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Variance risk premium in a small open economy with volatile capital flows: The case of Korea

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A B S T R A C T

This paper extends the research on the variance risk premium by considering a small open economy with volatile capital flows—the Korean economy. The empirical analysis in this paper finds that as in the US, the variance risk premium in Korea has a predictive power for the Korea Composite Stock Price Index (KOSPI) 200 stock returns over one-month and three-month horizons, indicating that it reflects the level of risk aversion in the Korean economy. The short-term forecasting ability of the variance risk premium is comparable to that of other popular predictor variables, such as the dividend yield and output gap. Moreover, a factor-augmented vector autoregression (FAVAR) analysis shows that the global liquidity sector is more important than the domestic macroeconomic sector in determining the variance risk premium. An increase in global liquidity significantly reduces both the variance risk premium and economic uncertainty.

1. Introduction

The variance risk premium (VRP) is defined as the difference between the option-implied variance (IV) and conditional variance for stock returns (CV). The IV and CV represent the expected future stock return variations under risk-neutral probability[1] and those under the actual (physical) probability, respectively. In particular, the discrepancy between those two probabilities for negative economic events (e.g., economic recessions or financial crises) reflects the degree of risk aversion in the market. In general, stock return variance tends to be high when an economy is in a bad state. Therefore, as pointed out by Bekaert, Hoerova, and Duca (2013), a higher VRP indicates that investors will react more fearfully to the emergence of negative economic developments. In line with this, Bekaert and Hoerova (2014) argued that the VRP and CV serve as measures for risk aversion and economic uncertainty, respectively.

In the past, research on the VRP focused on the topics related to financial engineering (e.g., derivative pricing) because stock market variance itself is an underlying asset for some financial derivative transactions. For example, an over-the-counter contract called the *variance swap* pays the difference between a standard estimate of the realized variance and the fixed variance swap rate. Carr and Wu (2009) showed that the variance swap rate is well approximated by the value of a particular portfolio of options, and proposed a direct and robust method for quantifying the VRP on financial assets.

Recently, Bollerslev, Tauchen, and Zhou (2009) examined the relationship between the VRP and future stock index returns. They presented a general equilibrium model allowing time-varying economic uncertainty, and showed that the VRP correlates positively with the level of risk aversion in the economy; thus a high (low) VRP predicts future high (low) aggregate market portfolio returns. Rosenberg and Engle (2002) and Bakshi and Madan (2006) made similar arguments. According to the empirical analysis of Bollerslev et al. (2009)

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[1] Risk-neutral probabilities are probabilities of future outcomes adjusted for risk. Under risk-neutral probability, the value of a financial asset (or related derivative value) is the expectation of its future pay-offs discounted by the risk-free rate.

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using the S&P 500 stock index, the VRP has the best forecasting performance on a quarterly horizon basis.[2] [3]

Bekaert et al. (2013) used the VRP to empirically investigate how risk aversion in economic agents affected the transmission mechanism of a central bank's monetary policy. To the best of my knowledge, their paper was the first to use the VRP to address a macroeconomic topic. Using the VRP (as a risk-aversion measure), the CV for stock index returns (as an uncertainty measure), the real Fed funds rate, and industrial production growth, they built a four-variable monetary vector autoregressive (VAR) model. Their analysis showed that a low interest rate policy would reduce risk aversion and meaningfully affect the real economy. Their result is similar in spirit to the risk-taking channel of monetary policy.

The studies described so far all focused on the US economy. In the present paper, I extend the research on the VRP to a small open economy with volatile capital flows—the Korean economy—to determine whether the main findings from the US economy also apply to the Korean economy. According to Kang (2012), capital flow volatility in Korea is substantially higher than in other emerging market countries, implying that the Korean economy is highly sensitive to changes in external economic environments.

Given the importance of capital flows in the Korean economy, I analyze the VRP in Korea, considering not only the domestic economy but also global liquidity, based on Bruno and Shin (2015a and b) and Kim et al. (2013), among others. They explain the mechanism by which the economic or financial situations of developed countries propagate into an emerging market through capital flows. In particular, they highlight the propagations of global liquidity through cross-border bank capital flows, and using the terms coined by Calvo, Leiderman, and Reinhart (1993, 1996), they emphasize the effect of the global "supply-push" factor on emerging market economies, rather than the country-specific "demand-pull" factor.

Similar in spirit to this paper, Yun (2019) investigates bond risk premia embedded in Korean government bonds. According to Yun (2019), the global liquidity factors, which have been extracted from the panel data set of various global liquidity variables, outperform the domestic macro factors in predicting excess bond returns in both in- and out-of-sample forecast analyses. The global liquidity and macroeconomic data sets used in Yun (2019) are also employed by the present paper.

I addressed several issues related to the VRP in Korea. To estimate the VRP, I needed to choose an accurate stock variance forecasting model, so I compared several monthly variance forecasting models for the KOSPI 200 index (the leading stock index of Korea) and performed a similar analysis for the S&P 500 index. Using the best volatility forecasting model for each index, I then estimated the VRPs for Korea and the US. In addition, I investigated the dynamic interactions between the two VRPs as a preliminary step for the remaining analysis.

Next, I analyzed the stock return forecasting ability of the VRP in Korea using monthly, quarterly, and annual KOSPI 200 returns. That analysis examined whether the VRP reflects the degree of risk aversion in the Korean economy as it does in the US economy. In addition, I considered other popular predictor variables, such as dividend yield, the price earnings ratio (PER), credit spread, term spread, and output gap, which have been studied for stock return predictability in past studies.

I studied the relationships among the VRP, economic uncertainty (proxied by CV), and domestic macroeconomic and global liquidity variables using regression and factor-augmented VAR (FAVAR) analyses. The FAVAR analysis is motivated by Bekaert et al. (2013), who applied the US VRP to a macroeconomic analysis of US monetary policy. However, the present paper differs from Bekaert et al. (2013) because I applied the FAVAR analysis using a large panel data set of economic indicators, and I included the global liquidity sector in my analysis to reflect the characteristics of the Korean economy.

The empirical analyses in this paper provide the following results. First, I found a close dynamic relationship between the VRPs of Korea and the US. This implies the possibility that risk aversion is globally propagated, suggesting the need to consider global factors in investigating the VRP in Korea.

Next, I also found that the VRP in Korea has short-term forecasting ability for stock index returns, such as monthly or quarterly returns. Thus, as in the US, the VRP in Korea likely reflects the level of risk aversion in the economy. The VRP's short-term forecasting ability is comparable to that of other popular predictor variables, such as the dividend yield and output gap.

