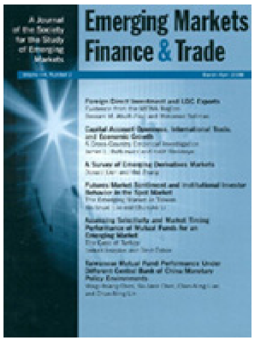

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Regime-Dependent Relationships Between the Implied Volatility Index and Stock Market Index

Jaeram Lee and Doojin Ryu

ABSTRACT: We examine regime-dependent dynamics between Korea's representative implied volatility index (VKOSPI) and stock market index (KOSPI 200) using a two-regime threshold vector error correction model (TVECM). By analyzing high-quality daily data from January 2003 to June 2013, we make the following interesting observations based on a model with regime splitting. First, regardless of regime, we observe a negative contemporaneous correlation between the VKOSPI and KOSPI 200. Second, while the KOSPI 200 generally leads the VKOSPI under normal market conditions (lower regime), this relationship is overturned when market volatility measured by the VKOSPI level is extremely high (upper regime). Third, in the TVECM framework, the effects of lagged VKOSPI on the KOSPI 200 are positive only in the upper regime, while the effects of lagged KOSPI 200 on the VKOSPI are positive only in the lower regime; this cannot be explained by the traditional framework of an asymmetric volatility phenomenon. Fourth, the KOSPI 200 exhibits greater sensitivity to implied volatility shocks in the upper regime than it does to those in the lower regime.

KEY WORDS: implied volatility, KOSPI 200, threshold vector error correction model (TVECM), VKOSPI.

Dynamics of market volatility and the interrelationship between stock market returns and volatility are traditionally important research topics in the field of financial economics because these are closely related to portfolio management, hedging strategies, option pricing, and investment strategies. In this context, market volatility reflects the overall risk and investor sentiment in an economy. Many developed countries have created implied volatility indexes that summarize the expectations and opinions of investors and their aggregate fear. These implied volatility indexes have proven successful as both trading indicators and fear gauges (Christensen and Prabhala 1998; Szakmary et al. 2003; Whaley 2000). VIX, the volatility index of the U.S. market, is a representative example. VIX not only provides meaningful information about the market state and investor sentiments, but also serves as an underlying asset for VIX-related derivatives and expands trading dimensions for investors (Lin and Chang 2009; Mencía and Sentana 2013; Wang and Daigler 2011). Because the VIX has a significant effect on the global financial community, previous studies have examined the dynamics of the VIX and the effect of the VIX on international financial markets and worldwide investors (Bollerslev et al. 2011; Cai et al. 2009; Kim et al. 2006; Koopman et al. 2005).

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Despite the abundance of articles on the VIX, there have been few studies of the VKOSPI (the volatility index of the KOSPI 200, Korea's stock market index), which is Korea's implied volatility index. Because the Korean economy is a leading emerging economy and market sentiments and investor opinions in the Korean market are of great interest to global investors, research on the implied volatility index, which can summarize the state of the Korean market, is urgently needed. Furthermore, considering that the VKOSPI is constructed from KOSPI 200 options, the most actively traded options in the world, its influence is substantial. Previous studies, however, examine only some basic properties of the VKOSPI using simple linear models such as linear regression or simple vector autoregression (VAR) framework (Han et al. 2012; Lee and Ryu 2013; Ryu 2012). In contrast, more advanced studies point out that market conditions or sentiment should be considered to specify volatility dynamics or to forecast future volatility (Lu et al. 2012; Sheu and Wei 2011). Considering these, in this paper, we analyze the regime-dependent dynamics of the relationship between the VKOSPI and the stock market index.

We conjecture that the relationship between the VKOSPI and the stock market index will vary under different market conditions according to the controversial return-volatility relationships reported in the previous studies. Many empirical studies have reported a strong negative contemporaneous relationship between returns and volatility (known as the "asymmetric volatility phenomenon"); however, the relationship between lagged volatility and returns or between lagged returns and volatility is not clear. There are two competing theories to explain the negative relationship between returns and volatility: the leverage hypothesis and the volatility feedback hypothesis. The leverage hypothesis expects lagged returns to negatively affect volatility because the sudden decline in equity leads to high leverage, which causes an increase in volatility (Black 1976; Christie 1982; Duffee 1995; Schwert 1990). The volatility feedback hypothesis implies a negative relationship between lagged volatility and returns because positive shocks in volatility increase the required return, which has a negative effect on the present price (Bekaert and Wu 2000; Campbell and Hentschel 1992; French et al. 1987; Wu 2001). Apart from those studies, several articles document a positive relationship between returns and volatility (Brandt and Kang 2004; Goyal and Santa-Clara 2003). Moreover, Yu and Yuan (2011) show that the market's mean-variance trade-off is positive in low-sentiment periods but unrelated to variance in high-sentiment periods. These contrasting observations may be due to changes in dynamics according to market conditions. Lu et al. (2012) document the nonlinearity of dynamics between the implied volatility index and the market index in Taiwan using threshold autoregression (TAR) models and threshold vector error correction models (TVECMs). Following their approach, we determine the dynamics between the VKOSPI and stock market returns according to market conditions using an embedded regime division. Moreover, we examine lagged relationships between the VKOSPI and market returns in each regime.

