

# Stock Returns and Implied Volatility: A New VAR Approach

*Bong Soo Lee and Doojin Ryu*

## Abstract

The authors re-examine the return-volatility relationship and its dynamics under a new vector autoregression (VAR) identification framework. By analyzing two model-free implied-volatility indices – the well-established VIX (in the United States) and the recently published VKOSPI (in Korea) – and their stock market indices, the authors find an asymmetric volatility phenomenon in both the developed and emerging markets. However, the VKOSPI shows impulse response dynamics that are quite different from those of the VIX. This finding can be attributed to the unique characteristics of the KOSPI200 options market, which determine the dynamics of the VKOSPI.

**JEL** G10 G15

**Keywords** Asymmetric volatility; vector autoregression; VIX; VKOSPI

## Authors

*Bong Soo Lee*, Florida State University, Tallahassee

*Doojin Ryu*, ✉ School of Economics, College of Business and Economics, Chung-Ang University, Seoul, South Korea, [doojin.ryu@gmail.com](mailto:doojin.ryu@gmail.com)

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## 1 Introduction

Financial economists have documented asymmetric return-volatility relationships in global stock markets. That is, stock market returns and volatility are inversely related, and this relationship is more noticeable for negative returns than for positive returns. Thus, in the time-series framework, negative return shocks have the greater impact on volatility. This asymmetric volatility phenomenon has been traditionally explained by two hypotheses: the leverage hypothesis and the volatility feedback hypothesis.

The leverage hypothesis explains the asymmetric relationship between individual stocks' returns and their volatilities based on the observation that a decrease in the stock price of a company results in its equity portion of the firm value becoming smaller while the debt value relative to the total firm value increases. As a result, the stock becomes more risky. Many early studies, including Black (1976), Christie (1982), Schwert (1990), and Duffee (1995), have adopted this hypothesis to explain the asymmetric volatility phenomenon detected in global stock markets.

The volatility feedback hypothesis is more general and is based on the positive inter-temporal relationship between expected return and conditional volatility. Whether positive or negative, a shock initially increases both current and future volatilities. However, since the increased volatility levels up the expected return and decreases the current stock price, a negative shock results in a stronger increase in volatility, whereas a positive shock restrains the volatility increase. The most representative studies that adopt this volatility feedback hypothesis are those by French, Schwert, and Stambaugh (1987) and Campbell and Hentschel (1992).

While these two competing hypotheses have been developed separately, recent studies tend to examine the two hypotheses simultaneously. For example, Bekaert and Wu (2000) propose a unified framework in which these two hypotheses can be investigated and tested together. Wu (2001), examining the hypotheses simultaneously, finds that both the leverage and volatility feedback effects generate asymmetric volatility.

More recently, related studies suggest that the two traditional hypotheses are not adequate to fully account for the asymmetric volatility in daily or higher-frequency levels, and they investigate volatility within the frameworks of trading-based or behavioral explanations. Avramov, Chordia, and Goyal (2006) argue that

trades by uninformed individual investors generate asymmetric volatility. Hibbert, Daigler, and Dupoyet (2008), and Han, Guo, Ryu, and Webb (2012) claim that the psychological bias of market participants is the main cause of the asymmetric volatility phenomenon observed in daily and intraday data.

Although numerous studies have examined asymmetric volatility at the firm and market levels, and many possible explanations for the phenomenon have been suggested and discussed, it remains unclear whether previous studies' methods<sup>1</sup> can provide findings that fully explain the dynamic return-volatility relationship. This is because such methods primarily rely on simple regression analyses or GARCH models, which possibly fail to describe the mechanism of the volatility response to shocks. In contrast, in this paper, we re-examine the asymmetric relationship between returns and volatility by employing a new vector autoregression (VAR) approach recently suggested in Lee's (2010) seminal paper. By adopting this VAR identification framework to analyze the dynamic impulse response behavior of volatilities to positive and negative return shocks, we can better understand the dynamics of the volatility response that has been overlooked in previous studies.

Another contribution of the current study is to examine the asymmetric behavior of the VKOSPI (Volatility Index of KOSPI200), a volatility index implied by the KOSPI200 options product, which represents the most liquid options contract in the world. In addition, we compare the asymmetric behavior of the VKOSPI with that of the VIX, on which most previous studies have focused. Given that little research has examined the VKOSPI, which provides the valuable information on market sentiment and investor attitude toward risk in the Korean market that represents a leading emerging economy, and given that substantial differences may exist between emerging and developed markets, this study has an additional academic value of providing new insights into these issues.

Our empirical results show that the asymmetric volatility phenomenon occurs in both developed (the United States) and emerging (Korea) markets. However, the dynamic volatility responses show quite different patterns across the markets. We explain the difference based on the KOSPI200 options market's unique characteristics and immaturity, which determine the dynamics of the VKOSPI.

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<sup>1</sup> Bekaert and Wu (2000) provide a good review of previous research.