Finally, the FAVAR analysis shows that the global liquidity sector is more important than the domestic macroeconomic sector in determining the VRP. Specifically, an increase in global liquidity reduces the VRP and economic uncertainty (measured by CV). However, as feedback to the domestic economy, the uncertainty shock is more significant than the VRP shock.

The rest of this paper is organized as follows. Section 2 explains finance theories related to realized variance and the VRP. Section 3 discusses the estimation results for the VRPs in Korea and the US. Section 4 examines the stock return forecasting ability of the VRP in Korea. Section 5 investigates the dynamic interactions among the VRP, economic uncertainty and global liquidity and domestic macroeconomic variables via regression and FAVAR analyses. Section 6 presents conclusions.

2. Realized variance and the variance risk premium

2.1. Realized variance

Since high-frequency stock price data (e.g., 5-min stock returns) became available, many studies have used realized variances in

[2] As a follow-up to Bollerslev et al. (2009), Bollerslev et al. (2014) conducted an empirical analysis of VRPs in eight developed countries: France, Germany, Japan, Switzerland, the Netherlands, Belgium, the United Kingdom, and the United States. That analysis confirmed that the findings of previous studies would hold in both the United States and other developed countries.

[3] Similar to the case of VRP, another option-based risk-aversion measure developed by Yoon (2017) has also shown short-term predictive power for future S&P 500 index returns.

stock variance forecasting analyses. The daily realized variance of stock returns is defined as the sum of the squares of intra-day high-frequency stock returns.

Realized variance is mainly used for stock variance forecasting. In the past, econometric models using daily asset returns (e.g., ARCH or GARCH models) were widely used for volatility forecasting. However, recent studies, pioneered by Andersen, Bolloerslev, Diebold, and Labys (2003), show that reduced-form models using realized variance seem to perform very well in forecasting volatility. These empirical analyses are well documented in a survey paper by Hansen and Lunde (2011).

To understand the concept of realized variance, suppose that a log stock price follows a conventional continuous-time diffusion process, as shown in Eq. (1).

$$dp(s) = \mu(s)ds + \sigma(s)dW(s), \qquad 0 \le s \le T, \tag{1}$$

where $\mu(s)$ and $\sigma(s)$ are the drift and spot volatility at time s (possibly, functions of some state variables), respectively, and $W(s)$ is a standard Brownian motion.

Next, define $p_{t,j}$ as the log stock price at time j ($j = 1,\ldots,M$) on date t when the stock trading period on date t is divided equally into $M + 1$ periods. Then, the continuously compounded intra-period returns can be expressed as Eq. (2).

$$r_{t,j} = p_{t,j} - p_{t,j-1}, \qquad j = 1, \ldots, M, \quad t = 1, \ldots, \quad T. \tag{2}$$

Next, the daily realized variance on date t is given in Eq. (3) using intra-period returns during date t. The subscript "$t-1,t$" explicitly indicates that intra-period returns are collected between the ends of the dates $t-1$ and t.

$$RV_{t-1,t} = \sum_{j=1}^{M} r_{t,j}^2, \qquad t = 1, \ldots, T. \tag{3}$$

As shown in Eq. (4), this daily realized variance is known to converge to the integrated spot variance on the same date as M tends to infinity.

$$RV_{t-1,t} \xrightarrow{p} \int_{t-1}^{t} \sigma(s)^2 ds \text{ as } M \to \infty. \tag{4}$$

In practice, however, there is a trade-off between bias and variance in estimating realized variance. Even though variance decreases as M increases, the bias also increases with the value of M because of market micro-structure noises such as the bid-ask bounce and discontinuous transactions. According to previous empirical studies about realized variance, 5-min interval data seems appropriate. Several studies have been conducted to improve the efficiency of estimating realized variance in response to market micro-structure problems (see Andersen and Benzoni (2009)).

The above discussion can be extended by introducing jump components into the stock price process. See Andersen, Bollerslev, and Diebold (2007) and Busch, Christensen, and Nielsen (2011) for further discussion.

2.2. *Variance risk premium*

As mentioned, the VRP on date t is defined as

$$VRP_t = IV_t - CV_t. \tag{5}$$

where IV_t is the option-implied variance of a given stock index (S&P 500 or KOSPI 200) over one month and CV_t ($\equiv E_t(RV_{t,t+22})$) is the conditional expectation of realized variance over the next month (22 trading days).

As for IV_t, the squares of VIX and VKOSPI can be used as a measure of IV_t for the S&P 500 and KOSPI 200, respectively. Both VIX and VKOSPI represent option-implied information about expected stock return variations under the *risk-neutral* measure for an upcoming month. Meanwhile, CV_t can be obtained in many ways. Recall that in contrast to IV_t, CV_t is the conditional expectation of stock return variations under the *actual* measure.

Given that stock return variations are very persistent, Bollerslev et al. (2009) assumed a random walk under which the expectation of future stock return variations is the current level of a stock returns' realized variance (i.e., $E_t(RV_{t,t+22}) = RV_{t-22,t}$). Their realized variance data are based on 5-min interval data. They use the New VIX index (source: CBOE) as an estimate for IV_t. As above, they estimated the VRP by computing difference between the option-implied and realized variances.

In contrast, Bekaert et al. (2013) and Bekaert and Hoerova (2014) estimated CV_t using a volatility forecasting model similar to the HAR-IV model proposed by Corsi (2009). To be specific, Bekaert and Hoerova (2014) decomposed the squared VIX index from the S&P 500 index options into stock market volatility (i.e., CV_t) and VRP and analyzed the predictive power of each component for future stock index returns. They used the heterogeneous autoregressive model of realized volatility (HAR-RV) by Corsi (2009) to estimate the stock market volatility and computed the VRP by subtracting the estimated stock market volatility from the VIX. In addition to stock index returns, they performed a forecast analysis on variables related to the real economy and financial stability.

If high-frequency stock index data are unavailable, the sum of daily stock-market returns can be considered the realized variance. This method was used by Bollerslev, Marrone, Xu, and Zhou (2014) to measure the VRP of eight countries. It turns out that the VRP is sensitive to the method of computing CV_t. Therefore, it is important to accurately estimate CV_t.