The TVECM framework is a useful tool to explore nonlinearity in terms of regime dependence (Chen et al. 2005; Dwyer et al. 1996; Martens et al. 1998). In this context, we investigate the regime-dependent dynamics of the implied volatility index and market index in the Korean market using a two-regime TVECM approach. The estimated threshold separates an extremely high VKOSPI level (upper regime) from ordinary market conditions (lower regime). As expected, we find significant differences in the return-volatility relationship between the two regimes. Although we observe a strong negative contemporaneous correlation in both regimes consistent with the leverage and volatility feedback hypotheses, the relationship between lagged implied volatility and stock market index is positive in the upper regime but is not significant in the lower regime. In contrast, the relationship between implied volatility and lagged stock market index is positive in the lower regime but is not significant in the upper regime. The lead-lag relationship between returns and implied volatility also changes dramatically according to regimes. The KOSPI 200 index leads the VKOSPI under typical market conditions (the lower regime), but this relationship is overturned in the upper regime. Moreover, the response of the KOSPI 200 index to shocks in the VKOSPI is larger and more persistent in the upper regime of VKOSPI than under typical market conditions.

The VKOSPI and Sample Data

The Korean government and the Korea Exchange (KRX) introduced KOSPI 200 options in July 1997. Since the first day of trading, the trading volume of KOSPI index options has increased continuously. The KOSPI 200 options contract is currently the single most actively traded derivative asset and the top options market in the world (www.futuresindustry.org/downloads/Complete_Volume(11-11_FI).pdf). Together with the continued increase in foreign and institutional trades, the rapid growth and abundant liquidity of the KOSPI 200 options market imply great interest in this market by investors worldwide.

The market prices of KOSPI 200 options reflect information shocks in the Korean market and investor opinions rapidly because there is fierce competition among options traders who analyze and monitor this market. In other words, the prices of options are informative and adjust expectations about the state of the Korean economy (Ahn et al. 2008, 2010; Guo et al. 2013; Kim and Ryu 2012; Ryu 2011, 2013, forthcoming; Ryu et al. forthcoming).

The KRX recently published the VKOSPI, the representative volatility index for the KOSPI 200 stock market index. The VKOSPI is constructed according to a model-free approach using the market prices of KOSPI 200 options, which are world-class derivatives. The VKOSPI is designed to capture the one-month future volatility of the KOSPI 200 spot price index. The VKOSPI successfully detects major macroeconomic events (Lee and Ryu 2014; Ryu 2012).

The VKOPSI is implied by the KOSPI 200 options prices and is constructed by a model-free variance expectation method (i.e., the fair variance swap method), implying that VKOSPI values are not affected by model biases. We use the daily time series of the VKOSPI, V_t, and the KOSPI 200, S_t, from January 2, 2003, to June 28, 2013, resulting in 2,609 observations. Though the KRX has officially reported the VKOSPI since April 13, 2009, the time series of the VKOSPI before this public announcement date can be constructed from the KOSPI 200 options price series using the fair variance swap method, which is also used in the construction of the VIX.[1] We conduct our analyses of the Korean market based on these daily data sets collected over a period including the recent financial crisis of 2007–8. The time series of the VKOSPI and KOSPI 200 are shown in Figure 1. Overall, the level of the VKOSPI is high when the KOSPI 200 is low. This feature demonstrates that the VKOSPI is an indicator of the stock market. We can investigate nonlinearity using regime division because our sample includes both recessions and recoveries. Summary statistics of the entire sample are shown in Table 1.

