2016), but they must quickly act on volatility information to make significant profits. The inconsistent evidence of volatility information trading in previous studies may be caused by their use of lower-frequency measures and lower-quality datasets. To address this, we conduct intraday analyses and clarify which intraday trades predict future market volatility.

Previous studies also use imprecise volatility measures. Chang, Hsieh, and Wang (2010) and Ni, Pan, and Poteshman (2008) define daily volatility of an underlying asset as the highest intraday price minus the lowest intraday price during each trading day. However, this daily volatility measure, which is a range-based volatility proxy, and other potential volatility measures, such as five-minute intraday return changes, fail to characterize future market volatility or capture actual asset price variances. Use of these realized volatility constructs in our intraday analyses requires using higher-frequency observations in the calculations because tick-by-tick price changes must be used to construct the intraday volatility series. This yields a noisy volatility measure because of microstructural biases such as bid-ask bounce problems and temporary illiquidity. Consequently, we employ the intraday time series of model-free implied volatility, which is similar to the US volatility index (VIX). The intraday implied volatility is more appropriate for examining volatility information conveyed by options trades, because it more clearly reflects market participants' aggregate expectations and opinions of future states and volatility, and its changes are directly related to the intraday flow of volatility information (Banerjee, Doran, & Peterson, 2007; Giot, 2005; Guo & Whitelaw, 2006; Lee & Ryu, 2019). Substantial information about future realized volatility is contained in the implied volatility index, which can effectively predict future volatility dynamics. As with options volume, the volatility index provides critical option-implied information (Busch, Christensen, & Nielsen, 2011; Jiang & Tian, 2005; Song, Ryu, & Webb, 2018).

To the best of our knowledge, no study has rigorously examined intraday volatility information trading using an options market microstructure dataset, despite its importance and implications. The vega-weighted net demand for volatility is calculated by investor type, option moneyness, and open-interest changes using option investors' net positions to examine whether quantity information contained in options trades can predict the intraday volatility dynamics of the underlying assets. Our empirical findings from the analyses on the KOSPI200 options intraday dataset are as follows. First, the aggregate options market demand for volatility does not predict the underlying asset's future volatility, indicating that volatility information contained in aggregate options volume is noisy or contaminated. Second, domestic investors generally have little volatility information, but trades by foreign institutional investors (especially foreign investment firms) significantly predict intraday volatility dynamics, indicating foreign investors are more sophisticated and better informed than their domestic counterparts. Third, foreign investment firms use their intraday volatility information advantage to trade highly levered options, which are speculative and liquid contracts. Fourth, while previous research finds directional information is more prominent in opening trades, orders by skillful foreign institutions to close existing positions convey volatility information, suggesting closing trades are initiated by more sophisticated, strategic orders. These findings are robust when the strong serial correlation of the intraday implied volatility series is controlled.

The rest of this paper proceeds as follows. Section 2 describes the characteristics of the KOSPI200 options market and explains why it is chosen for this study; we also discuss informed trading issues in the options market. Section 3 describes the construction of the study's sample and the predictive regression model used to examine the information content of vega-weighted volumes by investor and trade type. Section 4 presents our empirical findings and robustness checks. Finally, Section 5 concludes the study.

2. KOSPI200 options market and informed trading

The most representative index derivatives of the Korea Exchange (KRX), KOSPI200 options were introduced about 20 years ago; its options market is one of the most liquid and popular options markets worldwide (Yang, Ryu &Ryu, 2018). Although its trading volume has decreased due to recent interventions by both the Korean government and the administrative office that controls speculation and noisy trading, trading by global and local derivatives traders remains active. The market's small bid-ask spreads, absence of brokerage and exchange fees, low trading and capital gains taxes, and substantial market depth result in low transaction costs and few market frictions, creating a market with high liquidity and active investor participation. The quoted bid-ask spreads usually equal the minimum tick size, and there is sufficient market depth to promptly absorb adverse price movements and temporary price impacts caused by large trade orders. Informed investors are encouraged by its low fees and tax rates to select KOSPI200 options as a profitable trading vehicle. These properties increase the reliability of our estimation results, which are based on a sample of intraday quotes and trades.

The investor composition of the KOSPI200 options market enables us to investigate the trading behaviors of diverse investor types. There is balanced investor participation in this market, while other developed derivatives markets are dominated by institutional investors. Local and foreign traders, as well as individual and institutional investors, take balanced positions in KOSPI200 options trading. Options investors are classified in our raw microstructure dataset as individual investors, financial investment companies (including securities and futures companies), insurance companies, investment trusts, banks, pension funds, and government-owned firms. We use this classification and investor nationality to categorize options market participants into five investor groups: foreign investment firms, other (non-investment) foreign institutions, domestic investment firms, other (non-investment) domestic institutions, and domestic individuals. Table 1 reports the trading activities in the KOSPI200 options market by investor type; trades by domestic individual investors account for about one-third of the options market trading volume during the sample period of 2010 to 2014. The table also shows that financial investment companies conduct most of the domestic institutional trades in the KOSPI200 options market. Trades by other domestic institutional investors, such as insurance companies, investment trusts, banks, pension funds, and government-owned firms, represent only about 1% of all options trading volume.[2] Although options trading volumes have decreased since the 2012 market reform, Table 1 shows that the trading proportions of domestic individuals, domestic institutions, and foreign institutions are relatively unchanged. Trades by individuals are uninformed and noisy, while those made by institutions are better informed and more sophisticated; moreover, given the intense debate on whether domestic or foreign investors are informed, the investor composition in the KOSPI200 options market provides an ideal setting for examining investor type differences.

[Table 1 here]

The demand concentration and structure of the KOSPI200 index options market are also useful features for performing our microstructure analyses. In Korea, individual options contracts are traded over-the-counter (OTC), and their trading volumes are quite small. Although other options-like assets such as equity-linked securities (ELWs) are listed on the KRX, few have been traded since the ELW market breakdown in 2010. Therefore, investor demands for derivative assets with non-linear payoff structures are concentrated in the KOSPI200 options market, and investors with volatility information are likely to choose index options to take advantage of their information. The KOSPI200 options market is purely order-driven, with no designated market makers. This simple market structure makes it possible to trace the types of investors submitting orders, as differentiation between market makers and non-market makers is unnecessary (Park & Ryu, 2019).

Motivated by the institutional features, structure, and high-quality dataset of the KOSPI200

[2] When measuring investors' volatility information content in each moneyness or trade category, trades of these other domestic institutions represent a tiny portion of total options trades. Therefore, we exclude these non-investment domestic firms from the analyses.

options market, several studies investigate whether options market trading activities provide directional information about underlying asset returns. Although studies show the existence of informed trading in this market (Ahn, Kang, and Ryu, 2019; Lee, Kang, & Ryu, 2015), no significant directional information content is detected in overall options volume. For example, Ryu (2015) compares the directional information content of KOSPI200 futures and options trades and concludes that options trades are not informative, while futures trades contain significant directional information, indicating that the aggregate options trading volume provides ambiguous information about the evolution of spot returns. Bae and Dixon (2018) show that there is little information in options trades about expected spot returns and claim that investors with directional information prefer futures market trading to the trading in the options market. Studies attribute the lack of evidence of directional information to the noisy and uninformed traders that dominate the emerging options market (Webb, Ryu, Ryu, & Han, 2016). These studies suggest that although a significant number of investors are informed, the directional information conveyed by aggregate trading volume becomes noisy. However, in the index options market, information may be revealed through volatility information trading rather than directional information trading. To examine this previously unexplored possibility, we trace the "complete" quote and transaction records of the KOSPI200 index options market and exploit the detailed investor identification information contained in our dataset to determine which investors possess intraday volatility information.

The KOSPI200 options market opens at 9:00 a.m. and closes at 3:15 p.m. on regular trading days. The uniform pricing rule governs transactions during the last 10 minutes of daily trading and one hour immediately before the beginning of the daily session. During these two periods (i.e., from 8:00 to 9:00 a.m. and from 3:05 to 3:15 p.m.), all orders submitted are accumulated in a centralized limit order book and executed at a single market price during the last moments of each session. During the market's continuous trading session (from 9:00 a.m. to 3:05 p.m.), all submitted orders are electronically matched based on price and time priority. Though four different maturity months classify each option series, only the nearest-maturity contracts are actively traded; longer-term contracts are rarely traded. A "point" is the quoting unit of the KOSPI200 options market. Before the market reform in June 2012, one point corresponded to 100,000 Korean won (KRW) but increased fivefold to 500,000 KRW afterward.