3. Estimating the variance risk premium

3.1. Data

Computing the VRPs for the KOSPI 200 and S&P 500 indexes using Eq. (5) requires measurements for both IV_t and CV_t. For IV_t, the VKOSPI (source: Korea Exchange; available from 2003) and VIX (source: CBOE; available from 1990) indexes provide the option-implied variance data for the KOSPI 200 and S&P 500, respectively.

For estimating the CV_t, several variance forecasting models, such as those in Corsi (2009), can be used. In practice, 5-min realized variance measures for stock indexes are commonly used in variance forecasting models. In this case, the daily realized variance adds together the squared 5-min intraday returns and the squared close-to-open return. Unfortunately, the 5-min realized variance is available for KOSPI (787 names), not for the KOSPI 200 (200 names). However, because the KOSPI 200 accounts for more than 80% of the market capitalization of KOSPI, the correlation coefficient between the two indexes is more than 0.99.

For both KOSPI and S&P 500, 5-min realized variance data are available under the heading "*.rv" in the Oxford-Man Institute's Realized Library database (Heber, Lunde, Shephard, and Shephard (2009)). Because VKOSPI is available from 2003, I use a sample period of 2003–2017 for KOSPI 200. For the S&P 500, I use a sample from 2001 to 2017.

3.2. Model selection for variance forecasting

As noted above, the VRP is sensitive to the method of computing CV_t, so it is important to accurately estimate CV_t using a proper variance forecasting model. For this purpose, I used the HAR-RV models, pioneered by Corsi (2009), which is a simple AR-type model for realized variance that can consider different variance components over daily, weekly, and monthly time horizons, as shown in Eq. (6). This model is known as having a low computational cost and excellent variance forecasting performance.

Since the pioneering work of Andersen et al. (2003), many realized variance studies have shown that realized variance is highly persistent and is likely to have a long memory property. Despite the absence of true long-memory properties (the HAR-RV model assumes an I(0)-stationary variance process), the HAR-RV model can generate a high persistence of volatility in a way that is typical of long-memory processes. In addition, the HAR-RV model exhibits excellent volatility forecasting performance. Eq. (6) provides a model specification for the HAR-RV model and can be estimated via simple ordinary least squares.

$$RV_{t+22}^{(22)} = \beta_0 + \beta_D RV_t^{(1)} + \beta_W RV_t^{(5)} + \beta_M RV_t^{(22)} + \varepsilon_{t+22} \tag{6}$$

where $RV_t^{(h)}$ is proportional to the sum of daily realized variances from $t-h$ to t. To compare the coefficients, the measurement units have been standardized to a monthly basis, assuming 22 business days in a month. Thus, $RV_t^{(h)}$ is defined as

$$RV_t^{(h)} = \frac{22}{h}\sum_{j=1}^{h} RV_{t+h-(j+1),t+h-j}. \tag{7}$$

As explained earlier, I calculated the VRP in Korea for the KOSPI 200 index (because VKOSPI is subject to the KOSPI 200 index), but the daily realized variance is available only for the KOSPI index, rather than the KOSPI 200 index. Therefore, in Eq. (6), the right-hand-side *independent* variables are the daily realized variances calculated by 5-min returns for KOSPI, but the left-hand-side *dependent* variable is the sum of the squared daily KOSPI 200 returns over 22 days. The S&P 500 has no index discrepancy problem, so both the independent and dependent variables in Eq. (6) are the daily realized variances based on 5-min realized variances.

Additional predictive variables can be added to Eq. (6) to improve the variance forecasting performance. For example, Busch et al. (2011) showed that adding the IV of options (using VIX) can improve the forecasting power. In this paper, I also consider the HAR-RV-IV model wherein the IV of options is incorporated as an additional variable. In the analysis below, each volatility index (i.e., the VKOSPI or VIX) is squared and divided by twelve to facilitate the comparisons of regression coefficients.

Panel (a) of Table 1 shows the HAR-RV and HAR-RV-IV estimation results for the KOSPI 200. Panel (b) reports the estimation results of the same models for the S&P 500. The estimation periods are the daily data during 2003–2017 for the KOSPI 200 (3,693 observations) and during 2001–2017 for the S&P 500 (4,276 observations).

As shown In Table 1, the estimation results from the HAR-RV model for the KOSPI 200 and S&P 500 are similar. All the explanatory variables are significantly estimated and the adjusted R-squares are about 50%. The estimation results from the HAR-RV-IV model (which includes the IV of options as a predictor variable) are also similar for the KOSPI 200 and S&P 500. The IV coefficients for both the KOSPI 200 and S&P 500 indexes are statistically significant at the 1% level. The adjusted R-squares also increased after adding the IV data. For example, in the case of the KOSPI 200, the adjusted R-square for the HAR-RV model was 0.472, which rose to 0.485 in the HAR-RV-IV.

However, in the case of KOSPI 200, the coefficient for $RV_t^{(22)}$ became statistically insignificant after incorporating VKOSPI as an additional explanatory variable in the HAR-RV-IV model. Therefore, I additionally considered the HAR-Gets model (applying the *general-to-specific* method to the HAR-RV-IV model), which removes $RV_t^{(22)}$. The adjusted R-square of this model was 0.484, similar to that of the HAR-RV-IV model. In an additional out-of-sample forecasting experiment (not reported here to save space, but available upon request), the HAR-Gets model was superior to the HAR-RV-IV model in terms of the root mean squared error and mean absolute error. Therefore, I selected the HAR-Gets model as the final variance forecasting model for CV estimation for the KOSPI 200.

Table 1
Estimation results of variance forecasting models for the KOSPI 200 and S&P 500.