The VKOSPI series is positively skewed and has a heavy tail. This implies that V_t typically remains at low levels but occasionally jumps to high values. This tendency is consistent with the logarithm of V_t, $\ln V_t$, although it weakens considerably. In contrast, the KOSPI 200 series is slightly negatively skewed, and the negative excess kurtosis is

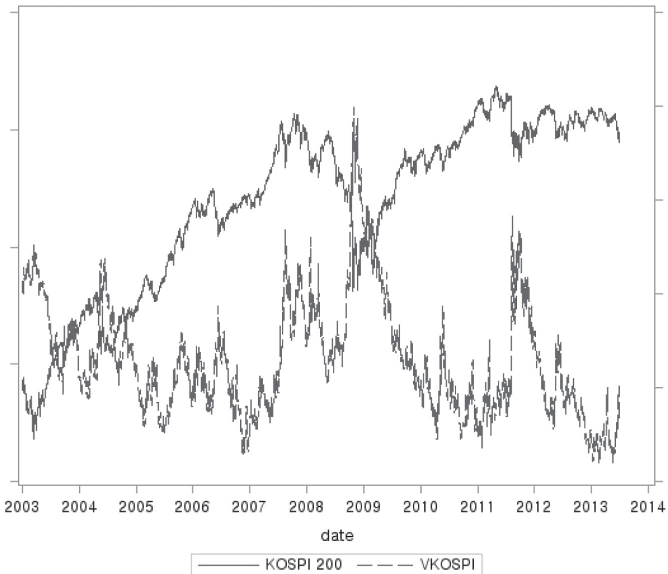

Figure 1. Time series of the KOSPI 200 and the VKOSPI: January 2, 2003–June 28, 2013

Table 1. Summary statistics

	V_t	S_t	$\ln V_t$	$\ln S_t$	$\Delta\ln V_t$	$\Delta\ln S_t$
Mean	24.65	188.8	3.149	5.180	–0.0003	0.0004
Minimum	13.30	65.64	2.588	4.184	–0.2637	–0.1091
Median	22.00	196.5	3.091	5.281	–0.0038	0.0010
Maximum	89.30	295.3	4.492	5.688	0.4167	0.1159
Standard deviation	9.455	59.89	0.3154	0.3661	0.0518	0.0152
Skewness	2.368	–0.3176	0.9985	–0.7722	1.060	–0.3777
Kurtosis	8.330	–1.120	1.182	–0.4931	6.582	5.015
Autocorrelation	0.9834	0.9989	0.9865	0.9991	–0.0517	0.0138
N	2,609					

Notes: The sample period is January 2, 2003–June 28, 2013. V_t denotes the VKOSPI; S_t denotes the KOSPI 200. N is the number of observations. Δ is the lag operator.

quite low relative to that of the implied volatility series. We consider $\ln V_t$ and $\ln S_t$ in the main analysis using the TVECM because they are closer to the normal distribution and the difference in S_t can be interpreted as a log return series. It should be noted that both level variables are highly persistent processes, whereas the differences are not. Considering that the autocorrelations of the level variables are close to one, the stationarity of the level series is doubtful. In contrast, the autocorrelations of the difference series are almost zero. This suggests that both V_t and S_t series are integrated by order one and might be cointegrated. Stationarity and cointegration test results are given in Table 2.

We conduct the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) stationarity test as well as four unit root tests: the augmented Dickey–Fuller (ADF) unit root test, the Phillips–

Table 2. Stationarity test and cointegration test results

Panel A: Stationarity test

	V_t	S_t	$\ln V_t$	$\ln S_t$	$\Delta \ln V_t$	$\Delta \ln S_t$
ADF	–3.17*	–2.39	–3.10	–2.02	–16.56***	–15.92***
PP	–3.79**	–2.44	–3.61**	–2.13	–55.54***	–50.47***
ERS	–3.30**	–2.34	–3.38**	–1.58	–23.80***	–8.48***
NP	–2.77*	–2.35	–2.69*	–1.59	–8.43***	–3.23**
KPSS	0.43***	0.61***	0.48***	1.12***	0.03	0.04

Panel B: Cointegration test

Rank	Trace	5 percent Critical value	Cointegrating vector	
0	23.1583	15.34	$\ln V_t$	1
1	3.7865	3.84	$\ln S_t$	0.3048

Notes: The test statistic of the NP test is MZ_t (Perron and Ng 1996). The null hypotheses of ADF, PP, ERS, and NP are nonstationarity; the null hypothesis of KPSS is stationarity. Panel B shows the Johansen's cointegration trace test result. The null hypothesis is that the number of cointegration vectors is smaller than or equal to the rank. The cointegrating coefficient of the log difference of the VKOSPI is normalized. * Null hypothesis can be rejected at the 10 percent significance level; ** null hypothesis can be rejected at the 5 percent significance level; *** null hypothesis can be rejected at the 1 percent significance level.

