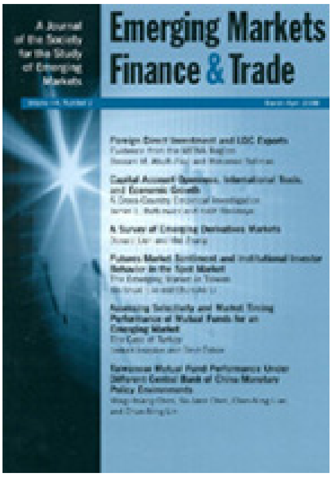

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Implied Volatility Index of KOSPI200: Information Contents and Properties

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Doojin Ryu

ABSTRACT: This paper investigates the properties and information contents of an implied volatility index based on Korea's index options contract, which is the most liquid options product in the world. Analyzing the recent 100-month-long volatility index series (VKOSPI; Volatility Index of KOSPI200) constructed using the KOSPI200 index and options prices, we measure the in-sample and out-of-sample forecasting performances of the implied volatility index and examine its quality as a market volatility indicator. The VKOSPI exhibits an asymmetric volatility response to positive and negative return shocks and has a significantly positive effect on the explanatory power of nested GARCH models. Though the VKOSPI provides slightly biased forecasts, as other risk-adjusted volatility measures also do, it outperforms the Black-Scholes implied volatility, the RiskMetrics approach, and the GJR-GARCH model (which generally shows the best in-sample performance among the GARCH-family models) in forecasting future realized volatilities.

KEY WORDS: Black-Scholes, GARCH, implied volatility, KOSPI200 Options, RiskMetrics, VKOSPI.

The dynamics of stock market volatility have received considerable attention from academicians and market practitioners. For hedging against various risks, managing portfolios, and pricing derivative assets whose prices depend on the volatility of the underlying assets, it is critical to accurately estimate and forecast stock market volatility. Although stock market volatility is traditionally measured by the standard deviation (or the variance) of changes in the asset price, elaborate methods and econometric models for identifying and estimating it have been proposed continuously, including the GARCH (generalized autoregressive conditional heteroskedasticity)-family models and the stochastic volatility and jump models. However, these models basically use historical data to estimate current and future volatility; thus the estimated volatility typically provides little information on future volatility or the expectation of investors regarding the future state of stock markets.

Recognizing this limitation and weakness of the "historical" volatility, another stream of research focuses on the information embedded in market prices of traded options. The volatility implied by option prices can reflect investors' expectation on future stock market conditions and their sentiments; therefore the "implied" volatility retains a forward-looking nature (Giot 2005; Sheu and Wei 2011). There are several ways to extract the implied volatility from option prices. For example, one can easily extract the underlying stock market volatility by using simple option pricing models such as the Black-Scholes (BS) model. However, if the volatility is extracted through option pricing models, the derived

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volatility naturally exhibits model-dependent biases. A good example of such biases is the volatility smile or smirk phenomenon, which is often detected in BS-implied volatility. It is a well-known stylized fact that, when the BS-implied volatility is plotted against strike price, the resulting graph shows the smile pattern (volatility smile phenomenon) or is downward sloping (volatility smirk phenomenon). This contradicts the theoretical prediction of the BS model, which indicates that the implied volatility should remain the same irrespective of the variation of the strike price.

Financial economists and policymakers need to develop a more accurate volatility proxy—one that is not influenced by the flaws embedded in option pricing models and that can take into consideration all actively traded options in an appropriate manner. In this regard, the volatility index (VIX) of the Chicago Board of Options Exchange (CBOE) is a successful proxy. VIX, which is constructed through a model-free method, represents a volatility index implied by Standard and Poor's (S&P) 500 index option prices and is known to be an informative indicator of the current state of the U.S. financial market and a significant predictor of future volatility. For an implied volatility index to be informative and to adequately reflect market sentiment, investors should actively participate in the options market. In other words, as investors' interest and participation in the options market increases, the implied volatility index extracted from option prices is likely to provide more meaningful information. The VIX satisfies these conditions in that S&P 500 options contracts are actively traded and that U.S. options and stock markets always receive considerable attention from global and local investors. On the contrary, for options markets in emerging countries, efforts to develop and utilize implied volatility indices have received little attention because such markets are less liquid and researchers and practitioners have shown little interest in them. Furthermore, such markets seldom report volatility indicators, although it is not difficult to calculate a volatility index.[1]

By contrast, recognizing the importance and applicability of an implied volatility index, the Korea Exchange (KRX) has recently developed a volatility index extracted from Korea Composite Stock Price Index 200 (KOSPI200) index options, the single most liquid options product in the world. As a result, there is growing interest in this index (called the Volatility Index of the KOSPI200, or VKOSPI) among investors and academicians worldwide. In particular, the information content and characteristics of the volatility index have aroused considerable interest. Despite its short history, the KOSPI200 options market ranks first in the world in terms of trading activity and investors' interest. In terms of trading volume, it dominates all other options markets, including the CBOE options markets. Unfortunately, however, few empirical studies have examined implied volatility from the liquid KOSPI200 options market, and little research has investigated the characteristics of the VKOSPI, the official implied volatility index published by the KRX. Options traders have recently started to consider the VKOSPI as their trading indicator (it has only been published since April 2009), and there is an urgent need for research on the VKOSPI considering the global prominence of the KOSPI200 options market and the increasing participation of foreign investors in Korea's financial market. In addition, the Korean government and the KRX are actively preparing to launch derivative products whose prices depend on the movement of the VKOSPI (e.g., VKOSPI futures and options). For the successful introduction of such VKOSPI-based derivative assets, a better academic understanding of the VKOSPI and a thorough examination of its characteristics are required.