3. Data and methodology

3.1 Sample data

We use model-free implied volatility (i.e., the VKOSPI) as a proxy for market volatility and extract a one-minute intraday sample. Figure 1 shows the sampled intraday patterns of the KOSPI200 spot index and the VKOSPI based on a one-minute sampling frequency. Panel A (Panel C) exhibits their intraday dynamics of the first (last) trading day in our sample period (January 2010 through June

2014). Panel B shows the dynamics at the first trading day of April 2010. Figure 1 illustrates a negative relationship between spot index and volatility, and also shows substantial intraday movements of the VKOSPI, reflecting the speed of information flows and sentiment changes in the KOSPI200 spot and options markets.

[Figure 1 here]

Our analysis uses an ultra-fine microstructure dataset consisting of all quotes and trades in the KOSPI200 index options market from January 2010 through June 2014. We use the following filtering procedure to alleviate concerns about market microstructural noises and biases. First, to precisely identify buy and sell trades and consider post-trade volatility changes caused by incoming options orders, transactions made and orders submitted during the continuous trading sessions are included in the final sample, and we exclude those made during the pre-opening and closing call market periods. Second, options contracts with time-to-maturity of less than five calendar days are excluded to mitigate the impact of the liquidity problem and the irregular trading behavior around options expiration dates.[3] Third, options contracts with less than two contracts traded during any given day are excluded from that day's sample.[4] Finally, all options with quoted prices equal to the minimum tick size are removed to eliminate the effects of tick size restrictions.

This dataset offers several advantages for our research. First, it contains an extensive and accurate time-stamped history of all quotes and transaction activity, such as trade date, option type, order type, transaction price, trading volume, and trade direction. Second, the dataset contains the information needed to determine the investor type on both ends of each transaction (i.e., domestic or foreign; individual or investment firm) and identify who submits each order. Our investor type classification is based on the assumption that the predictive ability of options orders for future spot volatility differs depending on the trading purpose and information processing ability of the submitting investor. Third, and most importantly, our dataset provides full investor identification with investor accounts, enabling us to track the positions of all options traders and classify each transaction as one that opens or closes an investor's position. Opening (closing) trades are used when investors conduct options transactions to open (close) new (existing) positions.

Observations for the first three-month period (January to March 2010) are used to precisely trace investors' positions on each options contract. After April 2010, we begin measuring the

[3] If the five calendar days include weekends and/or holidays, periods of fewer than five trading days are excluded. As a robustness check, we also include these near-maturity periods and exclude only the exact maturity dates. However, the empirical results are qualitatively similar.

[4] Our overall conclusions remain unchanged when this filtering process is not used.

information content of options volatility demand classified by options market characteristics. Exploiting order and trade details in our dataset, we classify each options trade by initiating investor type, option leverage, and trade type, including open-interest changes, to associate volatility information content with options market characteristics. The degree of option leverage is measured by option moneyness, where the moneyness of a call (put) is the ratio of the underlying (strike) to strike (underlying) price. An options contract is classified as deep out-of-the-money (DOTM) if its moneyness value is lower than 0.955, out-of-the-money (OTM) if the value is between 0.955 and 0.985, at-the-money (ATM) when the value is between 0.985 and 1.015, in-the-money (ITM) between 1.015 and 1.045, and deep in-the-money (DITM) if its moneyness value exceeds 1.045.

Table 2 presents the summary statistics of options trades by investor type and option moneyness. The investor-moneyness categories include the transaction prices, order sizes, number of transactions, number of contracts, trading values, and bid-ask spreads. Transaction prices and order sizes are shown as per-order average values, while both daily average values and full-period total values are presented for the number of transactions, the number of contracts, and trading values. The transaction price, order size measured in values, and daily bid-ask spread monotonically increase as an option goes into the money. The average order sizes are 4.52, 8.6, 13.58, 20.37, and 52.23 points for DOTM, OTM, ATM, ITM, and DITM options, respectively, indicating that ITM options trades are generally larger than ATM and OTM options trades. By contrast, trading volumes measured by the number of transactions, number of contracts, or trading value tend to decrease with option moneyness. The bigger (smaller) trading volume and smaller (bigger) spread for OTM (ITM) options indicate that the OTM options market is more liquid than the ITM options market.

[Table 2 here]

In terms of the number of contracts (*# of contracts (total)*), 22.2% of total DOTM options trades are initiated by domestic individuals, while only 8.79% of DITM options trades are initiated by that group. By contrast, trades initiated by foreign investment firms comprise 7.36% of DOTM options transactions, but 20.61% of DITM options trading. The figures in square brackets (parentheses) show the relative trading proportions within each investor type (to total options transactions). For example, in terms of the number of contracts, "[39.11%]" denotes the ratio of OTM options trading volume of foreign investment firms (173,920,135) to their total trading volume (444,721,074), and "(2.96%)" is the ratio of OTM options trading volume of foreign investment firms (173,920,135) to all options volume (5,869,884,122). These percentage values indicate that there are different participation rates for domestic and foreign investors across different option leverage and moneyness categories. Because the information advantages, trading motives, and experiences of each investor group may differ, the different investor compositions across option moneyness categories might imply differences in information content and the effect of options trades across moneyness categories (Barber, Odean, & Zhu, 2009; Dorn, Huberman, & Sengmueller, 2008; Erenburg, Kurov, & Lasser, 2006).

3.2 Variables and methodology

We construct the vega-weighted net options demand for volatility following Ni, Pan, and Poteshman (2008), to measure the volatility information embedded in options trades. If an options investor has superior information about underlying market volatility and trades in the options market on the basis of this information, the volatility demand change can be observed via the options trading volume. Since an option's vega captures the sensitivity of the option price to the underlying volatility and is positive irrespective of the option type, her volatility demand monotonically increases (deceases) if she buy (sells) calls or puts. Thus, for each option series, we calculate the net options demand for volatility (D_i^{σ}) in the i^{th} intraday five-minute time interval for each trading day. Equation (1) shows that D_i^{σ} is computed based on each t^{th} option price observation in the i^{th} interval:

$$D_i^{\sigma} = \sum_t \frac{\partial lnC_t}{\partial \sigma}(BuyCall_t - SellCall_t) + \sum_t \frac{\partial lnP_t}{\partial \sigma}(BuyPut_t - SellPut_t), \quad (1)$$

where C_t and P_t denote the t^{th} option prices of call and put options with a specific strike price (K) and maturity (T), respectively. σ is the volatility of the underlying asset.[5] $BuyCall_t$ ($SellCall_t$) represents the t^{th} number of bought (sold) call contracts of a specific options series. $BuyPut_t$ ($SellPut_t$) denotes the number of bought (sold) put contracts. Through vega weighting, Equation (1) measures the aggregate information on the underlying asset's volatility. Since the vegas of contracts differ depending on option prices, time-to-expiration, and strike prices, the demand for each contract is weighted according to its return to the option's per unit change in volatility. We approximate $\partial lnC_t/\partial\sigma$ and $\partial lnP_t/\partial\sigma$ using the respective Black–Scholes call and put vega values, as follows:

$$\frac{\partial lnC_t}{\partial \sigma} = \frac{1}{C_t}\frac{\partial C_t}{\partial \sigma} \text{ and } \frac{\partial lnP_t}{\partial \sigma} = \frac{1}{P_t}\frac{\partial P_t}{\partial \sigma}. \quad (2)$$

The five-minute intraday regression equation (Equation 3) is estimated to test whether the net volatility demand in the KOSPI200 options market predicts the future implied volatility of the underlying asset market after controlling for various potential determinants of the volatility dynamics:

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[5] The volatility parameter (σ) is estimated based on the historical volatility of the past 20 trading days using the one-minute intraday frequency data of the underlying index.

$$IV_i=\alpha+\beta D^{\sigma}_{i-j}+\gamma IV_{i-j}+\theta_1 OV_{i-j}+\theta_2 SR_{i-j}+\theta_3 SV_{i-j}+\theta_4|D^{r}_{i-j}|+\lambda_1 Begin+\lambda_2 End+\varepsilon_i, \text{ for } j=1, 2,\ldots, 5, \quad (3)$$

where the dependent variable IV_i is the i^{th} return of the KOSPI200 model-free implied volatility (i.e., the VKOSPI).[6] Considering that the VKOSPI is highly persistent and clustered (Han, Kutan, & Ryu, 2015), we use the volatility returns and incorporate the five lagged variables IV_{i-j} (j=1, 2,…, 5) to ensure stationarity of the volatility series. The independent variable D^{σ}_{i-j} captures the net options demand for volatility. The regression equation is estimated separately for different j values, and the coefficient β measures the j-step-ahead prediction of net options demand. A significantly positive value of β would suggest that sophisticated investors with volatility information constitute the majority of options traders.