Perron (PP) unit root test, the Elliott–Rothenberg–Stock (ERS) unit root test, and the Ng–Perron (NP) unit root test. The null hypothesis of KPSS is the integration of order one; the null hypotheses of ADF, PP, ERS, and NP are the integration of order zero. Obviously, we cannot reject the existence of a unit root in the level of S_t and the log transformation of S_t for all unit root tests; the KPSS test rejects stationarity at the 1 percent significance level. Results for the VKOSPI are somewhat vague. The unit root tests marginally support stationarity of V_t and $\ln V_t$; the KPSS test strongly rejects the stationarity. However, the test statistics of the unit root tests are not large enough to reject the null hypothesis for the unit root at the 1 percent significance level. Furthermore, extremely high autocorrelation (almost one) is observed. Thus, we consider V_t and $\ln V_t$ to be nonstationary series. The stationarity test results for the differenced series clearly support that they are stationary series. In addition, a cointegration relationship exists between $\ln V_t$ and $\ln S_t$. The cointegrating coefficient of $\ln S_t$, β, is 0.3048, which is greater than that of the Taiwan volatility index (0.2078) in Lu et al. (2012). This positive and relatively large value of β might reflect the strong negative contemporaneous correlation (–0.3826) between $\ln V_t$ and $\ln S_t$. It also implies that there is a long-run interaction between the Korean options market and stock market. At the same time, it indicates that the role of error correction in the Korean market might be more important than that in the Taiwan market. In summary, the overall results indicate that we can apply the VECM framework to specify regime-dependent dynamics between the two series.

Model Specification and Methodology

We use the TVECM framework, which is a general approach to analyze regime-dependent dynamics and threshold cointegration. In this framework, regimes are predetermined by threshold variables in the prior period and embedded thresholds, in contrast to stochastic regime-switching models. This framework is appropriate for cases in which there is a nonlinear relationship between the threshold variables and the target processes and/or the relationship is theoretically nested in the structural model. The relationship between the implied volatility index and spot index is widely documented; recent studies report that this relationship has an asymmetric feature (Bollerslev and Zhou 2006; Giot 2005; Han et al. 2012; Hibbert et al. 2008; Kim and Ryu 2014; Lu et al. 2012; Ryu 2012). However, the focus of most previous studies is the asymmetric effect of the spot return on the implied volatility. In this paper, we focus on the regime dependence and informational role of the implied volatility.

We apply the two-regime TVECM suggested by Hansen and Seo (2002) to analyze the regime-dependent dynamics of the VKOSPI and the KOSPI 200. In this framework, the sample is divided into two subsamples by a threshold, and dynamics are specified distinctly in each regime. We classify regimes according to the size of the error correction term, $\ln V_{t-1} + \beta \ln S_{t-1}$. The market condition is regarded as being in the lower regime when $\ln V_{t-1} + \beta \ln S_{t-1}$ is smaller than or equal to the threshold, τ, and in the upper regime when $\ln V_{t-1} + \beta \ln S_{t-1}$ is larger than the threshold. A positive value of β in the linear model indicates that the threshold might control the level of the VKOSPI and the KOSPI 200 in the same direction. However, the VKOSPI is dominant in $\ln V_{t-1} + \beta \ln S_{t-1}$, taking into account the average proportion of the VKOSPI (66.6 percent) and the extremely high correlation (0.94) between $\ln V_{t-1} + \beta \ln S_{t-1}$ and $\ln V_{t-1}$. Therefore, the upper regime actually indicates the condition that the VKOSPI is sufficiently high. For a given β and τ, the regimes are determined as follows:

$$\begin{aligned} i &= 1 \quad \text{if } \left(\ln V_{t-1} + \beta \ln S_{t-1}\right) \leq \tau \\ i &= 2 \quad \text{if } \tau < \left(\ln V_{t-1} + \beta \ln S_{t-1}\right). \end{aligned} \tag{1}$$