	KOSPI 200			S&P 500	
	HAR-RV	HAR-RV-IV	HAR-Gets	HAR-RV	HAR-RV-IV
Intercept	0.001***	0.001	0.001***	0.001***	0.000*
	(0.000)	(0.024)	(0.000)	(0.000)	(0.000)
$RV_t^{(d)}$	0.099***	0.224***	0.043**	0.122***	0.089***
	(0.021)	(0.045)	(0.017)	(0.018)	(0.021)
$RV_t^{(w)}$	0.262***	0.224***	0.246***	0.307***	0.290***
	(0.046)	(0.045)	(0.074)	(0.114)	(0.107)
$RV_t^{(m)}$	0.300***	0.076		0.298***	0.162 *
	(0.097)	(0.170)		(0.091)	(0.096)
$VKOSPI_t^2$ (VIX_t^2)		0.361**	0.424***		0.190**
		(0.144)	(0.059)		(0.085)
Adj. R^2	0.472	0.485	0.484	0.576	0.581

This table shows the estimation results for the HAR-RV and HAR-RV-IV models from Corsi (2009). For the KOSPI 200, the HAR-Gets (general--to-specific) model is additionally considered. Each model forecasts overlapping one-month-ahead stock index return variations. The estimation samples are daily KOSPI data for 2003–2017 (3,693 observations) and daily S&P 500 data for 2001–2017 (4,276 observations). The numbers in parenthesis are standard errors which are computed using Max[3,2 × horizon] Newey-West lags. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

For the S&P 500, on the other hand, all the coefficients were significantly estimated in the HAR-RV-IV model, making consideration of a separate HAR-Gets model unnecessary. Therefore, to estimate the VRP and CV, I used the HAR-Gets and HAR-RV-IV for Korea and the US, respectively. Henceforth, when I need to clearly distinguish between the Korean and US VRPs (or CVs), I use the terms KOR-VRP and US-VRP (or KOR-CV and US-CV).

3.3. The variance risk premium in Korea and the US

Panel (a) in Fig. 1 depicts time-series plots for both the VRP and CV for the KOSPI 200 (i.e., monthly KOR-VRP and KOR-CV) from 2003 to 2017. As noted, the KOR-VRP is the difference between the squared VKOSPI (representing IV) and the KOR-CV measure (implied from the HAR-Gets model). The KOR-VRP rises during periods of financial instability, such as the subprime and European sovereign debt crises. Occasionally, the CV exceeds the IV, leading to a negative VRP.

For comparison purposes, both the VRP and CV are estimated for S&P 500 (i.e., monthly US-VRP and US-CV), as shown in Panel (b) in Fig. 1. As with the KOSPI 200, the US-VRP rises during times of major financial instability. As can be seen in Panel (b) in Fig. 1, the US-VRP is also sometimes negative.

Considering Korea's economic structure as a small open emerging market economy, the KOR-VRP can be expected to have a close dynamic relationship with the US-VRP. As shown in Table 2, I conducted a Granger causality analysis between the KOR-VRP and US-VRP.[4] According to that analysis, the US-VRP Granger-causes the KOR-VRP significantly at lags 2–4. This implies a transmission of risk aversion from the US to Korea.

Furthermore, to examine the dynamic relationship between the VRPs more closely, I examined a bivariate VAR model for the KOR-VRP and US-VRP. Consistent with the Granger causality results, the US-VRP is placed first in the ordering of the bivariate VAR, and the usual Cholesky factorization is used to identify orthogonalized shocks. The lag order of the VAR is set to three as a result of the application of the Akaike information (AIC) criterion.

Fig. 2 shows the impulse responses estimated from this bivariate VAR model. As expected, a positive US-VRP shock tends to increase the KOR-VRP significantly for a considerable time. The results of variance decomposition (not reported here) show that US-VRP shocks explain about 54% of the variations in the KOR-VRP, implying an international transfer of risk aversion from the US to Korea.

However, this impulse response analysis is sensitive to the order of variables. Therefore, US-VRP shocks are more likely to be a common global shock that affects both the US and Korean VRPs at the same time, rather than a US-specific VRP shock. The close relationship between the US and Korean VRPs thus suggests that global factors are important when analyzing the determinants of the VRP in Korea (KOSPI 200).

4. Predicting stock index returns

4.1. Squared VKOSPI, conditional variance, and variance risk premium

This section analyzes the predictive power of the KOR-VRP for KOSPI 200 returns. Bollerslev et al. (2009) and Bekaert et al. (2013) found that the US-VRP has predictive power for the aggregate market portfolio (proxied by the S&P 500 index) because it represents the

[4] Before the Granger causality tests, I performed unit root tests for both the US-VRP and KOR-VRP through an augmented Dickey-Fuller test including only drift. For each VRP, the null hypothesis of the unit root was rejected at the 1% significance level.