We examine the net volatility forecasting ability of the options demand and whether the volatility demand conveys information beyond directional movements, market liquidity, and other information conveyed by other options trading activities as well. To this end, we control for several variables related to the options and underlying markets. First, we consider the relationship between the volatility dynamics and trading activities in related markets (Girma & Mougoue, 2002; Herbert, 1995; Moosa & Silvapulle, 2000). OV_i denotes the total number of options contracts traded in each i^{th} five-minute trading interval. SR_i and SV_i are the log return and log trading volume in the underlying KOSPI200 spot market, respectively. Second, if a substantial share of options traders uses their directional information, the ability of the net options demand to predict volatility can be deemed spurious rather than reflective of accurate volatility information contained in options trades. For example, options traders with positive (negative) directional information choose to buy call (put) options. If their information is superior, the underlying spot price increases (decreases) after they buy calls (puts), and its volatility increases. Meanwhile, their long positions in calls (puts) increase the net demand for options, resulting in a seemingly positive association between the net demand for options and future volatility of the underlying spot. To control the directional trading behavior in the options market, we incorporate the "return" demand, D^{r}_{i}, calculated as the difference between the sums of delta-weighted long and short options volumes. Finally, intraday dummy variables *Begin* and *End* are included to capture intraday volatility patterns. *Begin* (*End*) equals one if the options transaction occurs during the beginning (ending) period of the day from 9:00 to 10:00 a.m. (2:00 to 3:05 p.m.) and zero otherwise.

Table 3 presents the summary statistics of the variables used for our empirical analysis. *IV*

[6] IV_i is calculated as the average value of five one-minute VKOSPI returns for the i^{th} interval. The VKOSPI represents options-implied information and, because options market trading activity affects the dynamics of the VKOSPI, possibly contains the information embedded in options volumes. However, the VKOSPI measures the underlying asset's volatility (i.e., it is one of the best proxies for the return volatility of the underlying KOSPI200 spot market), not the options market volatility.

and *SR* are multiplied by 100 for scale adjustments. The net demand measures, D^σ and $|D^r|$, are divided by 10,000,000. As shown in Panel A, the net volatility demand of options, D^σ, has a negative mean value of -0.0022, indicating that, on average, investors take short volatility options positions. The average absolute net return demand for options ($|D^r|$) is 0.2349, reflecting the existence of directional trading in the KOSPI200 options market. Panel B presents the correlation coefficients between the volatility returns (*IV*) and other independent variables (D^σ, *SR*, *SV*, and $|D^r|$). *IV* and D^σ are negatively related, implying that the overall net demand for options may not predict volatility. *IV* and *SV* and $|D^r|$, which measure trading activities, are all positively related to each other. The negative correlations between spot returns (*SR*) and volatilities reflect asymmetric volatility (Chun, Cho, and Ryu, 2019). Panel C presents the descriptive statistics of net volatility demand (D^σ) by investor type, option moneyness, and open-interest changes. The average value of D^σ is positive for the trades of foreign investment firms but negative for domestic individuals, indicating that foreign investment firms are net volatility demanders while domestic individuals generally take short volatility positions. Panel C also shows that options traders who initiate opening (closing) trades generally take long (short) volatility positions.

[Table 3 here]

4. Empirical results

Table 4 reports the results of Equation (3) without the classification of options trades. When the options demands are motivated by volatility information trading, the coefficient of D^σ should be significantly positive. Our basic intraday time-unit period is a five-minute interval. We measure the ability of net options demand to predict the underlying volatility one period (i.e., five minutes) through five periods (i.e., 25 minutes) ahead. Panel A of Table 4 shows that none of the coefficients of volatility demand (D^σ) are significant, indicating insufficient evidence of volatility information in the options market.[7] Panels B and C show whether the ability to predict volatility differs before and after the recent market reform. As presented in the panels, the difference is not significant despite the change in the KOSPI200 options market trading environment. This finding suggests that the determinants of predictive ability are unchanged after the market reform. Thus, we focus on the results obtained using the entire sample.

[Table 4 here]

[7] Although Bae and Dixon (2018) report that options trades have some predictive power for future volatility, they fail to control for directional information trading. Furthermore, they examine only arbitrary straddle positions using near-the-money options.

As shown in Table 4, an analysis of the aggregate options trading volume indicates a low predictive power of the demand for volatility (D^{σ}). This unexpected result can be explained by the dominance of noisy, unsophisticated, and behaviorally biased investors with ambiguous volatility information in the KOSPI200 options market (Ahn, Kang, & Ryu, 2008; Yang, Lee, & Ryu, 2018; Yang, Choi, and Ryu, 2017). Even if a substantial number of sophisticated, professional investors successfully conduct volatility trading in the options market based on their superior volatility information, the effect of such trades can be diluted by that of noisy trades.

Therefore, the type of investors who submit each order and initiate each trade must be considered to examine the volatility information content of options demand. Furthermore, the trading motives of options market participants, their trading vehicles, and other traits of their options transactions differ substantially depending on their option moneyness choices and position changes. The literature on the KOSPI200 options market shows stark differences in the ITM and OTM options trading (Kim & Ryu, 2015; Park, Kutan, and Ryu, 2019; Sim, Ryu, and Yang, 2016; Yang, Kutan, & Ryu, 2018). Additionally, Pan and Poteshman (2006) and Ryu and Yang (2018) analyze the information quality of options volumes and claim that opening trades (i.e., buy or sell orders for brand new options positions) are generally more informative than closing trades (i.e., buy or sell orders to close existing positions). Consequently, we examine whether the new volatility demand from opening trades conveys better information. Our microstructure dataset enables us to identify investor categories for each options trade and to trace the real-time positions of each options market participant. An analysis of this informative dataset allows us to identify the initiator of each trade and determine whether each order is submitted to open or close the investor's position, thus tracking open-interest changes.

To determine the type of investors that possess superior volatility information and how they use their information in the index options market, which is the central theme of our research, we consider the investor type, option moneyness, and open-interest changes. Table 5 reports the estimation results of the regression for volatility demand by category.[8] We first classify options market participants as foreign investment firms (*Foreign Invest.*), foreign non-investment firms (*Foreign Non-invest.*), domestic investment firms (*Domestic Invest.*), and domestic individuals (*Individuals*), because these categories of investors have different information-processing abilities, trading motives and experiences, investor psychology, performance, and wealth.[9] Panel A of Table 5

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[8] To conserve space, we report only the estimated coefficients of the volatility demand (D^{σ}) and not those of the control variables.

[9] Existing studies report that the information superiorities, performances, and traits of the investors are quite different and heterogeneous (Bae, Stulz, & Tan, 2008; Brandt, Brav, Graham, & Kumar,

shows the estimation results when volatility demand (D^{σ}) is categorized by investor type. We find that foreign non-investment firms, domestic investment firms, and domestic individuals do not initiate options trades with volatility information, whereas foreign investment firms do. The volatility demand of foreign investment firms predicts the short-term, one-period-ahead underlying volatility; the estimated coefficient is 0.541 and *t*-statistic is 2.29 (i.e., the estimated β is significantly positive).

[Table 5 here]

Panel A of Table 5 shows that foreign investors have superior volatility information. Most foreign investors in the Korean derivatives market are sophisticated and have better information-processing skills, market timing, trading knowledge, and experience than domestic traders do; as such, they can profit from public and/or market-wide information in addition to their sophistication and trading advantages. Our results support prior findings (Chang, Hsieh, & Lai, 2009; Chang, Hsieh, & Wang, 2010; Kuo, Chung, & Chang, 2015; Lee & Wang, 2016) about the sophistication, trading experience, and trading skills of foreign investors in emerging options markets, as well as findings (Froot, O'Connell, & Seasholes, 2001; Richards, 2005) about the high influence of their capital flows in such markets.[10]

Chang, Hsieh, and Wang (2010) find that the volatility demand in the Taiwanese options market created by a specific volatility trading strategy of foreign institutional investors contains vital information and can predict one-day-ahead volatility, which is partially consistent with our findings. According to the authors, foreign investors profit from their volatility information by combining options and futures trades; other volatility transactions, such as straddle, strangle, and calendar spread trades (typical volatility trading strategies), convey little information. Their vague and contrasting results may be attributable to an inaccurate process of identifying volatility–sensitive options

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2009; Chan, Menkveld, & Yang, 2007; Chang, Hsieh, & Lai, 2009; Chung, Kim, & Ryu, 2017; Dvořák, 2005; Griffin, Harris, & Topaloglu, 2003; Grinblatt & Keloharju, 2000; Hau, 2001; Hsieh & He, 2014; Huang & Shiu, 2009; Kaniel, Liu, Saar, & Titman, 2012; Kaniel, Saar, & Titman, 2008; Kim, Ryu, & Seo, 2015; Kuo, Chung, & Chang, 2015; Lee, 2015; Ng & Wu, 2007; Seok, Cho, & Ryu, 2019).