The dynamics of the VKOSPI and the KOSPI 200 are specified by the following vector error correction model for each regime:

$$\Delta \ln V_t = c_i^v + \alpha_i^v \left(\ln V_{t-1} + \beta \ln S_{t-1}\right) + \sum_{j=1}^{p} \gamma_{i,j}^v \Delta \ln V_{t-j} + \sum_{j=1}^{q} \delta_{i,j}^v \Delta \ln S_{t-j} + \varepsilon_{i,t}^v \tag{2}$$

$$\Delta \ln S_t = c_i^s + \alpha_i^s \left(\ln V_{t-1} + \beta \ln S_{t-1}\right) + \sum_{j=1}^{p} \gamma_{i,j}^s \Delta \ln V_{t-j} + \sum_{j=1}^{q} \delta_{i,j}^s \Delta \ln S_{t-j} + \varepsilon_{i,t}^s, \tag{3}$$

where $\varepsilon_{i,t}^v$ and $\varepsilon_{i,t}^s$ are white noise processes that are independently distributed with a mean of zero and variance of σ_i^2. We set the lags of AR terms, p and q, to three based on the previous literature (Hibbert et al. 2008; Lu et al. 2012) and the Bayesian information criterion. For given values of β and τ, the coefficients in Equations (2) and (3) can be estimated by maximizing the log-likelihood function shown in Equation (4).

$$\ln L\left(\beta, \tau\right) = -\frac{n}{2} \ln \left|\Sigma\left(\beta, \tau\right)\right| - \frac{1}{2} \sum_{t=1}^{n} \varepsilon_t' \Sigma\left(\beta, \tau\right)^{-1} \varepsilon_t, \tag{4}$$

where $\Sigma = (1/n)\Sigma_{t=1}^{n} \varepsilon_t \varepsilon_t'$ and $\varepsilon_t = [\varepsilon_t^v \, \varepsilon_t^s]'$. To estimate β and τ, we find (β, τ), which maximizes the log-likelihood function $\ln L(\beta, \tau)$ using a grid search method over the area $B = [\beta_{\min}, \beta_{\max}]$, for β and $T = [\tau_{\min}, \tau_{\max}]$ for τ.

The coefficients of the model should vary in regimes if there are threshold effects in the dynamics of the VKOSPI and the KOSPI 200. Conversely, if the null hypothesis of the conventional vector error correction model can be rejected, the TVECM could be used. When β and τ are known, the following null hypothesis is testable using the Wald statistic, $W(\beta, \tau)$.

$$H_0: c_1^v = c_2^v, \alpha_1^v = \alpha_2^v, \gamma_{1,j}^v = \gamma_{2,j}^v, \delta_{1,j}^v = \delta_{2,j}^v, c_1^s = c_2^s, \alpha_1^s = \alpha_2^s, \gamma_{1,j}^s = \gamma_{2,j}^s, \delta_{1,j}^s = \delta_{2,j}^s.$$

However, under the null hypothesis of linear cointegration, we can estimate the linear cointegrating coefficient $\tilde{\beta}$ only, but not τ or regime-dependent coefficients. Therefore, Seo (2006) suggests the threshold test for this framework based on the supremum of the Wald statistic, sup$W$, as follows:[2]

$$\sup W = \sup_{\tau \in T} w(\tilde{\beta}, \tau). \tag{5}$$

We expect that the interactions of the VKOSPI and the KOSPI 200 will be different in different regimes. Granger causality tests between the VKOSPI and the KOSPI 200 are performed for each regime to evaluate these expectations. The VKOSPI does not Granger-cause the KOSPI 200 when the coefficients of the lagged terms related to the VKOSPI are not jointly different from zero, that is, $\alpha_i^s = 0$ and $\gamma_{i,j}^s = 0$. Similarly, the KOSPI 200 does not Granger-cause the VKOSPI when $\alpha_i^v = 0$ and $\gamma_{i,j}^v = 0$. If the Granger causality test results vary according to regime, the interaction between the VKOSPI and the KOSPI 200 depends on the level of the VKOSPI.

A conventional approach to evaluate the dynamic properties of a system is to use an impulse response function, which in our context can be defined as the effect of a shock at present on future prices. An impulse response function for linear models is independent of the history and magnitude of a shock. However, an impulse response for threshold models can be susceptible to both the history and magnitude of the shock. Following Martens et al. (1998), we consider the nonlinear impulse response function to be the difference between the conditional mean with and without shocks using a Monte Carlo simulation. We set the size of the shocks to positive and negative 1 percent to account for the direction of the shocks. In the presence of a threshold effect, the response of a market to shocks in another market can differ according to regime.