This paper is organized as follows. In Section 2, we introduce the KOSPI200 options market and the VKOSPI. In Section 3, we discuss the new VAR framework employed in this study. Empirical results and discussions are provided in Section 4. We give our conclusions based on the findings of this study in Section 5.

## **2 The KOSPI200 Options Market and the VKOSPI**

For the identification of the dynamic and asymmetric return-volatility relationship within this study's framework, which will be described in Section 3, implied volatility is a more appropriate construct than realized or historical volatility. This is because implied volatility can gauge the expectations and sentiments of market participants, whereas realized or historical volatilities contain little such information. Therefore, basing our analysis on each market's implied volatilities will provide rich implications for that market.

Among the implied volatility candidates, model-free implied volatility is known to have more explanatory power than the others that are dependent on option pricing models, such as the Black-Scholes or Heston models.<sup>2</sup> The most widely used model-free implied volatility indicator is the VIX, which represents the volatility index implied by the S&P500 option prices. The S&P500 options market and the VIX of the U.S. market have been discussed in numerous academic papers, and their characteristics are fully analyzed and well-known to academics and market practitioners.<sup>3</sup> In contrast, only a handful of studies have analyzed the KOSPI200 options, the most actively traded options in the world.<sup>4</sup> Further, to the best of our knowledge, only two published articles (Ryu, 2012; Han et al., 2012) examine the VKOSPI. Given that the KOSPI200 index options are top-tier options products due to their high trading volume and investor interest, there is good

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<sup>2</sup> If we derive implied volatility from option pricing models, it contains some model bias, of which representative examples are volatility smiles or smirks of the Black-Scholes model.

<sup>3</sup> See the recent studies of Giot (2005a, 2005b), Banerjee, Doran, and Peterson (2007), Becker, Clements, and McClland (2009), and Duan and Yeh (2010).

<sup>4</sup> Some recent studies, such as Ahn, Kang, and Ryu (2008, 2010), Ryu (2011), and Kim and Ryu (2012), have begun to address the market microstructure issues of the KOSPI200 options market.

reason to conduct research efforts based on the model-free implied volatility of the emerging market.

Since the Korea Exchange (KRX) introduced the KOSPI200 index options in 1997, the trading volume of the KOSPI200 options has sharply increased. Now, the KOSPI200 options market is the most liquid derivatives market in the world. From its earliest stage, it was dominated by highly speculative investors. Although the trading volume of professional and experienced investors has steadily increased, and their trading activity now accounts for a significant portion of the total trading volume, speculative traders and domestic individual investors are still major market players in the KOSPI200 options market.

Inspired by the great success of the KOSPI200 options market, the KRX published the VKOSPI, the official volatility index for the KOSPI200 stock index, on April 13, 2009. The VKOSPI is calculated from the KOSPI200 index and options prices based on the model-free method.<sup>5</sup> Therefore, the VKOSPI reflects the market sentiment and investor expectation embedded in the market prices of KOSPI200 options. Further, the VKOSPI can be regarded as a representative market indicator of the Korean market in that the transactions of the stocks underlying the KOSPI200 index and its options account for a dominant portion of the total transactions in the Korean financial market.

Ryu (2012) and Han et al. (2012) also find that the VKOSPI has desirable qualities as a stock market indicator, containing significant and meaningful information on the Korean financial market. They additionally report that the VKOSPI captures the major shocks to the global economy and shows movements similar to the VIX. In addition, the elaborate logic represented in its construction of equations (see Ryu, 2012) makes the VKOSPI a low-noise indicator and an accurate fear-gauge for the Korean market.

### **3 Empirical Framework**

Lee (2010) has developed his new VAR identification framework to examine the asymmetric effects on stock market returns of positive and negative inflation shocks that have the same magnitude but opposite signs. Further, with a slight

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<sup>5</sup> Refer to Ryu (2012) for further details about the VKOSPI.

modification, the new VAR framework can be used for investigating the asymmetric and dynamic relationship between any two economic variables. In this section, we briefly discuss Lee's framework, which we employ in this study to investigate the asymmetric volatility phenomenon.

We consider the following bivariate models:

$$\text{Bivariate vector autoregressive representation (BVAR): } Y_t = A(L)Y_{t-1} + u_t \quad (1)$$

$$\text{Bivariate moving average representation (BMAR): } Y_t = B(L)e_t \quad (2)$$

where  $Y_t = [Y_{1t}, Y_{2t}]^T$ ,  $u_t = [u_{1t}, u_{2t}]^T$ ,  $e_t = [e_{1t}, e_{2t}]^T$ ,  $\text{Var}(u_t) = \Omega$ ,  $\text{Var}(e_t) = I$ ,  $B^0 e_t = u_t$ , and  $L$  is the lag operator. In addition,  $b_{ij}$ ,  $B_{ij}(L)$ ,  $A_{ij}(L)$ , and  $\sigma_{ij}$  are the elements of a 2-by-2 matrix of  $B^0$ ,  $B(L)$ ,  $A(L)$ , and  $\Omega$ , respectively ( $i, j=1, 2$ ). The elements of  $A(L)$  and  $\Omega$  are obtained through the least squares estimation of Equation (1). By comparing Equations (1) and (2), we can obtain all elements of  $B(L)$  if each element of  $B^0$  is identified.<sup>6</sup>