[10] For all subsamples, we estimate our models and replicate all tables before and after the market reform. We find the same patterns of foreign investment firms' volatility-informed trading in the pre-reform sample as in the full sample, and OTM options trades have predictive power for future volatility. Foreign investment firms have significantly better volatility information than domestic traders before the reform. After the reform, their relative information advantage and dominance somewhat decrease, reflecting the reform's exclusion of noisy and novice individuals from the options market. We also find that the ATM options trades of domestic investors show some predictive power for future volatility in both pre-reform and post-reform periods, indicating that domestic investors with volatility information primarily trade the near-the-money options for their high sensitivity to volatility movements.

strategies and/or the small share contributed by such volatility trading to the total volatility trading. The Korean and Taiwanese options markets have similar characteristics and structures, and most of the speculators and hedgers who dominate options markets are directional traders rather than volatility traders (Lakonishok, Lee, Pearson, & Poteshman, 2006). Accordingly, we examine the information content of volatility demand based on key option market characteristics—including initiating investor type, option moneyness, and open-interest changes—rather than specific volatility–sensitive options strategies.

Panel B of Table 5 examines whether option moneyness explains the effects of volatility information trading. The option moneyness category reflects the leverage effect and sensitivity of options prices to underlying asset price changes, suggesting option moneyness may explain the predictive ability of volatility demand. The characteristics of each KOSPI200 options contract differ significantly in terms of spread size, depth, investor participation rate, and degree of informed trading depending on the contract's moneyness. We find that the net volatility demand constructed from OTM options trading predicts 10-minute-ahead volatility, but the demand from other moneyness options trading does not. This finding contrasts with that of Ni, Pan, and Poteshman's (2008) study, which attributes the significant volatility information content of ATM options to the high vega levels of ATM options (i.e., ATM options are sensitive to volatility changes) in the US market. Our results indicate greater importance of factors such as liquidity, speculative opportunities, and leverage than of sensitivity to volatility changes.

Panel C of Table 5 estimates the regression results separately for options trades that open new positions (open volumes) and close existing positions (close volumes). Studies consistently report that opening trades convey higher-quality directional information than closing trades (Hsieh & He, 2014; Pan & Poteshman, 2006). We test whether there is a higher concentration of informed trading in the volatility demand created by open volumes than that of close volumes. In contrast to the findings of existing studies on directional information, the estimated coefficients for both opening and closing trades are negative or insignificant, indicating insufficient evidence of volatility information trading. This puzzling result on an aggregate level motivates us to further classify options trades across multiple dimensions, considering various options market characteristics.

We estimate the regression using a two-dimensional classification: investor–moneyness categories (see Table 6) and investor–trade type categories (see Table 7). This would provide greater insight into the type of investors that use their superior volatility information and how they profit from this information through options trades. Table 6 shows that, regardless of which option moneyness category they use as their trading vehicle, the volatility trading of foreign non-investment firms is not informative. Panel A of Table 6 shows that the DOTM options trades of foreign investment firms predict future volatility, and foreign investment firms trade on their volatility information by exploiting the high leverage of DOTM options. The estimated coefficient for foreign investment firms using DOTM options is 0.753, with a *t*-statistic of 2.69. DOTM options may provide a cheaper or more effective means of trading on the information, given their higher degree of leverage and liquidity (Lee & Wang, 2016). Because uninformed individual investors provide ample liquidity and trading opportunities in the KOSPI200 (deep) out-of-the-money options market (Ryu, 2011; Ryu and Yang, *R&R*), foreign investment firms that possess sophisticated volatility information can find profitable opportunities in highly levered options trading. The volatility information embedded in the DOTM options trades of foreign investment firms could also be associated with the previous finding that they are net volatility demanders (see Panel C of Table 3). When investors open their positions, they are generally net volatility demanders (see Table 3), indicating that creating new options positions is related to volatility demand. Volatility informed investors might prefer smaller investments and avail the leverage effect of investing in DOTM options by taking long positions in the options market as a strategy for generating profits.

[Table 6 here]

Although the aggregate volatility demand of domestic individuals and that of investment firms are not informative, Panels C and D of Table 6 show that the ATM options trades of domestic investors have some predictive power for future volatility. The estimated coefficient of volatility trades initiated by domestic investment firms (domestic individuals) using ATM options is 1.164 (1.189), with a *t*-statistic of 2.77 (2.96), showing that the ATM options trades initiated by them convey some volatility information. Following rule-of-thumb volatility trading strategies, domestic investors with volatility information primarily trade the near-the-money options because they have the highest volatility sensitivity. The volatility trading of domestic investors is somewhat conservative compared to that of foreign investment firms, which are involved in speculative options trading and use highly leveraged out-of-the-money options, possibly reflecting their relative confidence and experience.

Table 7 reports the estimation results of the regression for volatility demand based on which type of investor initiates each options trade and the change in investors' positions (i.e., open-interest) following the transaction. Both domestic institutional and individual investors conduct options trades without volatility information, irrespective of whether they open or close positions. By contrast, although the demand for opening and closing trades does not convey volatility information when it is not considered separately by investor type, Panel A of Table 7 shows that the closing trades of informed foreign investment firms significantly predict underlying volatility. It is noteworthy that closing trades also contain significant volatility information considering that most studies examining directional information report that only opening trades predict future asset returns, whereas closing trades do not.

[Table 7 here]

Consider this example (and interpretation) of informative closing trades. Informed traders who expect a price increase (decrease) in an underlying asset can write puts (calls) and open a new short position, that is, an open-sell trade using put (call) options at time t. The trader profits from an increase (decrease) in the underlying spot price at time t+1. The information flows are fast, volatility levels are relatively high, and speculative trading prevails in the KOSPI200 spot and options markets; this means that the spot price often decreases (increases) after a price increase (decrease). Specifically, in this example, the spot price can decrease (increase) at time t+2. The informed trader, having an open-sell put (call) position, should close the existing position by submitting a close-buy order in the put (call) options market right before time t+2 (i.e., at time t+1). Such closing trades successfully predict volatility changes, and our analysis captures the volatility information contained in close-buy orders. Furthermore, the rapid information flow in the index options market induces informed traders to conduct “cheap lunch” trading. Timing is an essential factor when informed investors close their positions. These closing orders should be carefully considered and submitted based on the existing positions and portfolio dynamics. While opening trades are conducted by uninformed, noisy investors as well, we can infer that informed investors with open positions in the options market tend to discreetly close their positions based on prudent predictions and expectations. However, other explanations for the higher information quality of closing trades are also plausible. In the case of opening trades, hedging motives are included because hedgers open their options positions and maintain their positions without closing them. By contrast, the closing trades do not include such hedging needs. The net demand of volatility-informed investors may be better reflected in closing trades.

5. Conclusions

We empirically investigate whether intraday volatility information exists in the index options market using a unique, high-quality microstructure dataset of KOSPI200 options. Based on the vega-weighted net demand for volatility, we classify investors into four groups, to determine the types of investors that are informed about future stock market volatility and that conduct volatility information trading in a highly liquid options market. Our results have significant implications for forecasting market volatility and examining the effect of foreign firms versus domestic traders on market volatility. We find that the overall options market demand for volatility does not predict market volatility. This result suggests that the information quality of options trades is relatively low because uninformed and noisy domestic investors dominate the KOSPI200 options market. Second, the vega-weighted net demand of foreign investment firms conveys significant information about future volatility dynamics. By tracking the positions of all options market participants for all option moneyness categories and maturities, we find that foreign investment firms conduct volatility trading with highly levered options and that their intraday volatility information superiority is more prominent when they close rather than open positions. Finally, we find that the volatility demand of domestic traders who trade near-the-money options partially predicts market volatility, implying that their trades also convey some volatility information.