Empirical Results

Two-regime TVECM estimation results for the VKOSPI and KOSPI 200 are shown in Table 3. The cointegrating coefficient $\hat{\beta}$ is estimated to be 0.3031, which is similar in size than that of the linear VECM, $\tilde{\beta} = 0.3048$. The positive $\hat{\beta}$ implies that high (low) values of implied volatility attend a low (high) level of the market index in the long run. Therefore, the strong negative correlation between the implied volatility and the index, which is documented frequently in the literature, is mainly contained in the error correction term of the TVECM. The whole sample is split disproportionately into two subsamples by the estimated threshold, $\hat{\tau} = 5.004$. Most observations are classified as being in the lower regime, which has 2,209 observations (84.7 percent); the upper regime has only 400 observations (15.3 percent). Thus, the lower regime can be interpreted as typical market conditions; the upper regime indicates an extremely high VKOSPI level. This implies that the dynamics between the VKOSPI and the KOSPI 200 change dramatically when the VKOSPI level is tremendously high. The sup-Wald test, following Seo (2006), supports the existence of a threshold effect; sup$W$ (= 57.56) is greater than the critical value at the 1 percent significance level.

The estimated coefficients of the error correction term are different between regimes. The log difference of the VKOSPI is negatively affected by the error correction term $\ln V_{t-1} + \beta \ln S_{t-1}$, regardless of regime, although the influence of the error correction term is much greater in the upper regime than in the lower regime. In contrast, $\ln V_{t-1} + \beta \ln S_{t-1}$

Table 3. Two-regime TVECM estimation results

		Cointegrating coefficient	$\hat{\beta} = 0.3031$
		Threshold	$\hat{\tau} = 5.004$
		Coefficients	
Equation	Variable	Lower regime (84.7 percent)	Upper regime (15.3 percent)
$\Delta \ln V_t$	Constant	0.0766***	0.1972***
	$(\ln V_{t-1} + \beta \ln S_{t-1})$	–0.0166***	–0.0381***
	$\Delta \ln V_{t-1}$	–0.0098	–0.0768*
	$\Delta \ln V_{t-2}$	0.0032	0.0197
	$\Delta \ln V_{t-3}$	–0.0237	–0.1910***
	$\Delta \ln S_{t-1}$	0.2902**	–0.2029
	$\Delta \ln S_{t-2}$	0.1703	0.3551**
	$\Delta \ln S_{t-3}$	0.0515	–0.3351**
$\Delta \ln S_t$	Constant	0.0061	–0.0210
	$(\ln V_{t-1} + \beta \ln S_{t-1})$	–0.0012	0.0040
	$\Delta \ln V_{t-1}$	–0.0144	0.0513***
	$\Delta \ln V_{t-2}$	–0.0081	0.0267**
	$\Delta \ln V_{t-3}$	0.0058	0.0324**
	$\Delta \ln S_{t-1}$	–0.0347	0.1399***
	$\Delta \ln S_{t-2}$	–0.0288	0.0179
	$\Delta \ln S_{t-3}$	0.0569*	0.0205
Contemporaneous correlation		–0.6313	–0.7025

sup*W*	99 percent critical value	95 percent critical value	90 percent critical value
57.56	57.14	49.44	46.05

Notes: The coefficients are estimated from the following TVECM:

$$\Delta \ln V_t = c_i^v + \alpha_i^v (\ln V_{t-1} + \beta \ln S_{t-1}) + \Sigma_{j=1}^{p} \gamma_{i,j}^v \Delta \ln V_{t-j} + \Sigma_{j=1}^{q} \delta_{i,j}^v \Delta \ln S_{t-j} + \varepsilon_{i,t}^v$$

$$\Delta \ln S_t = c_i^s + \alpha_i^s (\ln V_{t-1} + \beta \ln S_{t-1}) + \Sigma_{j=1}^{p} \gamma_{i,j}^s \Delta \ln V_{t-j} + \Sigma_{j=1}^{q} \delta_{i,j}^s \Delta \ln S_{t-j} + \varepsilon_{i,t}^s$$

$\hat{\beta}$ is the estimated cointegrating coefficient of $\Delta \ln S_t$. $\hat{\tau}$ denotes the estimated thresholds. sup*W* is the supremum of the Wald statistic of the threshold test suggested by Seo (2006). Critical values of the sup*W* statistic are obtained from a residual bootstrap. * Statistical significance at the 10 percent level; ** statistical significance at the 5 percent level; *** statistical significance at the 1 percent level.

does not influence innovation in the KOSPI 200. This feature implies that the strong negative correlation between the KOSPI 200 and the VKOSPI is maintained by the rise and/or fall of the VKOSPI, not by changes in the KOSPI 200. Moreover, the higher absolute size of the coefficient in the upper regime indicates that this negative contemporaneous relationship is strictly enforced when the VKOSPI is high. Furthermore, the absolute size of the correlation in the upper regime (–0.7025) is larger than that in the lower regime (–0.6313), supporting the previous interpretations.