We can identify and estimate four components of  $B^0$  by using the relationship  $B^0(B^0)^T = \Omega$ , which is obtained by taking the variance of each side of the relationship  $B^0 e_t = u_t$ .

$$B^0(B^0)^T = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \begin{bmatrix} b_{11} & b_{21} \\ b_{12} & b_{22} \end{bmatrix} = \begin{bmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{12} & \sigma_{22} \end{bmatrix} = \Omega \quad (3)$$

$$b_{11}^2 + b_{12}^2 = \sigma_{11} \quad (4)$$

$$b_{11}b_{21} + b_{12}b_{22} = \sigma_{12} \quad (5)$$

$$b_{21}^2 + b_{22}^2 = \sigma_{22} \quad (6)$$

Equation (3) illustrates how we can estimate the elements of  $B^0$  from the estimated  $\Omega$  matrix. Equations (4), (5), and (6) represent the three restrictions implied by Equation (3).

To identify the four components of  $B^0$ , we need one additional restriction. We use the following additional restriction for the identification:

$$b_{11} + b_{12} = 0 \quad (7)$$

Equation (7) reflects the requirement that positive and negative shocks on the first variable  $Y_{1t}$  are the same size but with opposite signs. This restriction helps us

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<sup>6</sup> Equations (1) and (2) imply that  $B(L)$  is equal to  $[I - A(L)L]^{-1}B^0$ , where  $I$  is a 2-by-2 identity matrix.

to identify positive and negative return shocks and allows us to examine the dynamic effects of each type of return shock on the volatility. Therefore, Equations (4)-(7) yield the estimate of each element of the  $B^0$  matrix.<sup>7</sup> We employ this VAR framework to examine the asymmetric return-volatility relationship. If we set the first variable as the stock market return and the second variable as the stock market volatility, we can then analyze the dynamic responses of the volatility to positive and negative return innovations of the same magnitude.

#### 4 Empirical Results and Discussions

We compare daily VIX and VKOSPI data for the period from April 13, 2009, the date VKOSPI was announced, to September 9, 2011. To analyze the stationary process, we use the first-differenced volatilities and the corresponding stock market index (that is, S&P500 and KOSPI200) returns.<sup>8</sup>

We estimate the VAR model by using U.S. market data (S&P500 index returns and VIX) and Korean market data (KOSPI200 index returns and VKOSPI), separately. The first variable ( $Y_{1t}$ ) in the BVAR is the log return on the stock index and the second variable ( $Y_{2t}$ ) is the differenced implied volatility index in each market. Thus, the first error term,  $e_{1t}$ , indicates a positive return shock, and the second error term,  $e_{2t}$ , indicates a negative return shock. During the estimation procedure, we determine the lag-order of the VAR model by conducting a sequential likelihood ratio test, as in Rapach (2001). The test shows that the most appropriate number of lags for the VAR model is 6 and 8, respectively, for the U.S. and Korean market datasets. The estimated elements of the  $B^0$  matrix for the U.S. market data are somewhat different from those for the Korean market data: the coefficients estimates  $b_{11}$ ,  $b_{21}$ , and  $b_{22}$  are 0.0085 (0.0086), -0.3627 (0.0251), and 1.9059 (1.3794), respectively, for the U.S. (Korean) market data.<sup>9</sup>

Figures 1 and 2 show the dynamic impulse responses of stock returns and implied volatility to positive and negative return shocks for the U.S. and Korean

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<sup>7</sup> As in Lee (2010), we assume that  $b_{11}$  is greater than zero. We also take the higher value of the two possible solutions of  $b_{22}$ .

<sup>8</sup> The quoting unit for the stock indices is a point, and the volatilities are represented as percentages.

<sup>9</sup> For brevity, we present only the estimated element of the  $B^0$  matrix and the level of estimated coefficients related to the impulse responses (see Figures 1, 2, and 3). The estimated coefficients of  $A(L)$  can be provided by the authors upon request.

market data, respectively. The figures illustrate the asymmetric effects of positive (Panel A) and negative (Panel B) return innovations constructed to have the same magnitude (i.e.,  $b_{11}+b_{12}=0$ ).<sup>10</sup> To obtain the standard error bands of the impulse responses, we generate 1,000 bootstrap replications, as in Runkle (1987) and Rapach (2001). Figure 3 shows the upper and lower standard error bands for each impulse response.

Panel B of Figure 1 shows the response of changes in VIX to the S&P500 return shocks. Positive stock returns induce a decrease in volatility, and negative stock returns induce an increase in volatility. However, the magnitudes of the effects are quite different: negative return shocks have much stronger impacts on volatility changes than positive return shocks. The patterns of impulse responses shown in Figure 1 are consistent with the traditional hypotheses that explain the asymmetric volatility phenomenon.