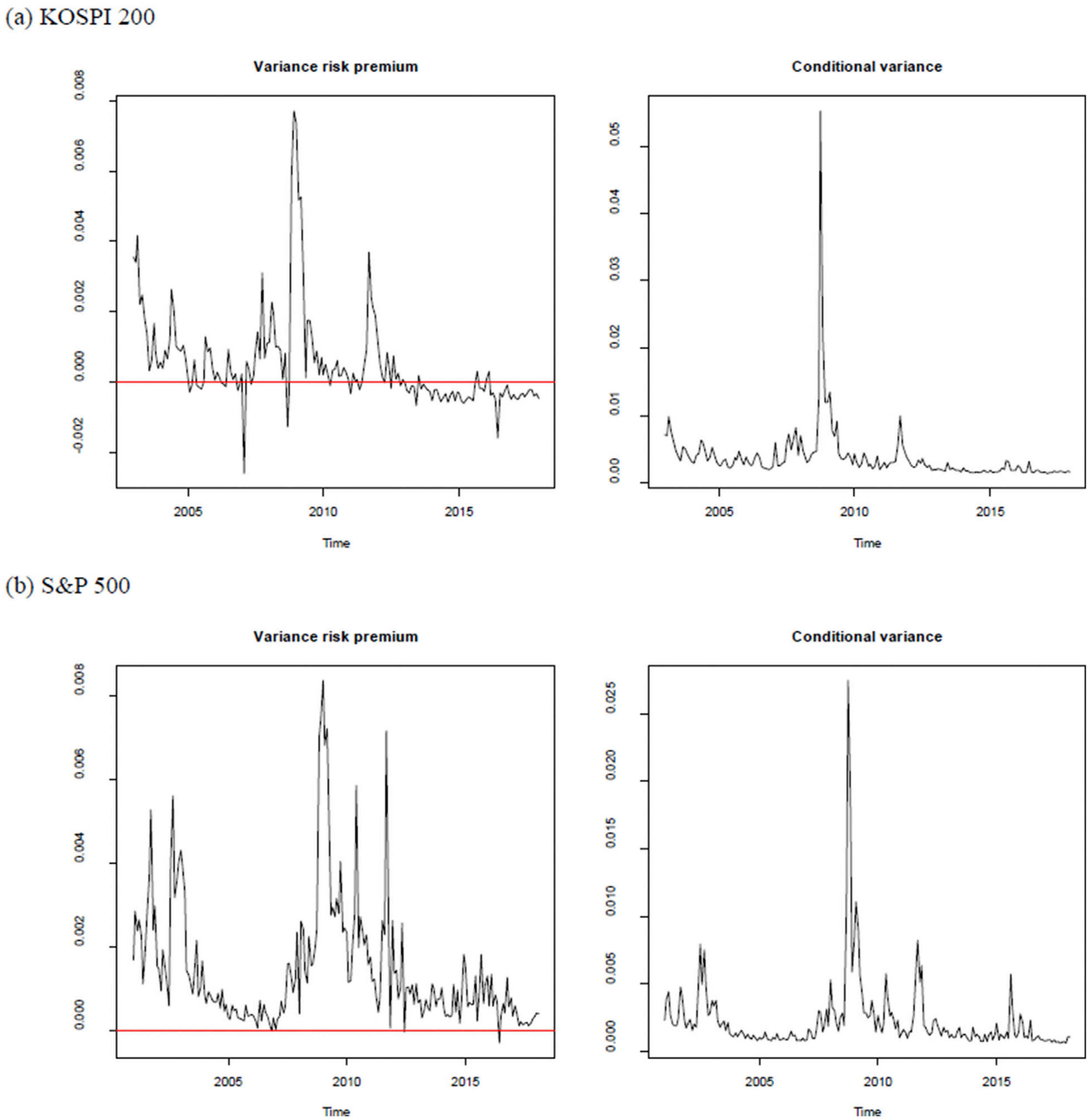


Fig. 1. Monthly estimates for the variance risk premiums (VRPs) and conditional variances for stock index returns (CVs) for (a) KOSPI 200 and (b) S&P 500. The estimation method for the VRPs and CVs is explained in Section 3.2. The sample periods are 2003–2017 for KOSPI 200 and 2001–2017 for S&P 500.

overall level of risk aversion in the economy. I next examine whether similar results apply to the KOR-VRP. In this section, all the VRPs and CVs are for Korea (KOSPI 200).

In Panel (a) of Table 3, two specifications are considered to predict the KOSPI 200 returns for each of monthly, quarterly, and annual horizons: (1) only the square of VKOSPI as a single predictor and (2) both CV and VRP, decomposed from the square of VKOSPI. Following Bekaert et al. (2014), the standard errors reported in Table 3 are computed using max$[3, 2 \times \text{horizon}]$ Newey-West (1987) lags.[5]

Panel (b) of Table 3 illustrates the same analysis using excess stock index returns, which are obtained by subtracting the risk-free

[5] Bekaert et al. (2014) suggested that this approach could improve the power of testing.

Table 2
Granger-causality tests for the variance risk premiums (VRPs) for Korea and the US.

H_0	Lags = 2	3	4	5	6
US-VRP≠>KOR-VRP	**0.025**	**0.041**	**0.043**	0.052	0.055
KOR-VRP≠>US-VRP	0.082	0.084	0.165	0.082	0.117

This table shows the p-values for the Granger-causality tests in both directions between the VRPs in the Korea and the US (denoted by KOR-VRP and US-VRP, respectively). Both VRPs are estimated as explained in Sections 3.2 and 3.3. The numbers in bold indicate significance at the 5% level.

rates (using the 1-year government bond discount rate as a proxy) from the actual stock index returns. The results in Panel (b) are very similar to the actual returns. Therefore, I focus on the actual returns in Panel (a).

Panel (a) in Table 3 shows that for both the monthly and quarterly returns, the decomposition of the squared VKOSPI into CV and VRP (corresponding to (2) above) significantly improves the predictive power for stock index returns. In particular, the coefficients for the VRP are statistically significant at the 5% level. For both the monthly and quarterly returns, when the squared VKOSPI alone is used as a single predictor (corresponding to (1) above), its coefficients are insignificant. On the other hand, when only the squared VKOSPI is included as a predictor for the annual return forecasts (corresponding to (1)), its coefficient is significant at the 10% level. When the squared VKOSPI is decomposed into VRP and CV (corresponding to (2)) for the annual return forecasts, only CV is significant at the 1% level, and the VRP is insignificant. These results suggest that the effectiveness of decomposing the squared VKOSPI for stock return prediction depends heavily on the forecasting horizons.

To better understand the predictive power of the VRP, CV, and squared VKOSPI across different forecasting horizons, Fig. 3 illustrates the variations in the estimation coefficients for the one-to twelve-month horizons when the (a) squared VKOSPI, (b) CV, or (c) VRP is set as a single predictor. In addition to those three variables, I consider other popular predictor variables that have been studied for stock return predictability in past studies. Those results (Panels (d)–(h) in Fig. 3) will be discussed in Section 4.2 below.

To facilitate comparisons among different predictors in the figures, each predictor variable is standardized to a zero mean and unit variance. The x-axis in each figure indicates the forecasting horizons, and the dotted lines represent the 90% confidence interval. Panels (a), (b), and (c) in Fig. 3 show that the squared VKOSPI and CV have similar significant predictive power over horizons longer than five months. On the other hand, the VRP has significant predictive power over short-term horizons of one to five months. These results are in line with those of previous studies using US stock indexes (e.g., S&P 500).

4.2. Variance risk premium and other popular predictor variables

As explained above, the VRP has short-term stock return predicting ability. Bollerslev et al. (2009) showed that in forecasting S&P 500 index returns, the US VRP outperforms other widely used stock return predictors, such as the PER, the corporate bond spread, and the consumption-wealth ratio (CAY in Lettau and Ludvigson (2001)). I next conduct a similar analysis for the VRP in Korea.

Table 4 shows that the stock return forecasts via the VRP and other popular predictor variables: dividend yield for KOSPI, PER for KOSPI,[6] credit spread (5-year AA-corporate bond yield minus 5-year treasury bond yield), and term spread (3-year treasury bond yield minus call rate). Additionally, the output gap represented by the industrial production (IP) gap is also considered as a predictor variable. The output gap is estimated via the Hodrick-Prescott (1997) filtering of the log of industrial production with a smoothing coefficient of 144,000. Cooper and Priestley (2009) have shown that the US output gap is a strong predictor for U.S. and G7 stock index returns. As a prime business cycle indicator that does not include the level of market prices, the output gap can be distinguishable from the other popular financial market predictors.

Table 4 shows the results for monthly, quarterly and annual return forecasts under two different specifications: (a) single variable predictions and (b) combined predictions using the VRP and one of the other variables. As before, to facilitate comparisons among different predictors, each predictor variable is standardized to a zero mean and unit variance.