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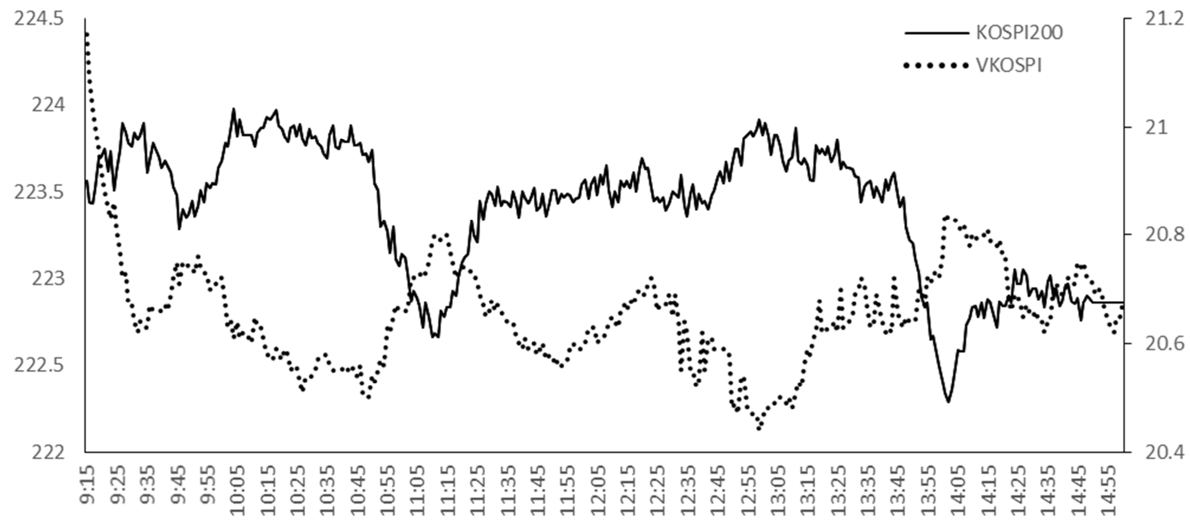
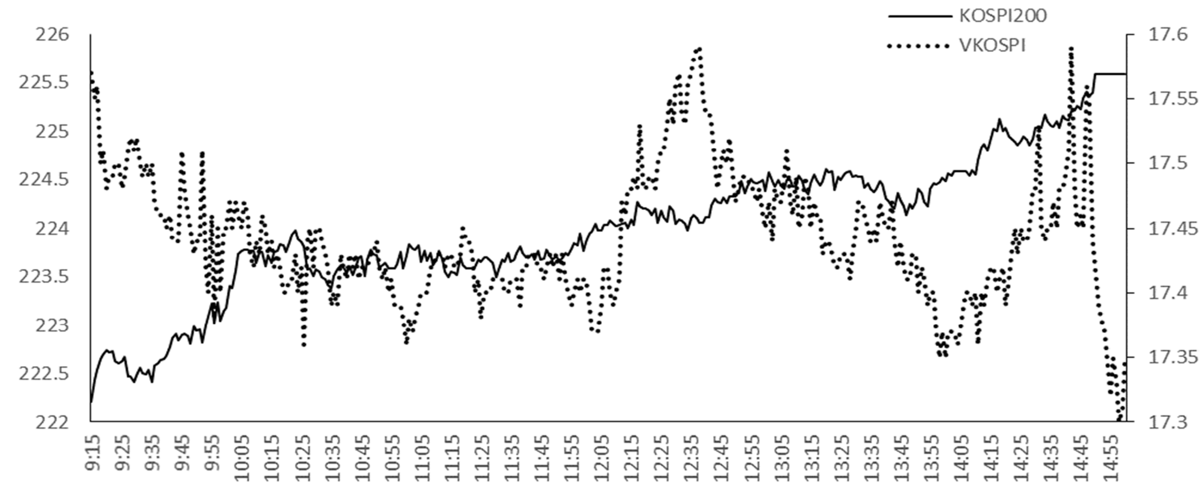
Figure 1
Intraday patterns of the KOSPI200 and VKOSPI

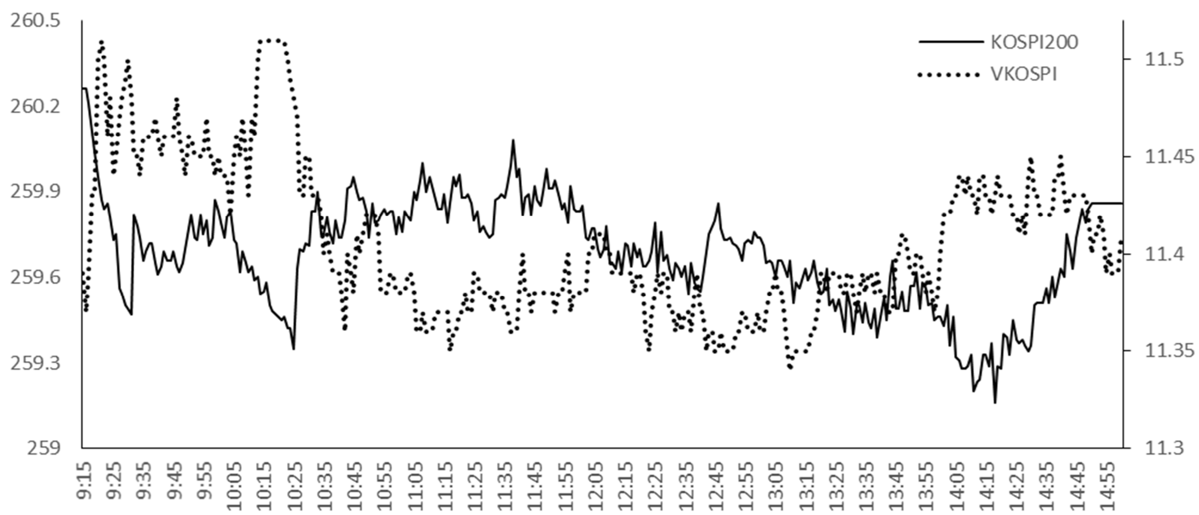
Panel A. January 5, 2010



Panel B. April 1, 2010



Panel C. June 30, 2014



Note: This figure shows the sampled intraday movements of the KOSPI200 spot price level (solid line) and VKOSPI (dotted line), based on a one-minute sampling interval.

Table 1
Trading volume by investor type

		Foreign Invest.	Foreign Non-invest.	Domestic Invest.	Domestic Non-invest.	Individuals
Panel A. Call options						
2010	Buy	23,030,845	329,211,014	267,011,720	15,406,462	204,543,074
	Sell	22,879,772	331,391,337	276,175,730	17,901,461	224,679,792
2011	Buy	52,890,241	416,549,685	239,973,039	7,635,513	215,709,851
	Sell	53,609,561	424,224,240	249,940,109	8,357,366	241,843,749
2012	Buy	43,251,093	173,131,203	92,460,211	3,024,838	78,424,476
	Sell	43,511,001	175,846,805	96,908,122	3,195,617	88,252,543
2013	Buy	17,954,637	63,500,357	29,969,358	1,220,056	30,728,772
	Sell	17,802,778	64,316,863	31,509,784	1,166,174	34,987,632
2014	Buy	3,793,739	22,962,479	13,036,054	373,520	11,709,023
	Sell	3,708,392	23,407,609	13,777,025	404,832	13,698,091
Total		282,432,059	2,024,541,592	1,310,761,152	58,685,839	1,144,577,003
		(5.86%)	(41.99%)	(27.19%)	(1.22%)	(23.74%)
Panel B. Put options						
2010	Buy	21,160,032	386,940,268	199,214,565	21,063,969	200,766,162
	Sell	21,114,476	392,673,438	210,104,625	24,349,749	221,900,132
2011	Buy	52,779,567	408,319,307	158,424,685	6,656,399	182,664,491
	Sell	53,222,517	415,764,161	166,704,457	7,534,811	204,651,263
2012	Buy	49,171,067	165,188,832	65,024,791	3,346,547	73,122,225
	Sell	48,836,825	167,335,674	69,474,861	3,506,315	81,800,011
2013	Buy	20,772,131	59,439,567	20,142,715	1,171,004	28,468,924
	Sell	20,360,571	60,012,473	22,028,171	1,205,857	32,240,316
2014	Buy	4,624,758	24,870,073	9,568,046	367,369	11,163,509
	Sell	4,359,601	25,001,396	10,394,861	388,655	12,945,723
Total		296,401,545	2,105,545,189	931,081,777	69,590,675	1,049,722,756
		(6.66%)	(47.29%)	(20.91%)	(1.56%)	(23.58%)

Note: This table presents the trend in trading volumes of KOSPI200 call and put options for five investor types: foreign investment firms (*Foreign Invest.*), foreign non-investment firms (*Foreign Non-invest.*), domestic investment firms (*Domestic Invest.*), domestic non-investment firms (*Domestic Non-invest.*), and domestic individuals (*Individuals*). The sample period is January 2010 to June 2014. *Buy* and *Sell* denote buy and sell options volumes, respectively. Trading volume is presented as the number of options contracts. Figures in parentheses are percentages.