The return-volatility relationship in the Korean market is somewhat different from that in the U.S. market. As shown in Panel B of Figure 2, both positive and negative return shocks initially influence volatility in the same direction, inducing an increase in volatility. However, a positive return shock induces only a slight initial increase in volatility, whereas a negative return shock induces a strong initial increase in volatility. That is, the negative return-volatility relationship induced by negative return shocks dominates the positive relationship induced by positive return shocks. As a result, consistent with previous studies, we observe asymmetric return-volatility relationships in the Korean market within KOSPI200 index return and VKOSPI data.

However, previous studies in this area employing the asymmetric GARCH model and simple regression approach have overlooked some unique features of the dynamic patterns of the volatility responses that exist in the emerging market, although they have reported the asymmetric volatility phenomenon. While the magnitude of the initial increase of the implied volatility in response to a positive return shock is small, this is in stark contrast with the result in the U.S. market in which the implied volatility decreases in response to a positive return shock. We attribute this unique pattern observed in the Korean market to the characteristics of

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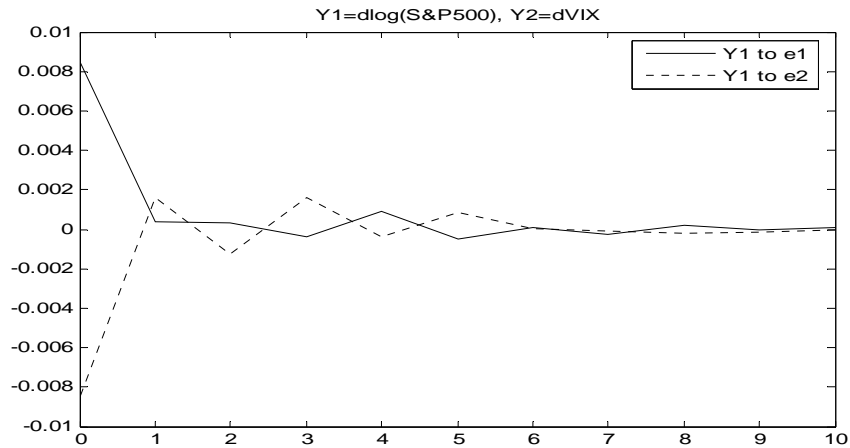
<sup>10</sup> Note that the two structural shocks,  $e_{1t}$  and  $e_{2t}$ , are normalized (i.e.,  $Var(e_t)=I$ ). Therefore, the figures present impulse responses of each variable to “unit” positive and negative shocks.



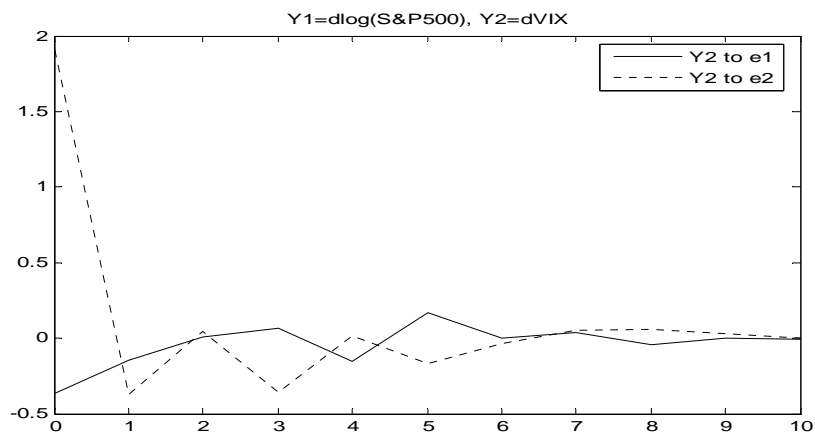
the KOSPI200 options market and the trading behavior in the Korean financial market.

Figure 1: Impulse responses in the U.S. market

Panel A: The impulse responses of the S&P500 return



Panel B: The impulse responses of change in the VIX

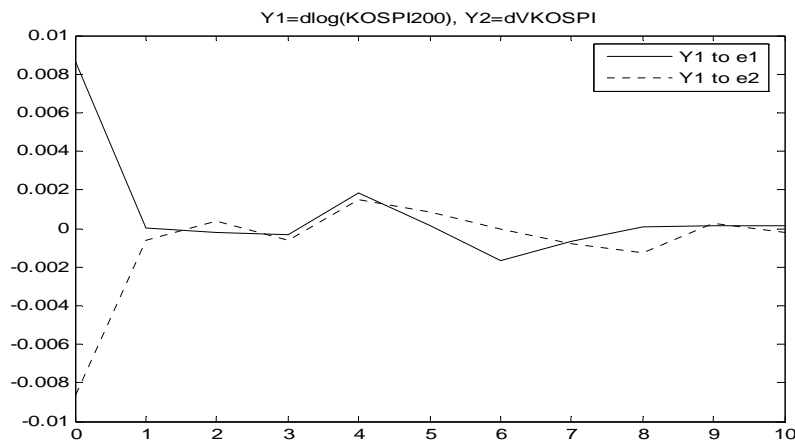


Notes: This figure shows the impulse responses of stock market return and volatility to positive and negative return shocks ( $e_{1t}$  and  $e_{2t}$ ) for the U.S. market. The VAR model used to calculate the impulse response is represented as follows:  $Y_t = B(L)e_t$ , where  $Y_t = [Y_{1t}, Y_{2t}]^T$ ,  $e_t = [e_{1t}, e_{2t}]^T$ , and  $L$  is a lag operator.  $Y_{1t}$  is the log return of the S&P500 index price, and  $Y_{2t}$  is the first-order difference of the VIX level. Panel A shows the impulse responses of the stock market return to positive and negative

