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Who has volatility information in the index options market?

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ABSTRACT

We examine volatility information embedded in the demand for options by analyzing data related to trades and investors. We find that overall demand for volatility in the options market does not predict stock market volatility but that foreign investors' vega-weighted net demand conveys significant information about future volatility dynamics. Foreign investors use their superior volatility information by trading near-the-money options with high vega values.

1. Introduction

Options markets attract informed investors through their higher leverage effects, lower transaction costs, and more speculative investment opportunities than those found in equity markets, which enables options trading to predict the dynamics of underlying markets (Chakravarty et al., 2004; Ge et al., 2016). However, empirical studies on the directional information content of options trading have yielded inconsistent results. Hu (2014), Pan and Poteshman (2006), Roll et al. (2010), and Ryu and Yang , (2018) provide evidence supporting the predictive ability of options trading for returns, whereas Chan et al. (2002), Fahlenbrach and Sandås (2010), and Ryu (2015) are more skeptical.

Given these mixed results, informed options trading must be examined from a different perspective. Options investors often use underlying assets to delta-hedge their holdings against risk from the assets' directional movements. Such hedging activities might create confounding effects when the directional information content in options trading is measured. Our study is motivated by the finding that options trading is better suited for speculative investors with superior information about market volatility dynamics. Recent studies on options markets focus on informed investors' net demand for volatility and analyze the resultant volatility information trading in the options markets (Chang et al., 2010; Gharghori et al., 2017; Ni et al., 2008; Rourke, 2014). However, these studies barely able to detect volatility information under specific conditions and trading strategies and thus fail to systematically address the characteristics of volatility information trading.

We use an elaborate setting and analyze high-quality data to examine whether options trades convey volatility information and offer information beyond direction. Importantly, we reveal which traders have access to volatility information in the KOSPI200 index options market and how they deploy this information by adjusting the net volatility demand for options.

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2. Data

Our dataset comprises all completed transactions and submitted orders of the nearest-maturity KOSPI200 options contracts during continuous trading sessions (9:00–15:00) from April 2010 to June 2014. For our net volatility demand measures, our dataset enables us to classify each option trade according to the type of initiating investor (i.e., domestic or foreign; individual or institution) and option leverage (moneyness), allowing us to associate the trade's volatility information content with option market characteristics.

Sophisticated options traders armed with volatility information have an incentive to choose options as their trading instrument, because the index options market is a highly liquid market with few frictions and low transaction costs. Most KOSPI200 options are relatively short-term contracts with a time-to-maturity of less than one month. Evidence of volatility information trading is more likely to be detected in KOSPI200 options than in options that are longer-term contracts, as the implied volatility of short-term contracts is more sensitive to underlying volatility changes than is that of longer-term contracts (Hsieh and Jarrow, Forthcoming).

3. Methodology and variables

If an options investor with superior information about the underlying market's volatility executes informed trades in the options market, changes in volatility demand can be observed from the volume of options trades. We measure the volatility information content realized by options trades by constructing the vega-weighted net demand for volatility, as shown in Eqs. (1) and (2).[1] An investor's volatility demand increases (decreases) with long (short) call and put option positions because the vega of an options contract measures its sensitivity to the underlying volatility, and the options vega has a positive value, irrespective of the option type (i.e., call or put). Unlike Chang et al. (2010) and Ni et al. (2008), we identify options demand based on whether the investor bets on a volatility increase or decrease. A long (short) options position (i.e., buying [selling] calls and puts) is defined as a net positive (negative) demand for market volatility, PD^{σ} (ND^{σ}):

$$PD_t^{\sigma} = \sum_K \sum_T \frac{\partial lnC_t^{K,T}}{\partial \sigma_t}(BuyCall_t^{K,T}) + \sum_K \sum_T \frac{\partial lnP_t^{K,T}}{\partial \sigma_t}(BuyPut_t^{K,T}), \tag{1}$$

$$ND_t^{\sigma} = \sum_K \sum_T \frac{\partial lnC_t^{K,T}}{\partial \sigma_t}(SellCall_t^{K,T}) + \sum_K \sum_T \frac{\partial lnP_t^{K,T}}{\partial \sigma_t}(SellPut_t^{K,T}). \tag{2}$$