Table 2
Summary statistics

	All	Moneyness				
		DOTM	OTM	ATM	ITM	DITM
Panel A. Overall						
Price	1.74	0.66	1.69	3.70	7.89	18.49
Order size (in contracts)	6.39	10.4	6.04	3.72	2.53	2.82
Order size (in value)	8.11	4.52	8.60	13.58	20.37	52.23
# of transactions (daily)	689,705	203,003	300,366	176,305	8,871	1,159
# of contracts (daily)	5,569,150	2,449,788	2,265,477	821,646	28,105	4,134
Trading value (daily)	6,702,949	1,591,561	2,767,756	2,052,602	214,336	76,695
Bid–ask spread (daily)	0.02	0.01	0.02	0.04	0.10	0.35
# of transactions (total)	726,948,614	213,964,862	316,585,461	185,826,366	9,350,054	1,221,871
# of contracts (total)	5,869,884,122	2,582,076,032	2,387,813,107	866,015,371	29,622,755	4,356,857
Trading value (total)	7,064,908,525	1,677,504,923	2,917,214,930	2,163,442,175	225,909,926	80,836,571
Panel B. Foreign investment firms						
Price	2.11	0.79	1.76	3.78	7.83	17.86
Order size (in contracts)	7.33	11.80	7.34	4.86	3.25	2.84
Order size (in value)	12.02	6.59	11.5	18.83	26.23	50.39
# of transactions (daily)	53,719	13,947	23,313	15,079	1187	195
# of contracts (daily)	421,937	180,269	165,010	70,780	5026	861
Trading value (daily)	662,628	149,457	240,020	216,144	41,224	15,948
Bid–ask spread (daily)	0.02	0.01	0.02	0.04	0.09	0.35
# of transactions (total)	56,619,802	14,699,752	24,572,141	15,893,001	1,251,198	203,710
	[100%] (7.79%)	[25.96%] (2.02%)	[43.4%] (3.38%)	[28.07%] (2.19%)	[2.21%] (0.17%)	[0.36%] (0.03%)
# of contracts (total)	444,721,074	190,003,602	173,920,135	74,601,872	5,297,355	898,110
	[100%] (7.58%)	[42.72%] (3.24%)	[39.11%] (2.96%)	[16.77%] (1.27%)	[1.19%] (0.09%)	[0.2%] (0.02%)
Trading value (total)	698,409,629	157,527,932	252,981,190	227,815,981	43,450,584	16,633,942
	[100%] (9.89%)	[22.56%] (2.23%)	[36.22%] (3.58%)	[32.62%] (3.22%)	[6.22%] (0.62%)	[2.38%] (0.24%)

Panel C. Foreign non-investment firms						
Price	1.85	0.69	1.72	3.79	7.94	18.59
Order size (in contracts)	6.29	8.52	6.25	3.86	2.46	2.72
Order size (in value)	8.93	4.79	9.36	14.17	19.81	50.76
# of transactions (daily)	347,850	104,892	144,908	91,010	6,243	798
# of contracts (daily)	2,719,434	1,139,760	1,126,042	431,446	19,374	2,811
Trading value (daily)	3,681,508	879,098	1,460,455	1,143,118	146,724	52,113
Bid–ask spread (daily)	0.02	0.01	0.02	0.04	0.10	0.35
# of transactions (total)	366,634,165	110,556,364	152,732,909	95,924,361	6,579,774	840,757
	[100%] (50.43%)	[30.15%] (15.21%)	[41.66%] (21.01%)	[26.16%] (13.2%)	[1.79%] (0.91%)	[0.23%] (0.12%)
# of contracts (total)	2,866,283,361	1,201,307,348	1,186,848,527	454,744,166	20,420,623	2,962,697
	[100%] (48.83%)	[41.91%] (20.47%)	[41.41%] (20.22%)	[15.87%] (7.75%)	[0.71%] (0.35%)	[0.1%] (0.05%)
Trading value (total)	3,880,309,523	926,568,914	1,539,319,835	1,204,846,453	154,646,908	54,927,413
	[100%] (54.92%)	[23.88%] (13.12%)	[39.67%] (21.79%)	[31.05%] (17.05%)	[3.99%] (2.19%)	[1.42%] (0.78%)
Panel D. Domestic investment firms						
Price	1.37	0.55	1.59	3.38	7.84	17.88
Order size (in contracts)	10.47	28.82	8.12	4.33	2.81	3.64
Order size (in value)	8.61	6.41	9.55	13.86	22.31	64.06
# of transactions (daily)	76,010	20,986	38,269	16,626	114	29
# of contracts (daily)	1,098,856	547,090	436,025	115,304	386	100
Trading value (daily)	873,264	224,665	425,506	219,134	2,738	1,891
Bid–ask spread (daily)	0.01	0.01	0.01	0.03	0.09	0.29
# of transactions (total)	80,114,123	22,119,026	40,335,816	17,523,706	113,519	22,056
	[100%] (11.02%)	[27.61%] (3.04%)	[50.35%] (5.55%)	[21.87%] (2.41%)	[0.14%] (0.02%)	[0.03%] (0%)
# of contracts (total)	1,158,194,023	576,632,609	459,570,158	121,529,991	385,094	76,171
	[100%] (19.73%)	[49.79%] (9.82%)	[39.68%] (7.83%)	[10.49%] (2.07%)	[0.03%] (0.01%)	[0.01%] (0%)
Trading value (total)	920,420,446	236,797,194	448,483,551	230,966,886	2,732,164	1,440,650

	[100%] (13.03%)	[25.73%] (3.35%)	[48.73%] (6.35%)	[25.09%] (3.27%)	[0.3%] (0.04%)	[0.16%] (0.02%)
Panel E. Domestic individuals						
Price	1.55	0.62	1.66	3.58	7.73	18.14
Order size (in contracts)	4.75	7.78	4.35	2.81	1.98	2.57
Order size (in value)	5.50	3.07	5.96	9.62	15.43	46.79
# of transactions (daily)	204,597	60,847	90,627	51,696	1,287	140
# of contracts (daily)	1,256,981	543,690	513,406	196,358	3,163	364
Trading value (daily)	1,424,373	322,862	617,278	4,550,392	22,448	6,759
Bid–ask spread (daily)	0.02	0.01	0.02	0.03	0.10	0.36
# of transactions (total)	215,645,489	64,132,240	95,520,854	54,487,912	1,356,852	147,631
	[100%] (29.66%)	[29.74%] (8.82%)	[44.3%] (13.14%)	[25.27%] (7.5%)	[0.63%] (0.19%)	[0.07%] (0.02%)
# of contracts (total)	1,324,857,866	573,049,227	541,130,241	206,961,097	3,334,258	383,043
	[100%] (22.57%)	[43.25%] (9.76%)	[40.84%] (9.22%)	[15.62%] (3.53%)	[0.25%] (0.06%)	[0.03%] (0.01%)
Trading value (total)	1,501,288,884	340,296,814	650,611,002	479,611,212	23,659,749	7,110,107
	[100%] (21.25%)	[22.67%] (4.82%)	[43.34%] (9.21%)	[31.95%] (6.79%)	[1.58%] (0.33%)	[0.47%] (0.1%)

Note: Based on five-minute time intervals, this table presents the average mid-quote price (*Price*), average order size in contracts (*Order size (in contracts)*), and average order size in value (*Order size (in value)*) for each investor type and moneyness category. It also shows the daily average number of transactions (*# of transactions (daily)*), daily average number of contracts (*# of contracts (daily)*), daily average trading value (*Trading value (daily)*), daily average bid–ask spread (*Bid-ask spread (daily)*), total number of transactions *(# of transactions (total)*), total number of contracts (*# of contracts (total)*), and total trading value (*Trading value (total)*) for each category. There are four types of investors: foreign investment firms (Panel B), foreign non-investment firms (Panel C), domestic investment firms (Panel D), and domestic individuals (Panel E). *DOTM*, *OTM*, *ATM*, *ITM*, and *DITM* refer to deep out-of-the-money, out-of-the-money, at-the-money, in-the-money, and deep in-the-money, respectively. The figures in square brackets denote the percentage values within each investor type. The figures in parentheses beneath the bracketed figures denote the percentage values of that item to the overall sample. The sample period is April 2010 to June 2014.