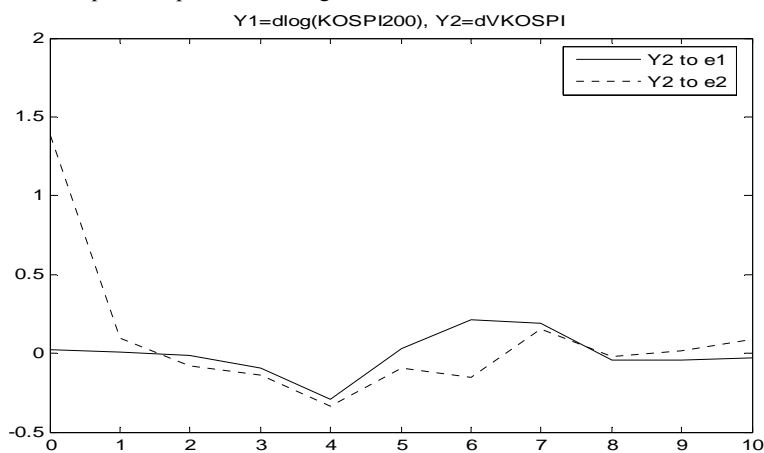
return shocks, and Panel B shows the impulse responses of the VIX change to positive and negative return shocks. The  $X$ -axis represents the passage of time after the shock (in terms of the trading days), and the  $Y$ -axis represents the magnitudes of coefficients of the impulse responses in each time interval.

*Figure 2: Impulse responses in the Korean market*

*Panel A: The impulse responses of the KOSPI200 return*



*Panel B: The impulse responses of change in the VKOSPI*



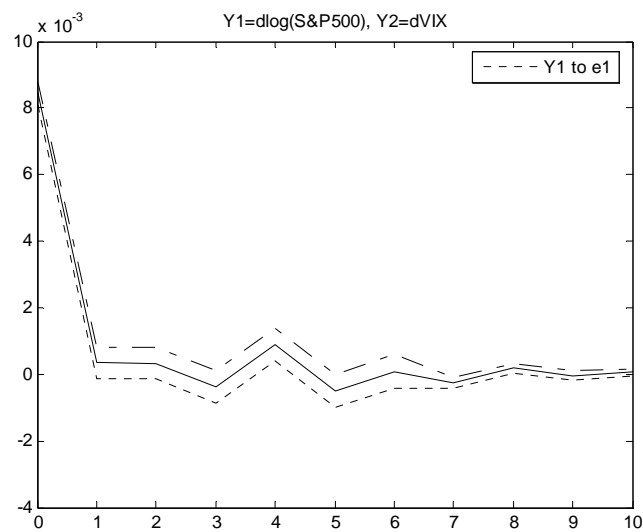
*Notes:* This figure shows the impulse responses of stock market return and volatility to positive and negative return shocks ( $e_{1t}$  and  $e_{2t}$ ) for the Korean market. The VAR model used to calculate the impulse response is represented as follows:  $Y_t = B(L)e_t$ , where  $Y_t = [Y_{1t}, Y_{2t}]^T$ ,  $e_t = [e_{1t}, e_{2t}]^T$ , and  $L$  is a lag operator.  $Y_{1t}$  is the log return of the KOSPI200 index price, and  $Y_{2t}$  is the first-order difference of the

VKOSPI level. Panel A shows the impulse responses of the stock market return to positive and negative return shocks, and Panel B shows the impulse responses of the VKOSPI change to positive and negative return shocks. The  $X$ -axis represents the passage of time after the shock (in terms of the trading days), and the  $Y$ -axis represents the magnitudes of coefficients of the impulse responses in each time interval.