Although traditional explanations of the dynamics between returns and volatility, that is, the leverage and volatility feedback hypotheses, focus on contemporaneous relationships, they also provide expectations of the effects of lagged variables. The leverage hypothesis implies a negative relationship between shocks on the lagged stock returns and future volatility; the volatility feedback hypothesis predicts a negative relationship between the lagged volatility and returns. However, some studies have documented a positive relationship between the lagged stock variance and the return on the market. We check the sign and significance of the short-run coefficient to verify the relationship between implied volatility and returns. In the VKOSPI equation, the effect of the lagged log difference of the KOSPI 200 is only significantly positive in the lower regime. In other words, the KOSPI 200 leads the VKOSPI under ordinary market conditions, but we do not observe this relationship when the VKOSPI remains at an extremely high level. The positive coefficient of the lagged KOSPI 200 in the lower regime cannot be explained by the leverage hypothesis. In the KOSPI 200 equation, the effect of the lagged log difference of the VKOSPI is significantly positive in the upper regime but not in the lower regime. This positive effect of the VKOSPI on the KOSPI 200 is confirmed in all lagged log differences of the VKOSPI, but, once again, it is hard to reconcile with the traditional volatility feedback hypothesis. Our results are more similar to those from an empirical study of return-volatility trade-off, which reports a positive correlation between lagged average stock volatility and returns due to variance risk premium. However, in contrast to Goyal and Santa-Clara (2003), who show that market volatility does not have the ability to forecast returns, we find that positive relationships between lagged market volatility and market returns are significant in the upper regime. The lack of a relationship in the previous study may be due to the regime-dependent dynamics. Our empirical findings imply that the variance risk premium matters only when the volatility is significantly high. When high future volatility is concerned, investors in the stock market might be pessimistic. Therefore, if a high VKOSPI level relates to low sentiment in the stock market, our results indicate that variance risk is priced only when sentiment is low, as in Yu and Yuan (2011). In summary, when the VKOSPI stays at a high level, the significance of the KOSPI 200 is curtailed, while the role of the VKOSPI becomes important.

This lead-lag relationship is confirmed by the Granger causality test results listed in Table 4. The KOSPI 200 Granger-causes the VKOSPI in the total sample and in the lower regime. However, it is overturned in the upper regime. The null hypothesis that the KOSPI 200 does not Granger-cause the VKOSPI cannot be rejected at the 5 percent significance level in the upper regime; the VKOSPI has an informational effect on the KOSPI 200 at an extremely high VKOSPI level. These results are consistent with the conclusions that the stock market leads the options market under typical market conditions, but the information content of the options market becomes significant when investors expect stock market volatility over the next thirty-day period to be extremely high. In other words, the informational effect of option trading is meaningful when investors are concerned that there may be severe market fluctuations.

Figure 2 shows the impulse response in the log difference of the KOSPI 200 to shocks in the log difference of the VKOSPI. Remarkably, returns responses are completely different by regimes. In the lower regime, the response of the KOSPI 200 is negatively associated with shocks in the VKOSPI, which is consistent with the volatility feedback hypothesis, even though the effects of the shocks are too small to be meaningful. In contrast, the KOSPI 200 moves in the same direction as the VKOSPI in the upper regime. The KOSPI 200 reacts much more sensitively to shocks in the VKOSPI in the upper regime than in the lower regime, consistent with the preceding results. In addition, the effect of shocks is more persistent when the VKOSPI is at a high level.

The impulse response in the log difference of the VKOSPI to shocks in the log difference of the KOSPI 200 is shown in Figure 3. The directions of the immediate responses

Table 4. Granger causality test results

	$\Delta\ln V_t \rightarrow \Delta\ln S_t$		$\Delta\ln S_t \rightarrow \Delta\ln V_t$	
	Wald statistic	*p*-value	Wald statistic	*p*-value
Total sample	5.28	0.2593	19.09	0.0008
Lower regime	5.83	0.2122	23.05	0.0001
Upper regime	9.91	0.0419	9.18	0.0567

Notes: The null hypotheses are H_0: The VKOSPI does not Granger-cause the KOSPI 200 and H_0: The KOSPI 200 does not Granger-cause the VKOSPI, respectively.