Motivated by these needs, this study investigates the information content and properties of the implied volatility index for the Korean market. More specifically, it examines the intertemporal relationship between the VKOSPI and the underlying KOSPI200 index and gauges the in-sample and out-of-sample forecasting performances of the VKOSPI. Considering the relatively small sample size (only 400 trading days) of the VKOSPI after the publication date, we also analyze the constructed volatility index series before the VKOSPI's inception (i.e., before April 2009). To the best of the author's knowledge, few studies have addressed these kinds of VKOSPI-related issues, despite the VKOSPI's importance and influence. Our empirical findings indicate that the VKOSPI (strictly speaking, the VKOSPI and the implied volatility index series constructed using the VKOSPI method) contains significant information content. Including the VKOSPI as an independent variable in the variance equation of each GARCH model dramatically increases the explanatory power of nested GARCH models. Further, though the VKOSPI provides slightly biased forecasts, as other risk-adjusted forecasts usually do, it not only shows considerably higher forecasting performance than the BS-implied volatility does, but also outperforms GJR-GARCH and RiskMetrics models, which are traditionally widely used. As a proxy for stock market volatility, the VKOSPI shares common features with volatility indices from other markets. For example, the VKOSPI increases sharply in bear markets and peaks for bad news or during financial crises. In addition, the VKOSPI is highly correlated with and shows movement similar to the VIX of the U.S. market. The study also reveals a significantly negative and asymmetric relationship between the stock market return and the implied volatility index, which is a well-known empirical regularity (Al Janabi et al. 2010; Black 1976; Campbell and Hentschel 1992; Christie 1982; French et al. 1987; Pindyck 1984).

Why KOSPI200 Options and Its Implied Volatility?

After thorough preparation, in July 1997 the Korean government and the KRX commenced with Korea's index options underlying the KOSPI200 index. Despite its short history, the KOSPI200 options market has grown rapidly, and the trading volume of the options has dominated all other derivatives worldwide.[2] It is reasonable to expect that the following properties of the KOSPI200 index and options data set make the implied volatility (derived from the index and index options) cleaner and make it an exact proxy for market volatility. First, the underlying 200 stocks composing the KOSPI200 index are actively traded, with the fifty largest and most actively traded stocks being primarily responsible for determining the KOSPI200 index price. As a result, the index does not have a significant nonsynchronous trading problem or a stale price problem. Second, there is no significant bid-ask bounce problem in option prices because the bid-ask spread of the options nearly equals the minimum tick size (Ahn et al. 2008, 2010). Third, the offer of many strike prices in the KOSPI200 options market since 2003 has enhanced the quality of estimation for the volatility index.

In addition to the ample liquidity and high-quality data set of the KOSPI200 options market, the active participation of domestic individual investors is an important characteristic as well. Although institutions are dominant market players in financial markets of developed countries, domestic individuals represent the most active investor group in the KOSPI200 index derivatives market (Kang and Ryu 2010; Kim and Ryu 2012; Ryu 2011, 2012a). Table 1 shows the trading activity of three types of investors (domestic individuals, domestic institutions, and foreigners) in the options market. Their trading activity is measured by the number of contracts traded and by the trading value over the sample period (from January 2003 to April 2011). Although domestic and foreign

Table 1. Trading volume by three investor types (January 2003–April 2011)

	Purchases	Sales	Total
Number of contracts			
Individuals	9,410,843,710 (40.31)	9,244,359,221 (39.60)	18,655,202,931 (39.96)
Institutions	8,763,031,827 (37.53)	8,978,389,868 (38.45)	17,741,421,695 (38.01)
Foreigners	5,170,716,481 (22.15)	5,121,842,929 (21.94)	10,292,559,410 (22.04)
Total	23,344,592,018 (100.00)	23,344,592,018 (100.00)	46,689,184,036 (100.00)
Trading value			
Individuals	699,279,352 (39.23)	699,213,441 (39.23)	1,398,492,793 (39.23)
Institutions	477,623,401 (26.80)	476,982,564 (26.76)	954,605,965 (26.77)
Foreigners	605,524,853 (33.97)	606,231,601 (34.01)	1,211,756,454 (33.99)
Total	1,782,427,606 (100.00)	1,782,427,606 (100.00)	3,564,855,212 (100.00)

Notes: Trading value is shown in millions of Korean won (KRW). Percentages are in parentheses.

institutional investors' participation in the market has steadily increased in Korea's derivatives market (Ryu 2012b), domestic individuals still account for more than one third of all trades in the options market.