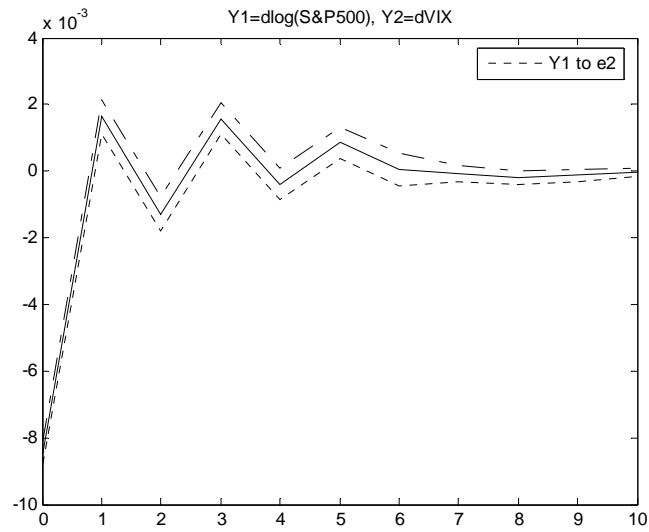
Figure 3: Standard error bands of the impulse responses

Panel A: United States (S&P500 and VIX)

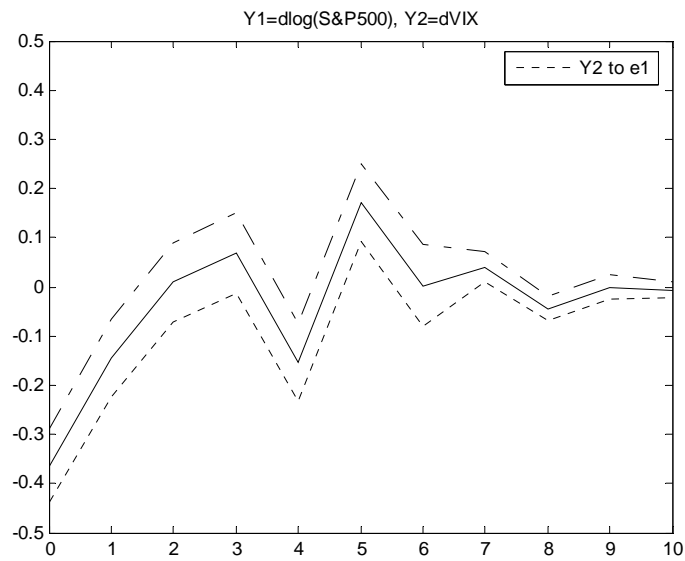
F1: Impulse response of the stock market return to a positive return shock



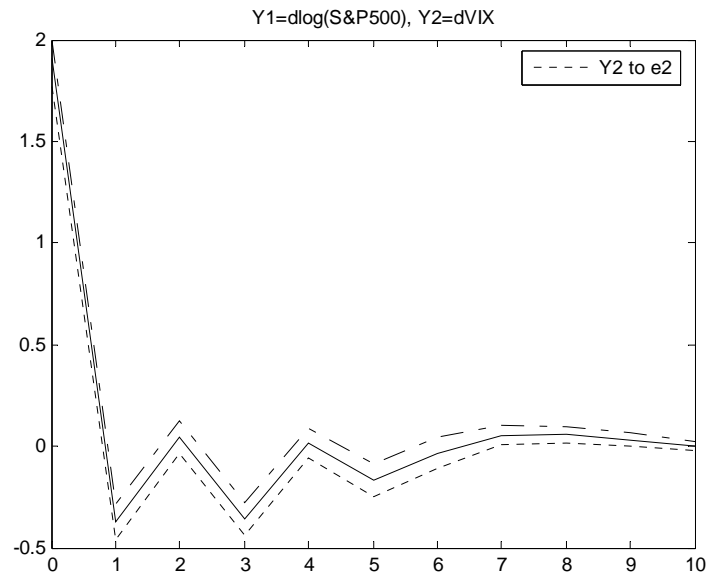
F2: Impulse response of the stock market return to a negative return shock



F3: Impulse responses of the volatility change to a positive return shock

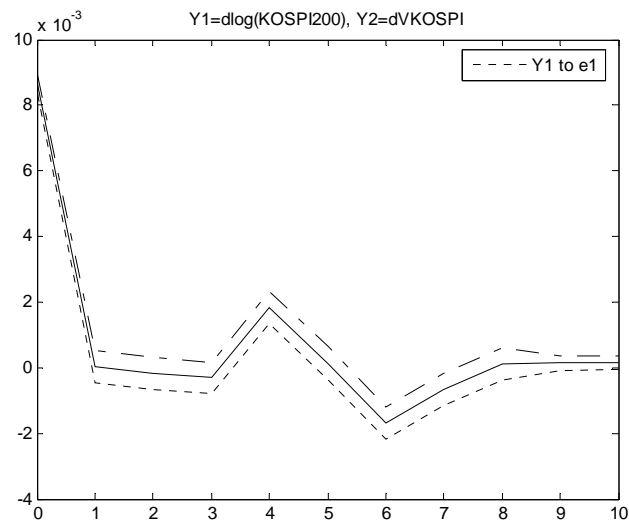


F4: Impulse responses of the volatility change to a negative return shock

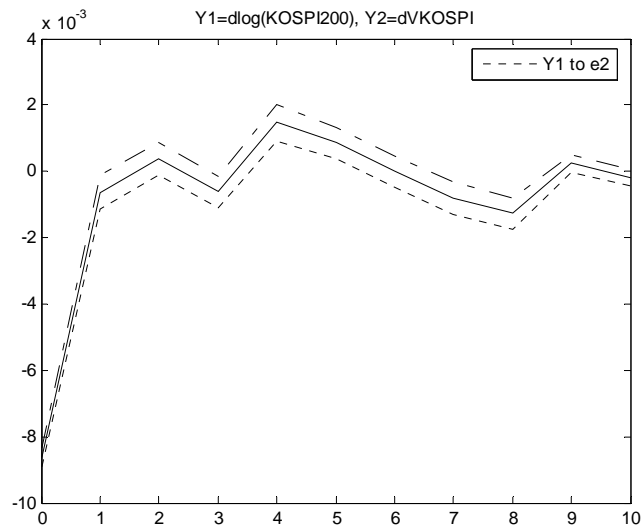


Panel B: Korea (KOSPI200 and VKOSPI)