Table 3
Descriptive statistics

Panel A. Descriptive statistics of key variables

Variable	Mean	StdDev	Min	Median	Max
IV	-0.0018	0.0874	-1.7306	0.0000	2.2736
D^{σ}	-0.0022	0.0478	-1.2950	-0.0004	2.3516
SR	0.0004	0.1399	-5.4955	0.0000	3.9157
SV	13.8531	0.5068	12.4387	13.8062	16.8444
$\|D^{r}\|$	0.2349	0.6386	0.0000	0.0558	32.5024

Panel B. Correlation coefficients

Variable	*IV*	D^{σ}	*SR*	*SV*	$\|D^{r}\|$
IV	1				
D^{σ}	-0.1323***	1			
SR	-0.4145***	0.2265***	1		
SV	0.0346***	-0.0340***	0.0088**	1	
$\|D^{r}\|$	0.0261***	0.0720***	-0.0074*	0.2264***	1

Panel C. Descriptive statistics of net demand for volatility (D^{σ}) by subsample

Variable	Mean	StdDev	Min	Median	Max
Investor type					
Foreign Invest.	0.0000	0.0020	-0.0742	0.0000	0.1523
Foreign Non-invest.	-0.0005	0.0152	-0.3494	-0.0001	0.6539
Domestic Invest.	-0.0003	0.0297	-0.9565	0.0000	1.2136
Individuals	-0.0013	0.0149	-0.4435	-0.0002	0.7366
Moneyness					
DOTM	0.0002	0.0402	-1.2882	0.0000	2.3578
OTM	-0.0021	0.0185	-0.5868	-0.0003	0.8034
ATM	-0.0004	0.0017	-0.0800	0.0000	0.0411
ITM	0.0000	0.0001	-0.0020	0.0000	0.0028
DITM	0.0000	0.0000	-0.0005	0.0000	0.0009
Open-interest changes					
Open	0.0025	0.0307	-0.7109	0.0004	1.3540
Close	-0.0047	0.0297	-0.9350	-0.0011	1.0813

Note: Based on five-minute time intervals, this table presents the summary statistics (mean, standard deviation, and minimum, median, and maximum values) and correlation coefficients of the main variables. *IV* is the average return of the model-free implied volatility index of the KOSPI200 derived from KOSPI200 options. D^{σ} is the net demand for volatility; *SR* and *SV* are the log return and log trading volume of the KOSPI200 index, respectively. $|D^{r}|$ is the absolute difference between the sum of the delta-weighted long and short volumes. There are four investor types: foreign investment firms (*Foreign Invest.*), foreign non-investment firms (*Foreign Non-invest.*), domestic investment firms (*Domestic Invest.*), and domestic individuals (*Individuals*). Moneyness is classified as deep out-of-the-money (*DOTM*), out-of-the-money (*OTM*), at-the-money (*ATM*), in-the-money (*ITM*), and deep in-the-money (*DITM*). Open-interest changes are categorized as open volume (*Open*) or close volume (*Close*). ***, **, and * indicate statistical significance at the level 1%, 5%, and 10% levels, respectively.

The sample period is April 2010 to June 2014.

Table 4
Volatility predictions by options volume

Panel A. Entire sample period (April 1, 2010 to June 30, 2014)

	j=1	*j*=2	*j*=3	*j*=4	*j*=5
Intercept	-0.041**(-2.57)	-0.031**(-2.01)	-0.018(-1.18)	-0.022(-1.45)	-0.019(-1.30)
D^{σ}_{t-j}	0.012(0.81)	0.011(0.89)	0.014(1.50)	0.015(1.58)	0.003(0.29)
IV_{t-j}	-0.074***(-5.14)	-0.010(-0.87)	-0.005(-0.46)	-0.006(-0.58)	0.013(1.17)
SR_{t-j}	-0.134***(-13.00)	-0.015(-1.51)	-0.011(-1.34)	-0.010(-0.90)	0.016(1.55)
SV_{t-j}	0.003**(2.44)	0.002*(1.90)	0.001(1.09)	0.002(1.37)	0.001(1.22)
$\|D^{r}_{t-j}\|$	0.002**(2.32)	0.001(1.43)	0.000(0.76)	-0.000(-0.40)	-0.000(-0.11)
Begin	-0.004***(-2.77)	-0.003**(-2.15)	-0.003*(-1.83)	-0.003*(-1.89)	-0.001(-0.92)
End	-0.004***(-3.45)	-0.003***(-3.24)	-0.003***(-2.86)	-0.003***(-3.00)	-0.003***(-3.00)
adj. R^2	0.0167	0.0004	0.0002	0.0002	0.0003

Panel B. Pre-regulation period (April 1, 2010 to June 14, 2012)

	j=1	*j*=2	*j*=3	*j*=4	*j*=5
Intercept	-0.070***(-2.60)	-0.050*(-1.93)	-0.028(-1.01)	-0.032(-1.24)	-0.030(-1.23)
D^{σ}_{t-j}	0.023(1.53)	0.013(0.98)	0.018*(1.73)	0.016(1.59)	0.001(0.13)
IV_{t-j}	-0.079***(-4.05)	-0.016(-1.05)	-0.006(-0.45)	0.005(0.39)	0.020(1.32)
SR_{t-j}	-0.16***(-11.93)	-0.022(-1.6)	-0.017(-1.51)	-0.010(-0.70)	0.020(1.46)
SV_{t-j}	0.005**(2.54)	0.004*(1.89)	0.002(1.00)	0.002(1.23)	0.002(1.22)
$\|D^{r}_{t-j}\|$	0.002**(2.10)	0.001(1.38)	0.000(0.50)	0.000(-0.60)	0.000(-0.40)
Begin	-0.006***(-2.84)	-0.005**(-2.25)	-0.004*(-1.85)	-0.004*(-1.82)	-0.002(-0.68)
End	-0.006***(-3.63)	-0.006***(-3.49)	-0.005***(-3.05)	-0.005***(-3.23)	-0.005***(-3.28)
adj. R^2	0.023	0.001	0.000	0.000	0.001

Panel C. Post-regulation period (June 15, 2012, 2012 to June 30, 2014)

	j=1	*j*=2	*j*=3	*j*=4	*j*=5
Intercept	-0.010(-0.64)	-0.002(-0.15)	0.010(0.68)	0.008(0.58)	0.017(1.12)
D^{σ}_{t-j}	-0.015(-0.27)	-0.007(-0.12)	-0.025(-0.53)	0.034(0.73)	0.051(1.11)
IV_{t-j}	-0.067***(-5.06)	0.004(0.37)	-0.002(-0.21)	-0.032***(-3.48)	-0.003(-0.28)
SR_{t-j}	-0.068***(-7.86)	0.002(0.21)	0.006(0.76)	-0.007(-0.82)	0.003(0.41)
SV_{t-j}	0.001(0.46)	0.000(0.02)	-0.001(-0.81)	-0.001(-0.72)	-0.001(-1.25)
$\|D^{r}_{t-j}\|$	0.009**(2.05)	-0.003(-0.85)	-0.001(-0.28)	-0.003(-0.82)	0.000(-0.05)
Begin	-0.001(-0.77)	-0.001(-0.32)	0.000(-0.12)	0.000(-0.19)	0.000(-0.15)
End	-0.001(-0.51)	0.000(-0.22)	0.000(0.09)	0.000(0.04)	0.000(0.17)
adj. R^2	0.006	0.000	0.000	0.001	0.000