For each trading day t, $C_t^{K,T}$ and $P_t^{K,T}$ denote the call and put prices, respectively, with strike price K and maturity T. Then, σ_t is the underlying volatility, calculated using one-minute spot price data for the previous 20 trading days. $BuyCall_t^{K,T}$ ($SellCall_t^{K,T}$) represents the number of bought (sold) call contracts with strike price K and maturity T. $BuyPut_t^{K,T}$ ($SellPut_t^{K,T}$) represents the number of bought (sold) put contracts with strike price K and maturity T. Using vega weighting, Eqs. (1) and (2) measure the aggregated information about the underlying spot market volatility.[2] We run the following regression to analyze whether net volatility demand in the KOSPI200 options market predicts market volatility, after controlling for various factors that could affect the volatility dynamics:

$$RV_t = \alpha + \beta_P PD^{\sigma}{}_{t-j} + \beta_N ND^{\sigma}{}_{t-j} + \theta_1 RV_{t-j} + \theta_2 IV_{t-j} + \theta_3 SR_{t-j} + \theta_4 SV_{t-j} + \theta_5 |D^r{}_{t-j}| + \varepsilon_t, \text{ for } j = 1, 2, \ldots, 5. \tag{3}$$

Here, RV_t is the realized volatility of the underlying asset on trading day t.[3] IV denotes the model-free implied volatility, calculated as the log return of the VKOSPI (Volatility Index of KOSPI200). SR and SV are the underlying log returns and underlying trading volume (in log), respectively. We control for the potential impact of options trades based on directional information by calculating the "return" demand, $|D^r|$, as the absolute value of the difference between the total volume of delta-weighted long positions and the total volume of short positions. Eq. (3) is estimated separately for different values of j, and coefficient β measures the j-day-ahead prediction of net option demand. A significantly positive (negative) β_P (β_N) indicates that options trades are initiated primarily by sophisticated investors possessing volatility information.

Table 1 presents summary statistics for the variables used in our empirical analysis. Here, IV and SR are multiplied by 100, and the net demand measures (i.e., PD, ND, and $|D^r|$) are divided by 10,000. On average, the demand for increased volatility (PD^{σ}: 4,584.1) is lower than the demand for decreased volatility (NP^{σ}: 4,849.7), indicating more short positions. Both volatility demand measures, PD^{σ} and NP^{σ}, are positively related to the volatility proxies (RV and IV). The two volatility measures, RV and IV, are highly and positively

[1] Our measure considers volatility traders (i.e., vega-informed investors) often simultaneously buying (or selling) calls and puts. Based on a net buying pressure measure and related implied volatility changes, Kang and Park (2008) claim that option price changes are driven mainly by directional (delta-informed) trading in the KOSPI200 options market. However, their measure often totally supports directional trading even under the existence of volatility trading. For example, if directional traders expecting underlying price increases "buy" 10 calls and "sell" 10 puts and volatility traders expecting underlying volatility increases simultaneously "buy" a call and a put, the net buying pressure of calls (puts) is calculated as +11 (-9). The call (put) implied volatility is increased (decreased) since the buying (selling) pressure is greater than the selling (buying) pressure in the call (put) options market. As a result, the coefficient of the call (put) net buying pressure measure becomes positive (negative), suggesting only directional trading despite the obvious existence of volatility trading.

[2] $\partial lnC_t^{K,T}/\partial\sigma_t$ ($\partial lnP_t^{K,T}/\partial\sigma_t$) is calculated as $\frac{1}{C_t^{K,T}}\frac{\partial C_t^{K,T}}{\partial\sigma_t}$ ($\frac{1}{P_t^{K,T}}\frac{\partial P_t^{K,T}}{\partial\sigma_t}$).

[3] For each trading day, the realized volatility is calculated as the difference between the highest and lowest intraday spot prices divided by their midpoint price and multiplied by 10,000. Our results remain the same for other realized volatility measures.