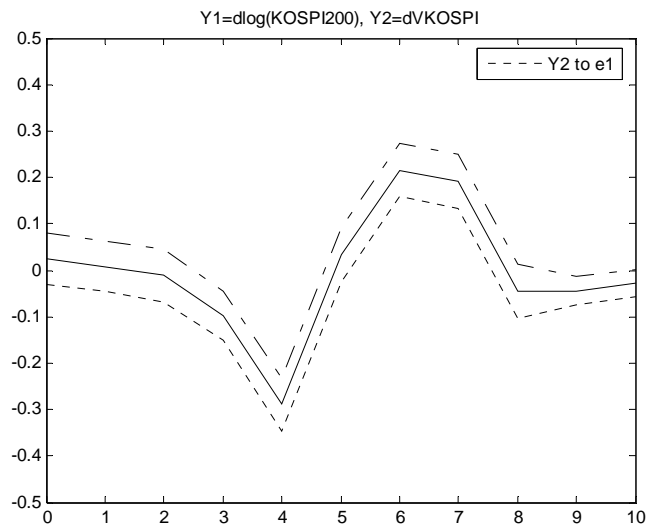
F1: Impulse response of the stock market return to a positive return shock



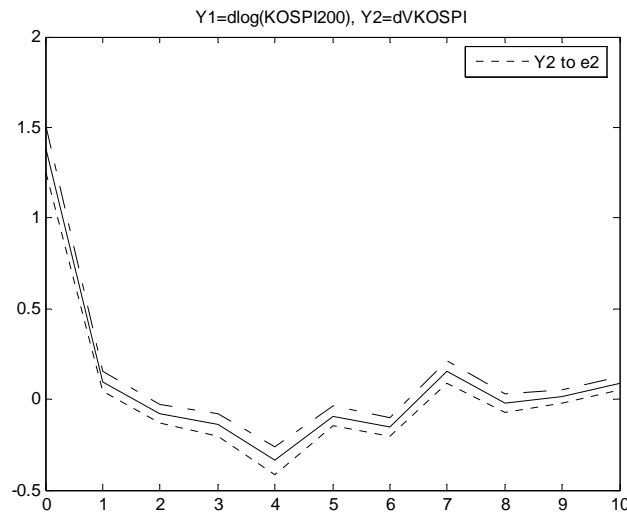
F2: Impulse response of the stock market return to a negative return shock



F3: Impulse responses of the volatility change to a positive return shock



F4: Impulse responses of the volatility change to a negative return shock



Notes: This figure shows the upper and lower standard error bands of each impulse response. The error bands are generated by 1,000 bootstrap replications. The VAR model used to calculate the impulse response is represented as follows:  $Y_t = B(L)e_t$ , where  $Y_t = [Y_{1t}, Y_{2t}]^T$ ,  $e_t = [e_{1t}, e_{2t}]^T$ , and  $L$  is a lag operator.  $Y_{1t}$  is the log return of the KOSPI200 index price, and  $Y_{2t}$  is the first-order difference of the VKOSPI level. Panel A (Panel B) shows the error bands of the impulse responses for the U.S. (Korean) market data. Impulse responses are presented in solid lines. Lower bands are presented in dotted lines, and upper bands are presented in dash-dot lines. The X-axis represents the passage of time after the shock (in terms of the trading days), and the Y-axis represents the magnitudes of coefficients of the impulse responses in each time interval.

One explanation for this pattern in the Korean market is that some options buyers overreact to the market signal. Uninformed or less informed traders tend to overly buy call options in response to a positive return shock, and this causes the additional increase of the call prices, leading to an increase of the implied volatility. If the magnitude of this increase is larger than that of the decrease caused by the positive return shock (as asymmetric volatility theories suggest), then the net effect we observe is an initial increase of the volatility in response to the positive return shock, as shown in Panel B of Figure 2. In contrast, traders might overly buy put options when they face a negative return shock, leading to an additional increase of the put prices and increased implied volatility. In this case,

the direction of the volatility change is consistent with asymmetric volatility theories (i.e., sharply increased volatility in response to a negative shock.).