Note: This table presents the estimated coefficients of the prediction regression based on the aggregate options volume level. Panel A shows the results for the entire sample period of April 1, 2010 to June 30, 2014. To check for possible effects of the regulatory change in June 2012, we divide our sample period into two subperiods. Panel B presents the results for the pre-regulation period (April 1, 2010 to June 14, 2012) and Panel C shows the results for the post-regulation period (June 15, 2012 to June 30, 2014). The VKOSPI average return is the dependent variable and the independent variables are the demand for volatility (D^{σ}) and various control variables with lagged periods from one to five. $IV_i=\alpha+\beta D^{\sigma}_{i-j}+\gamma IV_{i-j}+\theta_1 OV_{i-j}+\theta_2 SR_{i-j}+\theta_3 SV_{i-j}+\theta_4|D^{r}_{i-j}|+\lambda_1 Begin+\lambda_2 End+\varepsilon_i$, for j=1, 2,…, 5, where *IV* is the return of the model-free implied volatility index of the KOSPI200 derived from KOSPI200 options; D^{σ} is the net demand for volatility; *OV* is the number of options contracts; *SR* and *SV* are the log return and log trading volume of the KOSPI200 index, respectively. $|D^{r}|$ is the absolute difference between the sum of the delta-weighted long and short volumes, and *Begin* (*End*) equals one if a given option corresponds to the time period from 9:00 to 10:00 a.m. (from 2:00 to 3:05 p.m.), and zero otherwise. Numbers in parentheses are the Newey–West *t*-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5
Volatility predictions of options volumes by investor type, option moneyness, and open-interest changes

	j=1		*j*=2	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.
Panel A. Investor type				
Foreign Invest.	**0.541****	**(2.29)**	-0.237	(-1.19)
Foreign Non-invest.	0.037	(1.09)	-0.015	(-0.47)
Domestic Invest.	0.015	(0.75)	0.024	(1.15)
Individuals	0.017	(0.33)	0.026	(0.79)
Panel B. Moneyness				
DOTM	0.010	(0.52)	0.008	(0.50)
OTM	0.030	(1.42)	**0.032****	**(2.01)**
ATM	0.219	(0.99)	0.034	(0.17)
ITM	0.827	(0.09)	-2.462	(-0.3)
DITM	-260.264	(-0.89)	-174.749	(-0.94)
Panel C. Open-interest changes				
Open	0.032	(1.49)	0.020	(1.19)
Close	-0.002	(-0.12)	0.007	(0.40)

Note: This table presents the estimation coefficients of the prediction regression by investor type, option moneyness, and trading strategy. In Panel A, there are four investor types: foreign investment firms (*Foreign Invest.*), foreign non-investment firms (*Foreign Non-invest.*), domestic investment firms (*Domestic Invest.*), and domestic individuals (*Individuals*). In Panel B, option moneyness is categorized as deep out-of-the money (*DOTM*), out-of-the-money (*OTM*), at-the-money (*ATM*), in-the-money (*ITM*) or deep in-the-money (*DITM*). In Panel C, open-interest changes are categorized as open volume (*Open*) and close volume (*Close*). The VKOSPI is the dependent variable and the independent variables are the demand for volatility (D^{σ}) and various control variables with lagged periods from one to five. $IV_i=\alpha+\beta D^{\sigma}_{i-j}+\gamma IV_{i-j}+\theta_1 OV_{i-j}+\theta_2 SR_{i-j}+\theta_3 SV_{i-j}+\theta_4|D^{r}_{i-j}|+\lambda_1 Begin+\lambda_2 End+\varepsilon_i$, for j=1, 2, where *IV* is the return of the model-free implied volatility index of the KOSPI200 derived from KOSPI200 options; D^{σ} is the net demand for volatility; *OV* is the number of options contracts; *SR* and *SV* are the log return and log trading volume of the KOSPI200 index, respectively. $|D^{r}|$ is the absolute difference between the sum of the delta-weighted long and short volumes, and *Begin* (*End*) equals one if each option corresponds to the time period from 9:00 to 10:00 a.m. (2:00 to 3:05 p.m.), and zero otherwise. The sample period is April 2010 to June 2014. Numbers in parentheses are Newey–West *t*-statistics. ** indicates statistical significance at the 5% level.

Table 6
Volatility predictions of options volumes by investor type and option moneyness

	j=1		j=2	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.
Panel A. Foreign investment firms				
DOTM	**0.753*****	**(2.69)**	-0.248	(-0.98)
OTM	-0.018	(-0.06)	-0.078	(-0.30)
ATM	-3.272**	(-2.24)	-2.225	(-1.58)
ITM	23.906	(0.76)	19.697	(0.72)
DITM	447.457	(1.13)	-215.046	(-0.67)
Panel B. Foreign non-investment firms				
DOTM	0.045	(1.18)	-0.017	(-0.46)
OTM	0.024	(0.52)	0.009	(0.21)
ATM	-1.418***	(-3.50)	-0.774*	(-1.89)
ITM	-0.990	(-0.11)	-6.618	(-0.75)
DITM	-358.738	(-1.18)	-158.51	(-0.82)
Panel C. Domestic investment firms				
DOTM	0.009	(0.36)	0.020	(0.83)
OTM	0.039	(1.40)	0.053**	(2.09)
ATM	**1.164*****	**(2.77)**	0.509	(1.48)
ITM	-84.628	(-0.79)	-5.075	(-0.05)
DITM	547.462	(0.41)	189.289	(0.16)
Panel D. Domestic individuals				
DOTM	0.008	(0.13)	0.018	(0.42)
OTM	0.032	(0.56)	0.047	(1.05)
ATM	**1.189*****	**(2.96)**	0.414	(1.22)
ITM	1.507	(0.05)	10.418	(0.40)
DITM	-116.887	(-0.09)	62.717	(0.11)

Note: This table presents the estimated coefficients of the prediction regression by investor type, considering option moneyness. There are four investor types: foreign investment firms, foreign non-investment firms, domestic investment firms, and domestic individuals. *DOTM*, *OTM*, *ATM*, *ITM*, and *DITM* refer to deep out-of-the-money, out-of-the-money, at-the-money, in-the-money, and deep in-the-money options, respectively. The VKOSPI return is the dependent variable and the independent variables are the demand for volatility (D^{σ}) and various control variables with lagged periods from one to five. $IV_i=\alpha+\beta D^{\sigma}_{i-j}+\gamma IV_{i-j}+\theta_1 OV_{i-j}+\theta_2 SR_{i-j}+\theta_3 SV_{i-j}+\theta_4|D^{r}_{i-j}|+\lambda_1 Begin+\lambda_2 End+\varepsilon_i$, for j=1, 2, where *IV* is the return of the model-free implied volatility index of the KOSPI200 derived from KOSPI200 options, D^{σ} is the net demand for volatility; *OV* is the number of options contracts; *SR* and *SV* are the log return and log trading volume of the KOSPI200 index, respectively. $|D^{r}|$ is the absolute difference between the sum of the delta-weighted long and short volumes, and *Begin* (*End*) equals one if each option corresponds to the time period from 9:00 to 10:00 a.m. (from 2:00 to 3:05 p.m.), and zero otherwise. The sample period is April 2010 to June 2014. Numbers in parentheses are Newey–West *t*-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7
Volatility prediction by investor type and open-interest changes

	j=1		j=2	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.
Panel A. Foreign investment firms				
Open	0.153	(0.47)	-0.292	(-1.15)
Close	**0.711******	**(2.78)**	-0.035	(-0.16)
Panel B. Foreign non-investment firms				
Open	0.000	(0.01)	-0.029	(-0.72)
Close	0.061*	(1.70)	0.004	(0.10)
Panel C. Domestic investment firms				
Open	0.035	(1.31)	0.029	(1.22)
Close	-0.001	(-0.04)	0.025	(0.91)
Panel D. Domestic individuals				
Open	0.073	(1.54)	0.057	(1.64)
Close	-0.041	(-1.11)	-0.019	(-0.57)

Note: This table presents the estimated coefficients of the prediction regression by detailed investor type, considering trading strategies. There are four investor types: foreign investment firms, foreign non-investment firms, domestic investment firms, and domestic individuals. Trading strategies are categorized as open volume (*Open*) or close volume (*Close*). The VKOSPI return is the dependent variable and the independent variables are the demand for volatility (D^{σ}) and various control variables with lagged periods from one to five. $IV_i=\alpha+\beta D^{\sigma}_{i-j}+\gamma IV_{i-j}+\theta_1 OV_{i-j}+\theta_2 SR_{i-j}+\theta_3 SV_{i-j}+\theta_4|D^r_{i-j}|+\lambda_1 Begin+\lambda_2 End+\varepsilon_i$, for j=1, 2, where IV is the return of the model-free implied volatility index of the KOSPI200 derived from KOSPI200 options; D^{σ} is the net demand for volatility; OV is the number of options contracts; SR and SV are the log return and log trading volume of the KOSPI200 index, respectively. $|D^r|$ is the absolute difference between the sum of the delta-weighted long and short volumes, and *Begin* (*End*) equals one if the option corresponds to the time period from 9:00 to 10:00 a.m. (from 3:00 to 3:05 p.m.), and zero otherwise. The sample period is April 2010 to June 2014. Numbers in parentheses are Newey–West *t*-statistics. *** and * indicate statistical significance at the 1% and 10% levels, respectively.