Although the KOSPI200 options market's ample liquidity and unique investor participation rate make it one of the most remarkable options markets in the world, some corporate treasurers and regulators still maintain a skeptical view of the information quality of the prices and trades, pointing out that trades by highly speculative and short-term investors comprise the dominant portion of total transactions and that inexperienced individual investors, who make up the majority of options traders, are easily affected by market sentiments and behavioral biases. They often criticize the extremely speculative trading behavior of the KOSPI200 options market and compare the options market to a great casino.[3] If the information quality embedded in the options prices is actually low, the volatility implied by the options contains little information on the future market state and the implied volatility index will no longer be an appropriate indicator for risk management and investment decisions. Furthermore, futures and options, which underlie the volatility index and are scheduled to be launched soon, will not play a positive role in trading. Considering these important roles and influences of the volatility index, there is a real need to investigate its information content. The fact that previous studies have typically focused on implied volatility indices from developed countries further supports the value of this study regarding the emerging market.

VKOSPI and Sample Data

The VKOSPI represents the volatility of one-month-ahead KOSPI200 index prices. The level of the VKOSPI is determined by options traders' expectations and predictions on future volatility, which are revealed by the buying and selling pressures for KOSPI200 options. Therefore, it gauges options traders' fear and market sentiment concerning the underlying stock market. The VKOSPI is derived by the model-free variance expectation based on the method of "fair variance swap."[4] The variance swap is a derivative contract that obligates the buyer (investor) of the contract to pay a fixed amount proportional to the strike (K_{var}) for receiving the amount proportional to the level of the realized volatility (σ_R^2) from the seller (dealer) at a predetermined future point (at time T). The fair variance swap method regards the expected realized variance, which makes the value of the variance swap equal zero at time 0 (when the contract is entered into), as a fair variance. This fair variance, which implies the expected volatility by investors from time 0 to time T, is adopted as the volatility index.

The VKOSPI, which is derived by the fair variance swap method, is not dependent on the assumptions of specific option pricing models and can reflect all strikes of traded options. Specifically, the VKOSPI is calculated using the underlying KOSPI200 index price, risk-free rate, and market prices of the nearest and second nearest maturity KOSPI200 options. Equations (1)–(3) demonstrate this:

$$\text{VKOSPI} = 100 \times \sqrt{\left\{ T_1 \sigma_1{}^2 \left[\frac{N_{T_2} - N_{30}}{N_{T_2} - N_{T_1}} \right] + T_2 \sigma_2{}^2 \left[\frac{N_{30} - N_{T_1}}{N_{T_2} - N_{T_1}} \right] \right\} \times \frac{N_{365}}{N_{30}}} \tag{1}$$

$$\begin{aligned} \sigma_1{}^2 &= \frac{2}{T_1} \sum_{i=1}^{n} \frac{\Delta K_i}{K_i^2} e^{rT_1} Q(K_i) - \frac{1}{T_1} \left[\frac{F_1}{K_0} - 1 \right]^2, \\ \sigma_2{}^2 &= \frac{2}{T_2} \sum_{i=1}^{n} \frac{\Delta K_i}{K_i^2} e^{rT_2} Q(K_i) - \frac{1}{T_2} \left[\frac{F_2}{K_0} - 1 \right]^2, \end{aligned} \tag{2}$$

$$F_1 = S_1 + e^{rT_1} \times \left[C_1 - P_1 \right],\ F_2 = S_2 + e^{rT_2} \times \left[C_2 - P_2 \right],\ T_1 = \frac{N_{T_1}}{N_{365}},\ T_2 = \frac{N_{T_2}}{N_{365}}. \tag{3}$$

In the above equations, Equation (2) captures the fluctuation of the nearest (σ_1^2) and second nearest (σ_2^2) maturity contracts. N_{30} (N_{365}) denotes the number of days per month (year); N_{T_1} (N_{T_2}) indicates the number of days remaining until the nearest maturity (second nearest maturity) date; r denotes the (continuously compounded) risk-free interest rate calculated using the three-month Korean Certificates of Deposit rates (CD91 rates); and K_0 is the strike price closest to the underlying KOSPI200 index among the strike prices equal to or lower than the KOSPI200 index. For call (put) options, K_i is the ith highest (lowest) strike price compared to the level of K_0. S_1 (S_2) denotes the strike price with the least difference between the nearest maturity (second nearest maturity) call and put option prices; C_1 (P_1) is the price of the nearest maturity call (put) option; and C_2 (P_2) is the price of the second nearest maturity call (put) option.[5]

Although the VKOSPI has been published since April 13, 2009, an implied volatility index series can be made using the above equations. The volatility index series, which is constructed using option prices prior to the publication of the VKOSPI, is also model-free and reflects the options traders' fear and sentiment. The final sample period spans more than eight years, from January 3, 2003, to April 12, 2011, giving 2,057 daily observations. The daily data on the KOSPI200 index, option prices, and the VKOSPI are obtained from the KRX.[6] Table 2 shows the descriptive statistics for daily values of the KOSPI200 index, VKOSPI, and VIX. The time series distribution of the stock index price exhibits

Table 2. Descriptive statistics for the daily KOSPI200, VKOSPI, and VIX values

	KOSPI200 index		VKOSPI		VIX	
	Level	Log-return	Level	First-order difference	Level	First-order difference
Mean	171.03	0.0006	25.65	–0.008	20.85	–0.004
Median	176.29	0.0014	23.06	–0.080	18.17	–0.090
Standard deviation	54.56	0.0156	9.78	1.750	0.23	0.039
Skewness	–0.07	–0.4106	2.42	2.428	2.23	0.346
Kurtosis	–1.07	5.2936	8.29	34.336	6.49	20.411
Minimum	65.64	–0.1090	14.15	–13.920	9.89	–17.360
Maximum	282.03	0.1154	89.30	23.000	80.86	16.540