Among market practitioners, it is widely believed that, in the KOSPI200 options market, domestic individual investors tend to regularly and overly buy options and overreact in response to positive news of the underlying market (Kim and Ryu, 2012). Further, the existence of special options accounts makes buying KOSPI200 options easier to implement than writing them. Since early in the history of the KOSPI200 options market, the KRX has promoted options trading by inducing individual investors to open special accounts that prohibit them from writing options, instead of requiring relatively lower levels of margin accounts. Given that noisy individuals with little wealth and trading experience prefer using the special accounts, they are even more likely to overreact and be affected by the behavioral biases. These tendencies seem to result in somewhat different patterns in the VKOSPI responses, compared to the U.S. market responses.

Table 1 reports the forecast error variance decomposition of stock returns and volatility and shows the proportion of returns and volatility that can be explained by positive and negative return shocks. In the United States as well as in Korea, more than 90% of the volatility forecast error variance is explained by negative return shocks. Further, for three trading days following the arrival of a negative return shock, it explains more than 99% of the forecast error variance of volatility in the U.S. market. In the Korean market, it explains a lower portion of about 96%. This suggests that the asymmetric volatility phenomenon is somewhat stronger in the U.S. market. In the Korean market, although the negative return shock plays a dominant role, compared to the U.S. market, the positive return shock shows a relatively significant influence on the dynamic stock-volatility relationship.



Table 1: Forecast error variance decomposition of stock returns and volatility

Panel A: United States (S&P500 return and VIX)

Days-ahead	0	1	2	3	4	5	6	7	8	9	10
Percent of return variance attributable to positive return shock	50.000	49.869	49.834	49.736	50.137	49.912	50.807	50.735	50.229	50.217	50.212
Percent of return variance attributable to negative return shock	50.000	50.131	50.166	50.264	49.863	50.088	49.193	49.265	49.771	49.783	49.788
Percent of IV variance attributable to positive return shock	0.032	0.035	0.042	0.529	4.373	4.403	6.348	7.783	7.866	7.944	7.948
Percent of IV variance attributable to negative return shock	99.968	99.965	99.958	99.471	95.627	95.597	93.652	92.217	92.134	92.056	92.052

Panel B: Korea (KOSPI200 return and VKOSPI)

Days-ahead	0	1	2	3	4	5	6	7	8	9	10
Percent of return variance attributable to positive return shock	50.000	49.135	48.624	47.866	48.085	47.941	47.943	47.962	47.961	47.957	47.958
Percent of return variance attributable to negative return shock	50.000	50.865	51.376	52.134	51.915	52.059	52.057	52.038	52.039	52.043	52.042
Percent of IV variance attributable to positive return shock	3.496	3.889	3.890	3.878	4.426	5.077	5.076	5.109	5.150	5.149	5.150
Percent of IV variance attributable to negative return shock	96.504	96.111	96.110	96.122	95.574	94.923	94.924	94.891	94.850	94.851	94.850

Notes: This table presents the forecast error variance decomposition of stock market returns and the decomposition of the implied volatilities. The VAR model used to calculate the coefficients is represented as follows:  $Y_t = B(L)e_t$ , where  $Y_t = [Y_{1t}, Y_{2t}]^T$ ,  $e_t = [e_{1t}, e_{2t}]^T$ , and  $L$  is a lag operator.  $Y_{1t}$  is the log return of the S&P500 or KOSPI200 index price, and  $Y_{2t}$  is the first-order difference of the VIX or VKOSPI level. The table presents the percent of each variance attributable to each orthogonal shock ( $e_{1t}$  or  $e_{2t}$ ) during the period that spans from the current date (time  $t$ ) to 10 days after the current date. Panel A shows the results for the U.S. market, and Panel B shows the results for the Korean market.

## 5 Conclusions

Employing the new VAR identification framework proposed by Lee (2010), this study clearly demonstrates the negative and asymmetric relationship between stock market returns and implied volatility in the U.S. and Korean markets. Additionally, we find differences in impulse response dynamics between the United States (a developed market) and Korea (an emerging market), which can be attributed to the unique characteristics and the market behavior of the KOSPI200 options market.

This paper demonstrates that the new VAR framework can be employed to investigate the asymmetric and dynamic relationship between two economic variables. A number of studies have examined various properties of the VIX, including asymmetric volatility, but few have focused on the VKOSPI. In this regard, this paper contributes to the literature by being the first to analyze the asymmetric and dynamic responses of the VKOSPI by employing the new VAR framework.

This study is expected to be a stepping-stone for further empirical research on the VKOSPI and other implied volatility indices of global financial markets. Some possible extensions are as follows. To describe the volatility dynamics, investigators might decompose the VKOSPI into observed and unobserved components based on state-space models (e.g., Kalman filtering). Researchers could apply signal noise filtering techniques to eliminate the noise that might be embedded in the VKOSPI.<sup>11</sup> Recently, the KRX has been preparing to launch some new derivatives underlying the VKOSPI (e.g., VKOSPI futures and VKOSPI options). The asymmetric volatility may show different patterns after these VKOSPI-related derivatives are actively traded.

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<sup>11</sup> However, considering the desirable properties and elaborate nature of the VKOSPI, explained in Section 2, their probability is relatively low.

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