Table 1
Summary statistics.

Panel A. Descriptive statistics of key variables					
Variable	Mean	Std.	Min.	Median	Max.
RV	136.06	86.21	28.12	114.86	1,030.03
PD^{σ}	4,584.08	4,467.51	162.10	2,573.27	40,991.00
ND^{σ}	4,849.73	4,696.99	151.05	2,734.56	37,292.00
IV	0.10	5.30	−23.20	−0.19	42.12
SR	0.01	1.17	−6.65	0.02	5.06
SV	18.21	0.32	17.49	18.21	19.36
$\|D^r\|$	4.07	7.54	0.00	1.26	77.18

Panel B. Correlation coefficients						
Variable	RV	PD^{σ}	ND^{σ}	IV	SR	SV
PD^{σ}	0.1903***					
ND^{σ}	0.1795***	0.9928***				
IV	0.2893***	−0.0125	−0.0016			
SR	−0.1502***	0.0609**	0.0287	−0.7254***		
SV	0.4490***	0.5223***	0.5235***	0.0593*	0.0160	
$\|D^r\|$	0.1263***	0.6645***	0.6885***	0.0388	−0.0555*	0.2727***

Table 2
Volatility predictions by aggregate option volumes.

	$j = 1$	$j = 2$	$j = 3$	$j = 4$	$j = 5$
Intercept	−520.37**	−376.03**	−385.76*	−421.86**	−528.36**
	(−2.15)	(−2.16)	(−1.79)	(−2.27)	(−2.19)
$PD^{\sigma}_{t\text{-}j}$	0.0065	0.0132	0.0118	0.0091	−0.0025
	(1.41)	(1.38)	(1.55)	(1.07)	(−0.48)
$ND^{\sigma}_{t\text{-}j}$	−0.0046	−0.0117	−0.0094	−0.0076	0.0032
	(−1.15)	(−1.33)	(−1.38)	(−0.97)	(0.64)
$RV_{t\text{-}j}$	0.41***	0.48***	0.36***	0.42***	0.39***
	(4.91)	(10.35)	(4.72)	(8.21)	(5.97)
$IV_{t\text{-}j}$	−2.79***	−1.04*	−2.75**	−2.93**	−2.86**
	(−3.35)	(−1.90)	(−2.35)	(−2.57)	(−2.50)
$SR_{t\text{-}j}$	−24.10***	−15.03***	−13.93**	−14.20*	−9.34**
	(−5.09)	(−4.48)	(−2.40)	(−1.89)	(−2.09)
$SV_{t\text{-}j}$	32.85**	24.26**	25.53**	27.18***	33.34**
	(2.48)	(2.54)	(2.13)	(2.66)	(2.50)
$\|D^r{}_{t\text{-}j}\|$	−0.82**	0.36	−0.18	0.44	0.05
	(−2.01)	(1.13)	(−0.40)	(0.86)	(0.11)
adj. R^2	0.28	0.34	0.20	0.24	0.21

Note. Newey–West *t*-statistics are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

correlated.[4] The negative correlations between spot returns (SR) and volatility measures (RV and IV) reflect an asymmetric volatility phenomenon (Song et al., 2018).

Table 2 reports the estimation results without classifying options trades. The coefficient of PD^{σ} (ND^{σ}) should be significantly positive (negative) if the demand for options contains volatility information. None of the coefficients of volatility demand (PD^{σ} and ND^{σ}) are significant, however, indicating that the aggregate options demand does not predict future underlying volatility. This unexpected result might be caused by the dominance of noisy or unsophisticated investors, who have ambiguous volatility information, diluting the information effect produced by large groups of sophisticated, professional investors (Yang et al., 2017).

Therefore, the types of investors who submit orders and initiate trades must be considered when examining the volatility information embedded in the demand for options. Furthermore, the trading motives of option market participants and the characteristics of their options transactions differ with option moneyness, which is an important criterion for investors, and position changes. The literature on the KOSPI200 options market shows that in-the-money (ITM) and out-of-the-money (OTM) options markets differ significantly in terms of leverage, investor composition, order size, and information content (Chung et al., 2016).