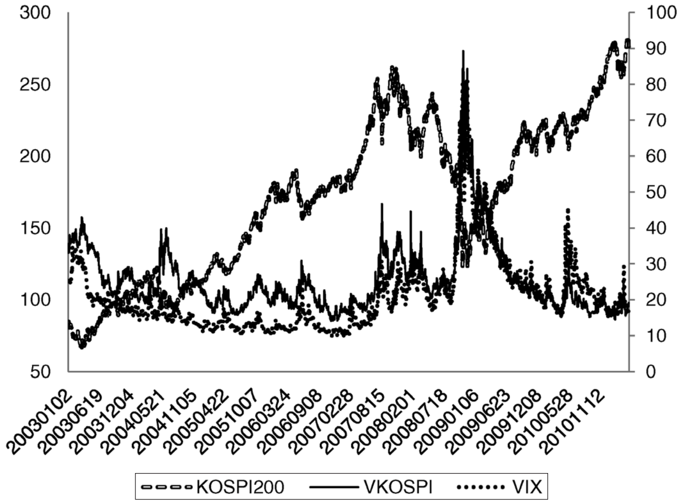

Figure 1. Trends of the KOSPI200 index, VKOSPI, and VIX (January 2003–April 2011)

relatively low skewness and kurtosis values, whereas the volatility distributions tend to be skewed with fat tails. Each descriptive statistic of the level of the VKOSPI is greater than the corresponding value of the level of the VIX, suggesting that the Korean market is more volatile and sensitive to external shocks than the U.S. market is.

Figure 1 shows the trend of the KOSPI200 index price and the movements of the two volatility indices (VKOSPI and VIX). The level of the VKOSPI tends to be slightly higher than that of the VIX, but the trends are quite similar. The VKOSPI also responds directly to macroeconomic shocks and major worldwide news. For example, the VKOSPI increases sharply in response to bad news about the global economy, such as the Iraq War (March 2003), concerns about the contraction of the Chinese economy (April 2004), the U.S. subprime crisis (August 2007), the bankruptcy of Lehman Brothers and the rejection of bills on relief loans (September 2008), and concerns about the secular stagnation of the global economy (October 2008).

Empirical Results

Relationship Between VKOSPI and KOSPI200 Index Returns

In the first empirical analysis, we examine the relationship between VKOSPI and KOSPI200 index returns by using the model proposed by Fleming et al. (1995) (Equation (4)), which can detect the intertemporal and asymmetric relationships between changes in stock market volatility and stock market return:

$$\begin{aligned} \Delta VKOSPI_t = \alpha + \beta_{-2} r_{t-2} + \beta_{-1} r_{t-1} + \beta_0 r_t + \beta_0^{abs} |r_t| \\ + \beta_{+1} r_{t+1} + \beta_{+2} r_{t+2} + \gamma \Delta VKOSPI_{t-1} + \varepsilon_t. \end{aligned} \tag{4}$$

In Equation (4), $\Delta VKOSPI$ denotes the daily change in the VKOSPI; r_t is the daily log return of the KOSPI200 index price at time t; and ε_t is an error term. The lead and lag coefficients β_{-2}, β_{-1}, β_1, and β_2 capture the intertemporal relationship between return and volatility; and the coefficients β_0 and β_0^{abs} detect the asymmetric or negative relationship

Table 3. Intertemporal relationship between VKOSPI and KOSPI200 index returns

Period	Whole period (January 2003–April 2011)	Preperiod (March 2003–April 2009)	Postperiod (April 2009–April 2011)
Corr.	–0.6384	–0.6318	–0.7010
Obs.	2,053	1,510	499
Adj. R^2	0.450	0.454	0.509
α	–0.278	–0.315	–0.165
	(–6.69)	(–5.93)	(–3.06)
β_{-2}	8.182	8.444	7.255
	(4.41)	(3.79)	(2.37)
β_{-1}	1.754	1.346	4.742
	(0.73)	(0.46)	(1.10)
β_0	–69.415	–71.246	–66.486
	(–37.44)	(–32.03)	(–21.86)
β_0^{abs}	26.853	28.926	21.372
	(10.05)	(9.05)	(4.47)
β_{+1}	8.022	9.265	0.299
	(4.35)	(4.20)	(0.10)
β_{+2}	2.944	3.783	–1.355
	(1.59)	(1.71)	(–0.45)
γ	–3.204	–3.947	–0.476
	(–4.34)	(–4.27)	(–0.48)

Notes: The eight coefficients are estimated based on the following regression equation:

$$\Delta VKOSPI_t = \alpha + \beta_{-2}r_{t-2} + \beta_{-1}r_{t-1} + \beta_0 r_t + \beta_0^{abs}|r_t| + \beta_{+1}r_{t+1} + \beta_{+2}r_{t+2} + \gamma\Delta VKOSPI_{t-1} + \varepsilon_t.$$

The *t*-statistics are in parentheses. Obs. denotes the number of observations, Adj. R^2 is the adjusted R^2 value for each regression, and Corr. indicates the simple correlation between $\Delta VKOSPI$ and the log return of the KOSPI200 index.

between return and volatility. If β_0^{abs} is significant and positive and β_0 is significant and negative, then this is supportive evidence for an asymmetric response of changes in expected volatility to positive and negative return shocks.