In the single-variable predictions for monthly returns, the VRP is the only predictor that is significant at the 10% level. Its adjusted R-square is the highest at 2%. For this monthly horizon, combining the VRP with the credit spread increases the adjusted R-square to 3.7%.

In the single-variable predictions for quarterly returns, the IP gap is the most significant variable, with the highest adjusted R-square of 6.0%. The VRP is also significant, with an adjusted R-square of 4.6%.[7] When the two variables are jointly used for quarterly return forecasts, their adjusted R-square rises to 7.6%, indicating that the VRP contains additional information that the IP gap does not provide.

Finally, in the annual return forecasts, as in the US, the dividend yield shows excellent forecasting ability for stock index returns. Its adjusted R-square of 29.3% is much higher than that of the other variables. As in the results in the previous subsection, the predictive power of the VRP is not impressive for annual return forecasts.

In sum, the VRP shows good forecasting ability for monthly and quarterly return forecasts. Its predictive power for stock index returns is comparable to that of the other popular predictor variables.

Fig. 3 shows the forecasting ability of those predictor variables across 1–12 month forecasting horizons. Among them, the VRP,

[6] Both the dividend yield and PER for KOSPI are available from 2004, so the prediction samples for those variables (2004–2017) are shorter than for the other predictor variables (2003–2017).

[7] For quarterly returns in Table 4, dividend yield is not statistically significant, though its adjusted R-square of 4.9% is higher than that of VRP. This result is possible because of the shorter sample period used for the dividend yield (2004–2017) due to data availability.

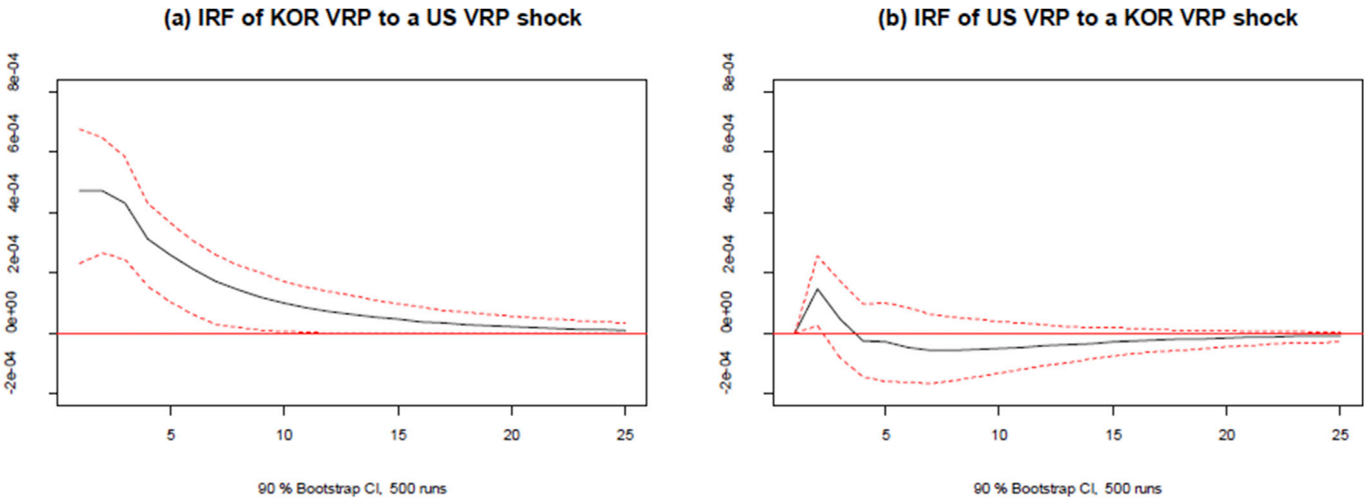


Fig. 2. Impulse responses from a bivariate vector autoregressive (VAR) model using monthly variance risk premiums (VRP) for Korea and the US. The US VRP is placed first in the ordering of the VAR. Structural shocks are identified via the Cholesky factorization. The lag order of the VAR model is set to two based on the AIC criterion. The sample period is 2003–2017. Dotted lines indicate 90% confidence intervals.

Table 3
KOSPI 200 return predictions via option-implied variance (IV), conditional variance for stock index returns (CV), and the variance risk premium (VRP).

	Monthly returns		Quarterly returns		Annual returns	
	(1)	(2)	(1)	(2)	(1)	(2)
(a) Actual returns						
Intercept	0.007*	0.008*	0.004	0.004	0.004	0.004
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
$VKOSPI_t^2$	0.175		0.844		0.666*	
	(0.902)		(0.914)		(0.359)	
CV_t		−1.239**		0.017		0.456***
		(0.540)		(0.271)		(0.104)
VRP_t		8.181**		5.526***		1.857
		(3.678)		(1.956)		(1.589)
Adj. R^2	−0.006	0.028	0.015	0.048	0.046	0.050
(b) Excess returns						
Intercept	−0.024***	−0.023***	−0.006	−0.006	0.002	0.002
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
$VKOSPI_t^2$	−0.501		0.618		0.610*	
	(0.833)		(0.939)		(0.368)	
CV_t		−1.789***		−0.167		0.410***
		(0.541)		(0.250)		(0.110)
VRP_t		6.788*		5.062**		1.741
		(3.578)		(2.051)		(1.628)
Adj. R^2	−0.004	0.021	0.005	0.033	0.037	0.040

For the monthly, quarterly, and annual KOSPI 200 returns, two different specifications are considered: (1) the IV (squared VKOSPI) is used alone as a single predictor, and (2) both the CV and VRP, decomposed from the IV, are used as joint predictors. The standard errors reported in the table are computed using Max[3,2 × horizon] Newey-West (1987) lags. The sample comprises monthly data for 2003–2017. Panel (a) provides the actual return predictions, and Panel (b) provides the excess returns predictions (The KOSPI 200 excess return is KOSPI 200 actual return minus the risk-free rate represented by the 1-year government bond discount rate).

dividend yield, and IP gap show remarkable predictive power: VRP performs well in the short run, dividend yield is best in the mid- and long-term, and the IP gap is highly predictive in almost all forecasting horizons. It is interesting to note that the strong predictive ability of the output gap, which was supported by Cooper and Priestley (2009), is also evident in Korea.