Information on investor types and option moneyness categories can help us determine which investors possess volatility information and how they use this superior knowledge when trading options. To examine who has superior volatility information and

[4] The correlation between the realized volatility level (RV) and log return of VKOSPI (IV) is about 29% (see Panel B of Table 1). The correlation between the RV and VKOSPI levels increases to about 67%.

Table 3
Volatility predictions of option volumes by investor type and option moneyness.

	PD^{σ}		ND^{σ}	
Individuals				
ITM	67.8835	(0.74)	6.2512	(0.10)
ATM	−0.1165***	(−2.96)	0.0798**	(2.56)
OTM	−0.0016	(−0.15)	0.0089	(0.72)
Institutions				
ITM	−175.731	(−1.25)	171.7807*	(1.79)
ATM	−0.058*	(−1.68)	0.0419	(1.46)
OTM	0.0074	(0.70)	−0.0006	(−0.06)
Foreigner				
ITM	−0.8780	(−0.11)	19.4034*	(1.76)
ATM	0.0959**	(2.15)	−0.1033**	(−2.29)
OTM	0.0182	(1.01)	−0.0102	(−0.58)

Note. Newey–West *t*-statistics are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

how this information is implemented in options trades, Table 3 presents the estimation results of prediction regression based on two-dimensional classifications (investor–moneyness categories).[5] We first classify option market participants as domestic individuals (*Individuals*), domestic institutions (*Institutions*), or foreign investors (*Foreigners*), with heterogeneous information-processing abilities, trading motives and experience, psychologies, performance, and wealth (Ahn et al., 2008).

We find that neither domestic individuals nor institutions initiate options trades based on volatility information, regardless of the option moneyness category they choose, while foreign investors' at-the-money (ATM) options trades predict future volatility. The estimated coefficient for the positive (negative) demand of foreign investors for ATM options is 0.0959 (−0.1033), with a *t*-statistic of 2.15 (−2.29), indicating that the ATM options they invest in convey volatility information. These results suggest that foreign investors apply their volatility information by exploiting the high volatility sensitivity of ATM options and that the options market actively adjusts to foreigners' net demand for volatility of near-the-money options. We therefore infer that most foreign investors participating in the KOSPI200 options market are sophisticated investors. These investors either possess greater information than domestic investors or have trading advantages in the case of public or market-wide information; these advantages include better information-processing skills, good market timing, and superior trading knowledge and experience, especially in index derivatives trading (Chang et al., 2010; Ryu, 2011). Considering that ATM options are highly sensitive to volatility changes, it is natural that sophisticated investors with information about volatility dynamics would trade ATM options. If foreign investors speculate primarily to bet on future volatility changes, their ATM trades can predict market volatility.

The finding that foreign investors who are informed about volatility use ATM options also implies that they construct straddle positions using ATM calls and puts rather than strangle positions requiring OTM options. This, in turn, indicates that they expect relatively small or moderate movements in underlying asset prices rather than the large movements preferred by investors in strangle positions. This implication is plausible, as the underlying price can change within a limited bound during a day, and only short-term contracts are actively traded in the KOSPI200 options market. Overall, our results support the notion that foreign investors have superior volatility information and that they exploit this information by trading ATM options, which are volatility-sensitive trading instruments used to construct straddle positions that can be profitable even when asset prices change marginally.

4. Conclusion

We construct the vega-weighted net demand for volatility to determine the types of investors who have and use information about underlying market volatility in the highly liquid options market. We find that the aggregate demand for volatility in the options market does not predict future spot volatility but that foreign investors' vega-weighted net demand does convey significant information about future volatility dynamics. Foreign investors—equipped with better trading skills, more experience, and greater wealth and resources—use their volatility information by trading high-vega options.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2018.10.008.

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[5] For brevity's sake, we report only the coefficients and *t*-statistics of volatility demand (PD^{σ} and ND^{σ}) at t–1, and not those of the control variables.

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