We run the regression equation separately for the whole sample period (*Whole period:* January 2003 to April 2011), for the period before the publication of the VKOSPI (*Preperiod:* January 2003 to April 2009), and for the period after the launch of the VKOSPI (*Postperiod:* April 2009 to April 2011). Table 3 shows the estimation results, including the number of observations, adjusted R^2, coefficient estimates, and *t*-statistics (in parentheses) for each period. The table also reports the correlation between $\Delta VKOSPI$ and the log return of the KOSPI200 index price. The absolute value of the negative correlation coefficient is higher for the postperiod than for the preperiod. The adjusted R^2 value for the whole sample is 0.450. The adjusted R^2 value for the postperiod (0.509) exceeds that of the preperiod (0.454). This indicates that the relationship between stock market volatility and stock market return has been stronger since the launch of the VKOSPI. This may be because only sophisticated investors were able to infer the volatility index from option prices before the publication of the VKOSPI, whereas all investors have been easily able to observe the volatility index after the VKOSPI publication in April 2009. This situation might result in a stronger relationship between the KOSPI200 index return and the VKOSPI for the postperiod. A negative γ coefficient indicates a negative autocorrelation in the first-order differenced VKOSPI series. However, this autocorrelation coefficient is not significant for the postperiod. One possible interpretation is that many investors, especially technical traders, have actively exploited the patterns of volatility change (e.g., the persistence and autocorrelation of volatility) since publication of the VKOSPI. Consequently, the postperiod may not show this pattern.

The table also suggests that the VKOSPI can detect the asymmetric volatility phenomenon well. For all the samples, the coefficients β_0^{abs} are positive and highly significant, and the coefficients β_0 are negative and significant, which supports a negative relationship between stock market volatility and the stock market return. The absolute value of the coefficient β_0 is much higher than that of the coefficient β_0^{abs} for each sample. These results clearly demonstrate that the expected volatility represented by the implied volatility index responds asymmetrically to positive and negative return shocks. The pairwise Granger causality test indicates the direction of causality. Based on the p-values of the test, the hypothesis that the VKOSPI does not Granger-cause the KOSPI200 index return ($p = 0.16$) cannot be rejected, whereas the hypothesis that the index return does not Granger-cause the VKOSPI ($p = 0.05$) can be rejected. This indicates that causality runs from stock market return to stock market volatility rather than in the opposite direction.

In-Sample Model Fit

Following Frijns et al. (2010), we examine the in-sample performance of the VKOSPI and measure the effect of the VKOSPI on model fit under the following GARCH framework:

$$\text{Mean equation: } r_t = \mu + \varepsilon_t,\ \varepsilon_t \sim N(0, h_t) \tag{5}$$

$$\text{Variance equation: } h_t = \omega + \alpha h_{t-1} + \beta \varepsilon_{t-1}^2 + \gamma I_{t-1} \varepsilon_{t-1}^2 + \delta IV_{t-1}^2. \tag{6}$$

Here, μ indicates the average daily KOSPI200 index return; h_t denotes the conditional variance; and I_t is an indicator variable taking 1 if ε_t is negative and 0 otherwise. The error term ε_t, which is normally distributed with mean 0 and variance h_t, captures the innovation of the daily return. To compare the performance of the VKOSPI (which is the model-free implied volatility) with that of the BS-implied volatility (which depends on the functional structure of the BS option model), IV_t is allowed to take the rescaled daily VKOSPI or the BS-implied volatility derived from ATM (at-the-money) options. The variance equation describes how the conditional variance series, $\{h_t\}$, evolves over time and can nest various GARCH specification. For example, if γ and δ are set to 0, the restricted variance equation corresponds to the standard GARCH model. The single restriction that δ is equal to 0 implies that the GJR-GARCH model, which can describe the asymmetric volatility phenomenon, is adopted. If α is restricted to 0, the variance equation reduces to the equation of an ARCH-type model. If there is no restriction on the coefficients, the variance equation represents the equation of GJR-GARCH model with exogenous implied volatility. We name this general version the GJR-GARCH-VKOSPI model, or the GJR-GARCH-BS model.

By using the quasi-maximum likelihood estimation (QMLE) method, which provides heteroskedasticity consistent estimates (Blair et al. 2001; Bollerslev and Wooldridge 1992), model parameters are estimated in Equations (5) and (6). Table 4 shows the QMLE results, including the coefficient estimates, t-statistics (in parentheses), and log-likelihood values. The table sorts all the models based on the size of their log-likelihood values. Except for the ARCH-type models, the standard GARCH model yields the lowest log-likelihood value and the highest persistence value ($\alpha + \beta = 0.987$).