5. Relationships among the variance risk premium, global liquidity and macroeconomic variables

5.1. *Determinants of variance risk premium: regression analysis*

This section describes regression analyses about the determinants of the VRP in Korea. Given that the Korean economy is a small open emerging market economy, its VRP might be closely connected to global liquidity or capital flows. Considering that commonly used capital flow variables are available only at the quarterly frequency, I perform regression analyses, using the end-of-quarter VRP as a dependent variable in each quarterly regression. Using the end-of-quarter VRP as a dependent variable will also help to prevent potential endogeneity in the regressions.

I consider three candidate variables as capital-inflow indicators. The first is a capital inflow variable used in Choi, Kang, Kim, and Lee (2017), which is the sum of inbound direct investments, inbound portfolio investments, and inbound other investments (source: IFS) divided by the dollar-denominated GDP. The second variable is the bank capital flows used in Bruno and Shin (2015a, b), defined as the growth of cross-border loans in BIS-reporting banks on their banking sector counterparts in Korea (available from the BIS Locational Statistics). Because banks are still the most important institutions in the Korean financial market, the bank capital flows are expected to be an important capital-flow variable. Third, the US broker-dealer leverage is also considered. Among others, Forbes and Warnock (2012), Bekaert et al. (2013), Kim, Shin, and Yun (2013), Adrian and Shin (2014), and Bruno and Shin (2015a,b) have all highlighted the global banking channel, in which the bank leverage cycle plays a role in determining the transmission of financial conditions across borders through banking sector capital flow. Based on those past studies, I form a leverage factor using aggregate quarterly data on the levels of total financial assets and liabilities of security broker-dealers, as seen in Table L.129 of the Federal Reserve Flow of Funds. The leverage factor is defined as a log change in the level of the broker-dealer leverage.

In addition to those capital-inflow variables, I also consider indicators reflecting the foreign exchange market conditions: monthly growth rate of the won-dollar exchange rate (FX growth) and the log of realized variance of FX growth (FX-RV; this is the square root of the average daily squared FX growth over a quarter.). Furthermore, some indicators reflecting the state of the Korean macroeconomy are also used. As a business cycle indicator, I use the GDP gap, which is estimated via the Hodrick-Prescott (1997) filtering the log of GDP with a smoothing coefficient of 1600. Choosing the GDP gap as a business cycle indicator is based on the empirical finding in Section 4.2 that the forecasting ability of the IP gap for stock index returns is remarkable across almost all forecasting horizons. I consider the call rate (end-of-quarter) and M2 growth (quarter end-of-quarter) as indicating domestic liquidity conditions and consider CPI growth and

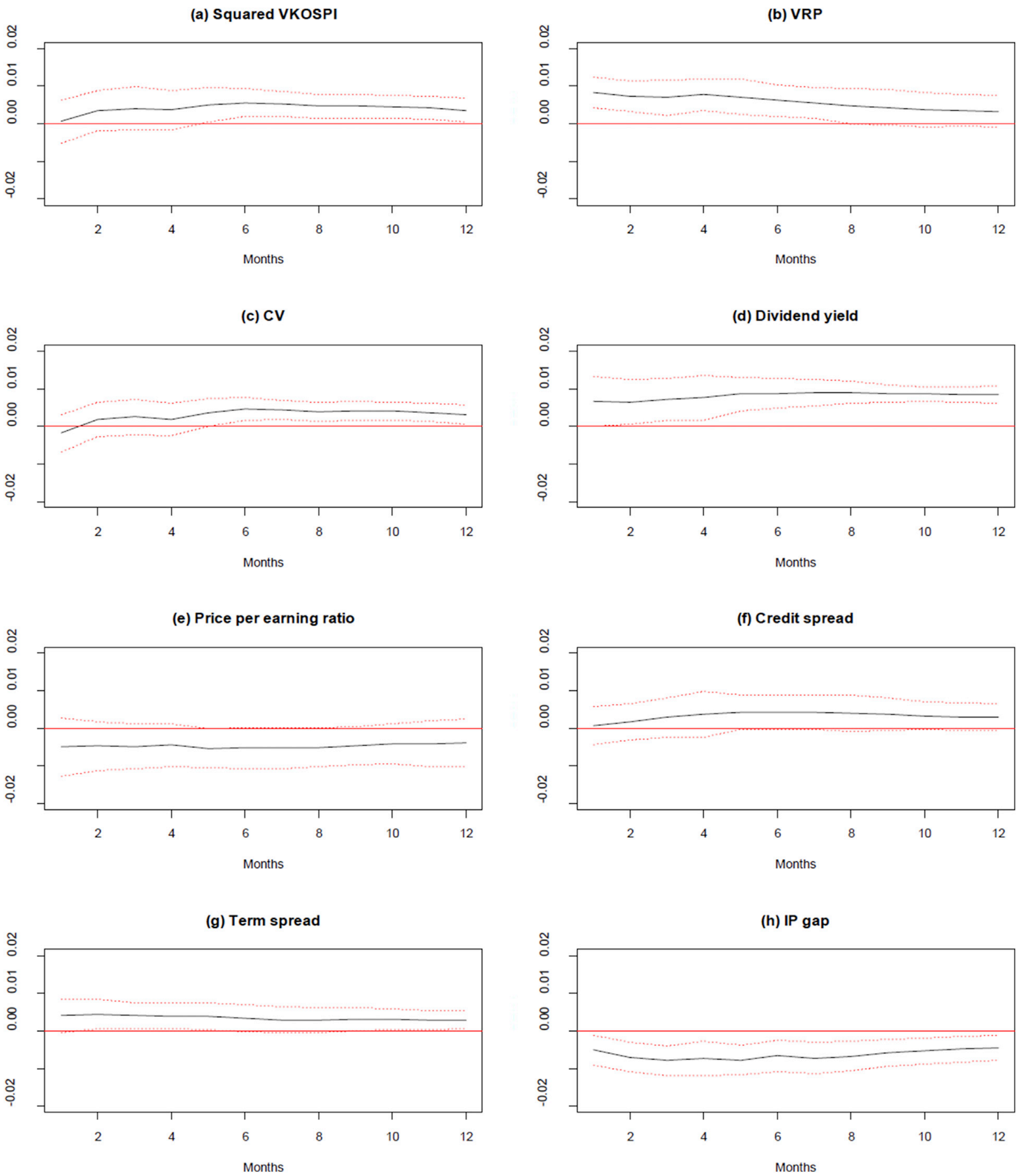


Fig. 3. KOSPI 200 return predictions via the variance risk premium (VRP) and other predictor variables. Each picture shows variations in the estimation coefficients for one-to 12-month horizons when each predictor variable is used as a single predictor. The details of the predictor variables are explained in Sections 4.1 and 4.2. In each figure, the x-axis indicates the forecasting horizons, and the dotted lines represent 90% confidence interval.