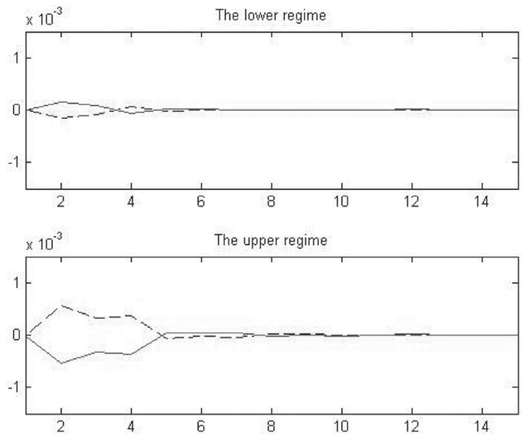

Figure 2. Impulse response functions: $\Delta\ln V_t \rightarrow \Delta\ln S_t$

Notes: The impulse response functions are differences between the conditional mean of the log difference of the KOSPI 200 with and without shocks to the log difference of the VKOSPI calculated by a Monte Carlo simulation with 10,000 replications. We set the size of the shocks to be ±1 percent. The dashed line indicates positive shocks; the solid line indicates negative shocks.

are opposite according to regime. A negative reaction consistent with the leverage hypothesis is observed in the upper regime, but it fluctuates as time passes. Therefore, it may represent overreaction of the VKOSPI rather than be caused by risk adjustments. This confirms that the VKOSPI can be used as a fear gauge of the market. The impulse response in the lower regime is similar to the impulse response in the log difference of the KOSPI 200 in the upper regime. If the positive response is due to a general lead-lag relationship between the implied volatility and market returns, the impulse response function results confirm our interpretation of the short-run coefficients.

Conclusions

We investigate the regime-dependent dynamics of the implied volatility and market indexes in the Korean market using a two-regime threshold vector error correction model framework. Typical market conditions are classified as the lower regime, while the upper regime represents an extremely high level of the VKOSPI. There are marked differences

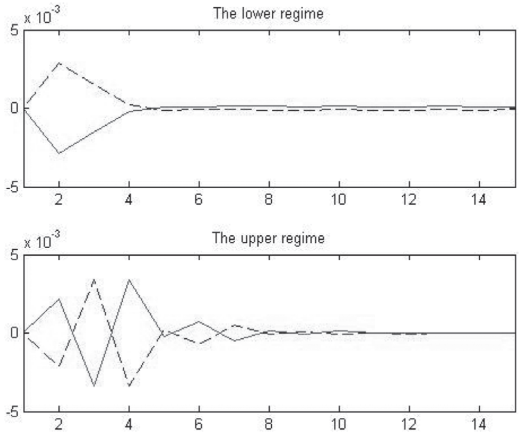

Figure 3. Impulse response functions: $\Delta \ln S_t \rightarrow \Delta \ln V_t$

Notes: The impulse response functions are differences between the conditional mean of the log difference of the VKOSPI with and without shocks to the log difference of the KOSPI 200 calculated by a Monte Carlo simulation with 10,000 replications. We set the size of the shocks to be ±1 percent. The dashed line indicates positive shocks; the solid line indicates negative shocks.

in the dynamic features of these regimes. Negative contemporaneous correlation is a common tendency, regardless of regime, but is more dominant in the upper regime than in the lower regime. The relationship between the lagged VKOSPI and the KOSPI 200 is positive only in the upper regime, while the relationship between the lagged KOSPI 200 and the VKOSPI is positive only in the lower regime, which is hard to explain by traditional means such as the leverage and volatility feedback hypotheses. Empirical results indicate that the KOSPI 200 leads the VKOSPI in a typical regime, but this is reversed when investors expect extremely high future volatility. Finally, the KOSPI 200 is more susceptible to shocks in the VKOSPI in the upper regime than in the lower regime.

This paper is the first to examine the regime-dependent dynamics of the VKOSPI and the KOSPI 200. KRX plans to launch the VKOSPI futures in the near future to provide a direct hedging tool to assess volatility risk without concern for the level of the KOSPI 200 stock market index. Our results, however, indicate that the VKOSPI futures can be affected by the KOSPI 200. Considering the global position of the KOSPI 200 options market and the launch of VKOSPI-based derivatives, we hope that this study triggers future research.

Notes

1. For further discussion of the VKOSPI, refer to Ryu (2012) and the official documents provided by the KRX (www.krx.co.kr). The titles of the relevant documents are "V-KOSPI200 Methodology" and "VKOSPI200_Brochure."

2. The critical values of the sup*W* statistic are obtained from residual bootstrap estimations.

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