Table 4. In-sample performance

	ω	α	β	γ	δ	Log-likelihood	Excess likelihood
GJR-GARCH-VKOSPI	1.5E-06	0.744	–0.089	0.275	0.001	5,988.1	273.7
	(5.18)	(14.39)	(–3.09)	(7.78)	(4.23)		
GJR-GARCH-BS	4.7E-06	0.785	–0.094	0.244	0.001	5,982.8	268.4
	(2.28)	(32.13)	(–3.71)	(9.16)	(253.18)		
GJR-ARCH-VKOSPI	–3.0E-05		–0.067	0.090	0.004	5,960.6	246.2
	(–3.00)		(–1.90)	(2.10)	(14.87)		
GARCH-VKOSPI	–3.7E-05	–0.270	–0.047		0.005	5,956.4	242.0
	(–2.67)	(–1.21)	(–1.89)		(5.46)		
ARCH-VKOSPI	–3.1E-05		–0.038		0.004	5,955.3	240.9
	(–3.08)		(–1.58)		(14.69)		
GJR-GARCH	5.6E-06	0.896	0.003	0.139		5,945.4	231.0
	(4.20)	(49.84)	(0.18)	(5.66)			
GARCH-BS	2.1E-06	0.693	0.045		0.001	5,935.8	221.4
	(0.64)	(7.15)	(2.07)		(2.58)		
GARCH	3.0E-06	0.911	0.076			5,922.8	208.4
	(2.87)	(58.37)	(5.28)				
GJR-ARCH-BS	6.2E-05		–0.119	0.187	0.002	5,909.5	195.1
	(852.89)		(–5.30)	(4.48)	(14.60)		
ARCH-BS	5.0E-05		–0.013		0.003	5,894.2	179.9
	(3.31)		(–0.51)		(7.67)		
ARCH(1)	1.8E-04		0.302			5,714.4	
	(18.97)		(4.38)				

Notes: Based on the mean equation ($r_t = \mu + \varepsilon_t$, $\varepsilon_t \sim N(0, h_t)$) and the variance equation ($h_t = \omega + \alpha h_{t-1} + \beta\varepsilon^2_{t-1} + \gamma I_{t-1}\varepsilon^2_{t-1} + \delta IV^2_{t-1}$), the model parameters are estimated using the QMLE method. The z-statistics are in parentheses. Excess likelihood shows the excessive value of log-likelihood for each model compared to the log-likelihood value for the simple ARCH model.

Including the additional term capturing the asymmetric volatility effect increases the log-likelihood value (see GJR-GARCH). This implies that asymmetric volatility responses to positive and negative return shocks are a widespread phenomenon in the Korean stock market.

Table 4 shows that the model-free volatility index is a more informative indicator of stock market volatility than historical volatility is. Although GARCH models are known to successfully describe volatility dynamics and clustering, including the VKOSPI as an exogenous explanatory variable in the variance equation enhances the explanatory power of the GARCH framework. Including the VKOSPI in the standard GARCH model specification increases the log-likelihood value by 33.5 (compare GARCH with GARCH-VKOSPI). The VKOSPI seems to still provide additional information on the stock market volatility even after incorporating the asymmetric volatility phenomenon into the model. Even the simplest VKOSPI-related model, ARCH-VKOSPI, outperforms the GJR-GARCH, which reflects the asymmetric volatility and exhibits the best-fitting performance among the GARCH-family models without the implied volatilities. When both the volatility asymmetry and the model-free implied volatility are considered (see GJR-GARCH-VKOSPI), the model yields the highest log-likelihood value.

The table also suggests that the model-free implied volatility is more elaborate than the model-dependent implied volatility. Unlike the case of the VKOSPI, the model-dependent BS-implied volatility only marginally increases the log-likelihood value. The models related to the BS-implied volatility (ARCH-BS, GJR-ARCH-BS, and GARCH-BS) are all inferior to the VKOSPI-related models, and even yield poorer performances than the GJR-GARCH that does not include any implied volatility in its specification. Only the most complicated form, GJR-GARCH-BS, shows comparable performance to the VKOSPI-related models; however, this model is also outperformed by the GJR-GARCH-VKOSPI.

Out-of-Sample Forecasting Performance

We compare the empirical performances of the VKOSPI, RiskMetrics approach, GJR-GARCH model, and BS-implied volatility, in terms of forecasting future realized volatility. Equation (7) is used to calculate the *k*-day future realized volatility at time *t* from the daily stock return r_{t+i}. Following Frijns et al. (2010), the out-of-sample performance of each forecasting measure (RiskMetrics, GJR-GARCH, BS-implied volatility, and VKOSPI) is evaluated on the basis of the percentage of future realized volatility (for 1, 5, 10, 21, and 63 trading days) explained by each forecaster.

$$RV_{k,t} = \sqrt{\sum_{i=1}^{k} r_{t+i}^2}. \tag{7}$$

Equation (8) shows the daily volatility process under the RiskMetrics approach, where r_t is the daily stock return at time t; V_t is the time t volatility determined by the approach; and λ describes the volatility persistence in the process.[7] This RiskMetrics approach, which was developed by JP Morgan, is also known as the exponential smoother because it uses an exponential weighting technique that puts less weight on outdated observations. It is also classified as a random walk process because the sum of the weights on the past squared return, r_{t-1}^2, and the past variance, V_t, is equal to unity (i.e., $(1 - \lambda) + \lambda = 1$). We use Equation (9) to calculate the total *k*-day-ahead volatility forecasted by the RiskMetrics approach (i.e., the forecaster under the RiskMetrics approach).

$$V_t = (1 - \lambda) r_{t-1}^2 + \lambda V_{t-1} \tag{8}$$

$$RM_{k,t} = \sqrt{k V_t}. \tag{9}$$

Equations (10) and (11) explain the GJR-GARCH model and Equation (12) shows the *i*-step-ahead forecaster based on the conditional volatility of the GJR-GARCH model.[8] The total *k*-day-ahead volatility forecast by the GJR-GARCH model is described in Equation (13) (i.e., the forecaster under the GJR-GARCH model).

$$\text{Mean equation: } r_t = \mu + \varepsilon_t,\ \varepsilon_t \sim N(0, h_t) \tag{10}$$

$$\text{Variance equation: } h_t = \omega + \alpha h_{t-1} + \beta \varepsilon_{t-1}^2 + \gamma I_{t-1} \varepsilon_{t-1}^2 \tag{11}$$

$$h_{t+i} = \omega[1 + F + F^2 + \ldots + F^i] + F^i h_t, \text{ where } F = \alpha + \beta + 0.5\gamma \tag{12}$$

$$GJR_{k,t} = \sqrt{\sum_{i=1}^{k} h_{t+i}}. \tag{13}$$

Equation (14) (Equation (15)) shows the simple *k*-day-ahead volatility forecast based on the current level of the VKOSPI, $VKOSPI_t$ (BS-implied volatility, BS_t). Here, *TD* denotes the number of total trading days per each year.

$$VKOSPI_{k,t} = \sqrt{\frac{k}{TD}} VKOSPI_t \tag{14}$$

$$BS_{k,t} = \sqrt{\frac{k}{TD}} BS_t. \tag{15}$$

For each forecaster ($X_{k,t}$), we run the following regression and measure the forecasting performance based on the adjusted R^2 values of each regression.

$$RV_{k,t} = \alpha + \beta X_{k,t} + \varepsilon_t. \tag{16}$$

Table 5 demonstrates the outstanding forecasting power of the VKOSPI for the near future. The adjusted R^2 values indicate that the forecaster using the VKOSPI outperforms all other forecasters in predicting future realized volatility.[9] In particular, when the forecast horizon is five, ten, or twenty-one trading days, more than half of the change of future realized volatility is explained by the current level of the VKOSPI (i.e., the adjusted R^2 values are greater than 50 percent). The table reports the highest adjusted R^2 value (0.557) when the forecaster is the VKOSPI and the forecast horizon is ten trading days. This implies that the VKOSPI is optimal in predicting ten-day-ahead future realized volatility, although the volatility index is designed as a one-month-ahead volatility measure. This may be due to the behavior of traders in the KOSPI200 options market, where extremely short-term options are more actively traded than longer-term ones.

To examine the components of forecasting errors by each forecaster, we carry out Mincer-Zarnowitz decomposition analysis that decomposes the mean-squared error (*MSE*) into three terms: *squared bias, inefficiency,* and *residual variation.* Equation (17) shows this procedure. To calculate the terms presented in this equation, the estimated coefficient βs and the R^2 values from the regression equation (16) are used.

$$MSE = (\mathrm{E}[RV_{k,t}] - \mathrm{E}[X_{k,t}])^2 + (1 - \beta)^2 \mathrm{Var}(X_{k,t}) + (1 - R^2)\mathrm{Var}(RV_{k,t}). \tag{17}$$

Table 6 reports the MSE and Mincer-Zarnowitz percentage decomposition by forecaster and forecast horizon. For the BS-implied volatility and VKOSPI, which are volatilities

Table 5. Out-of-sample performance

	RiskMetrics			GJR-GARCH			Black-Scholes			VKOSPI		
	α	β	Adj. R^2	α	β	Adj. R^2	α	β	Adj. R^2	α	β	Adj. R^2
RV-1	0.001	0.692	0.161	–0.001	0.807	0.190	0.001	0.675	0.160	–0.002	0.770	0.188
	(2.03)	(19.60)		(–0.87)	(21.67)		(1.38)	(19.56)		(–2.39)	(21.51)	
RV-5	0.004	0.806	0.432	–0.001	0.988	0.484	0.002	0.814	0.462	–0.003	0.901	0.509
	(5.87)	(38.96)		(–1.82)	(43.30)		(3.32)	(41.42)		(–3.53)	(45.49)	
RV-10	0.008	0.788	0.487	–0.007	1.132	0.515	0.006	0.784	0.506	–0.001	0.868	0.557
	(8.75)	(43.53)		(–6.09)	(46.06)		(6.45)	(45.25)		(–1.16)	(50.07)	
RV-21	0.016	0.733	0.478	–0.031	1.487	0.468	0.014	0.723	0.488	0.005	0.791	0.526
	(12.94)	(42.77)		(–13.15)	(41.87)		(10.91)	(43.61)		(3.74)	(47.03)	
RV-63	0.053	0.529	0.306	–0.187	2.798	0.273	0.050	0.525	0.317	0.040	0.563	0.327
	(23.74)	(29.71)		(–16.98)	(27.42)		(21.81)	(30.43)		(16.04)	(31.16)	

Notes: Each forecaster by RiskMetrics, GJR-GARCH, BS-implied volatility, and VKOSPI is evaluated based on the regression equation ($RV_{k,t} = \alpha + \beta X_{k,t} + \varepsilon_t$, where k is 1, 5, 10, 21, or 63). $X_{k,t}$ denotes a k-day ahead forecast at time t, and Adj. R^2 shows the adjusted R^2 value for each regression.

Table 6. Mincer-Zarnowitz percentage decomposition

	RV-1	*RV*-5	*RV*-10	*RV*-21	*RV*-63
RiskMetrics					
MSE	1.34E-04	2.63E-04	4.22E-04	8.13E-04	2.72E-03
Bias^2	8.20	1.50	0.75	0.33	0.04
Inefficiency	2.92	2.95	4.40	7.61	21.22
Residual Variation	88.88	95.55	94.85	92.06	78.74
GJR-GARCH					
MSE	1.30E-04	2.40E-04	3.90E-04	8.07E-04	2.50E-03
Bias^2	8.32	1.39	0.33	0.03	1.63
Inefficiency	1.02	0.01	0.94	6.03	10.72
Residual Variation	90.65	98.60	98.72	93.93	87.65
Black-Scholes					
MSE	1.41E-04	2.66E-04	4.31E-04	8.41E-04	2.81E-03
Bias^2	12.45	5.85	4.82	3.81	2.30
Inefficiency	3.24	2.81	4.66	8.30	21.92
Residual Variation	84.31	91.34	90.52	87.88	75.78
VKOSPI					
MSE	1.48E-04	2.72E-04	4.32E-04	8.51E-04	2.86E-03
Bias^2	18.83	14.93	14.72	13.27	9.68
Inefficiency	1.39	0.70	1.57	4.17	16.39
Residual Variation	79.78	84.37	83.71	82.56	73.93

Notes: $Bias^2 = (\mathrm{E}[RV_{k,t}] - \mathrm{E}[X_{k,t}])^2$; $Inefficiency = (1-\beta)^2\mathrm{Var}(X_{k,t})$; $Residual\ Variation = (1-R^2)\mathrm{Var}(RV_{k,t})$. β and R^2 are obtained from the regression equation ($RV_{k,t} = \alpha + \beta X_{k,t} + \varepsilon_t$, where k is 1, 5, 10, 21, or 63), and $X_{k,t}$ is a forecaster by RiskMetrics, GJR-GARCH, BS-implied volatility, or VKOSPI. The *Bias*^{2}, *Inefficiency*, and *Residual Variation* are in percentage values.

implied by option prices, the relatively higher portion of the MSE is explained by the squared bias compared to the cases of GJR-GARCH or RiskMetrics, where the volatility forecaster is derived as return-based volatility under the physical measure. This result is consistent with previous studies, including Bollerslev and Zhou (2006), Christoffersen and Mazzotta (2005), and Poon and Granger (2003), which attribute the bias of the implied volatilities to the priced volatility risk and claim that because implied volatilities are risk-adjusted and market-based expectations, they endogenously produce such biases.[10]

Conclusions

This paper appears to be the first study to examine the information quality and properties of the VKOSPI, the official volatility index for the Korean stock market. Though the VKOSPI yields slightly biased forecasts because it is a risk-adjusted volatility measure, the volatility index clearly contains forward-looking information content and is a strong candidate for becoming a powerful and efficient forecaster. As a stock market volatility proxy, the VKOSPI also exhibits features consistent with the volatility index measures in other developed markets. Considering that the VKOSPI has been recently publicized and that VKOSPI-based derivatives are ready to launch, further academic research on the VKOSPI is urgently needed. This study can serve as a stepping stone for future research.

Notes

1. Apart from the CBOE, several exchanges in developed markets publish volatility indices. For example, Deutsche Borse AG, Germany (DBAG) publishes VDAX and VSTOXX, which are extracted from DAX index options and DJ STOXX 50 index options, respectively. Euronext also reports various indices, including VCAS (France, CAC 40 options), VAEX (Netherlands, AEX options), VBEL (Belgium, BEL20 options), and VFTSE (United Kingdom, FTSE 100 options). Recently, the NSE (India) has started to publish NIFVIX, which is extracted from NIFTY 50 index option prices.

2. For the specific figures related to the trading volume, refer to the Web site of Futures Industry Association (www.futuresindustry.org). The magazine *Asian Risk* nominated the KOSPI200 options markets as the most remarkable derivatives market.

3. The high concentration of trading volume on high-leverage options (i.e., OTM [out-of-the-money] options) and short-term options supports their arguments. However, academics believe that the price of KOSPI200 options can be sufficiently informative because of the existence of sophisticated institutional traders and experienced, skillful foreign investors.

4. The new VIX of CBOE is also calculated by the fair variance swap method. See Britten-Jones and Neuberger (2000), Carr and Wu (2006), Demeterfi et al. (1999), Jiang and Tian (2007), and Taylor et al. (2010) for further discussion of the model-free method and the concept of fair variance swap.

5. For more details, see the KRX (www.krx.co.kr) documents *V-KOSPI200 Methodology* (the equations) and *VKOSPI200_Brochure* (the relationship between the trends of VKOSPI and the global economic shocks).

6. Recently, the KRX has also started to provide historical VKOSPI data.

7. λ is set to 0.94 following Christoffersen and Mazzotta (2005) and Frijns et al. (2010).

8. During the estimation and forecasting stages, data reflecting 500 trading days before each current date (t) is used to initialize the GJR-GARCH. This initialization method is also applied to the RiskMetrics approach.

9. The GJR-GARCH model shows performance comparable to the VKOSPI only for forecasting one-day-ahead realized volatility.

10. The author is grateful to the anonymous referees for their constructive comments on this point.

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