Table 4
KOSPI 200 return predictions via the variance risk premium (VRP) and other predictor variables.

	intercept		β_{VRP}		β_{other}		Adj. R^2
Monthly returns							
VRP	0.798*	(0.410)	0.846*	(0.441)	–	–	0.0202
Dividend yield	0.639	(0.429)	–	–	0.671	(0.542)	0.0109
PER	0.639	(0.430)	–	–	−0.502	(0.442)	0.0034
Credit spread	0.798*	(0.415)	–	–	0.070	(0.450)	−0.0055
Term spread	0.798*	(0.407)	–	–	0.411	(0.350)	0.0005
IP gap	0.798**	(0.404)	–	–	−0.514	(0.331)	0.0039
VRP + Dividend yield	0.639	(0.430)	0.566	(0.722)	0.386	(0.800)	0.0139
VRP + PER	0.639	(0.430)	0.680	(0.510)	−0.345	(0.488)	0.0139
VRP + Credit spread	0.798**	(0.392)	1.662*	(0.850)	−1.130	(0.783)	0.0369
VRP + Term spread	0.798*	(0.408)	0.794*	(0.444)	0.237	(0.302)	0.0166
VRP + IP gap	0.798**	(0.406)	0.759	(0.494)	−0.238	(0.446)	0.0164
Quarterly returns							
VRP	0.836	(0.526)	0.708**	(0.275)	–	–	0.0463
Dividend yield	0.637	(0.557)	–	–	0.720	(0.545)	0.0487
PER	0.637	(0.587)	–	–	−0.483	(0.420)	0.0185
Credit spread	0.836	(0.556)	–	–	0.291	(0.508)	0.0031
Term spread	0.836	(0.542)	–	–	0.413	(0.317)	0.0120
IP gap	0.836*	(0.493)	–	–	−0.798***	(0.259)	0.0604
VRP + Dividend yield	0.637	(0.548)	0.223	(0.425)	0.608	(0.654)	0.0468
VRP + PER	0.637	(0.561)	0.440	(0.319)	−0.381	(0.418)	0.0320
VRP + Credit spread	0.836*	(0.504)	1.040**	(0.485)	−0.461	(0.527)	0.0514
VRP + Term spread	0.836	(0.519)	0.648**	(0.272)	0.269	(0.246)	0.0480
VRP + IP gap	0.836*	(0.489)	0.480	(0.318)	−0.622**	(0.306)	0.0758
Annual returns							
VRP	0.735	(0.493)	0.341	(0.259)	–	–	0.0396
Dividend yield	0.654	(0.481)	–	–	0.870***	(0.139)	0.2927
PER	0.654	(0.641)	–	–	−0.411	(0.402)	0.0602
Credit spread	0.735	(0.488)	–	–	0.305	(0.225)	0.0305
Term spread	0.735*	(0.432)	–	–	0.301**	(0.152)	0.0295
IP gap	0.735*	(0.389)	–	–	−0.463**	(0.210)	0.0782
VRP + Dividend yield	0.654	(0.459)	−0.290	(0.382)	1.015***	(0.292)	0.3133
VRP + PER	0.654	(0.618)	0.128	(0.413)	−0.381	(0.483)	0.0602
VRP + Credit spread	0.735	(0.490)	0.252	(0.488)	0.123	(0.425)	0.0367
VRP + Term spread	0.735	(0.454)	0.289	(0.276)	0.238	(0.185)	0.0551
VRP + IP gap	0.735*	(0.414)	0.195	(0.340)	−0.390	(0.325)	0.0855

For the monthly, quarterly and annual KOSPI 200 returns, two different specifications are considered: (1) a single variable is used as a predictor, and (b) both the VRP and the selected variables introduced in Section 4.2 are used as joint predictors. All the predictor variables are standardized to have a zero mean and unit variance. The numbers in parenthesis are standard errors which are computed using Max[3,2 × horizon] NeweyWest (1987) lags. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.

GDP deflator growth (quarter-on-quarter growth) as indicating the domestic inflation.

Table 5 shows the results of quarterly regressions under various specifications. First, the capital inflow to GDP ratio (Eqs. (1) and (4)), bank capital flow growth (Eqs. (2) and (5)), and leverage factor growth (Eqs. (3) and (6)) are found to be statistically significant in most specifications (except for Eq. (6)). Reflecting favorable global-liquidity conditions, an increase in capital inflow or leverage seems to decrease the VRP.

As for the FX-related variables, the FX volatility (FX-RV in Eqs. (4)–(6)) is more significant than the FX growth rate (Eqs. (1), (2), and (3)). A rise in the FX volatility increases the VRP, as shown in Eqs (5) and (6). The FX volatility is an important risk factor, especially for foreign investors engaging in carry trades. For example, in the case of carry trade, in which foreign investors borrow in dollars and invest in Korean securities without hedging the FX risk, FX volatility serves as an important investment risk source.

It appears that domestic macroeconomic variables are also important in determining the VRP. The GDP gap provides a significant negative sign for all specifications, which is consistent with the results for the forecasting ability of the IP gap in Section 4.2. The call rate has a significant positive sign. In addition, domestic inflation, as represented by CPI growth (Eqs. (1), (2), and (3)) or GDP deflator growth (Eqs. (4) and (5)), tends to increase the VRP.

In this static regression analysis, global capital flow variables and domestic macroeconomic conditions are all important in determining the VRP. In the next section, I examine the relative importance of those variables from a more dynamic perspective through the FAVAR analysis.

5.2. FAVAR analysis

This section analyzes the dynamic interactions among the VRP, CV, and the global liquidity and domestic macroeconomy sectors through a FAVAR analysis. As noted above, the VRP and CV have macroeconomic interpretations as measures for risk aversion and economic uncertainty, respectively. The FAVAR analysis in this paper is motivated by Bekaert et al. (2013), who examined dynamic

Table 5
Quarterly regression analysis: determinants for variance risk premium.

	(1)	(2)	(3)	(4)	(5)	(6)
Capital inflow to GDP ratio	-.546***			-.821***		
	(0.286)			(0.193)		
Bank capital flow growth		−0.578**			−0.374*	
		(0.259)			(0.194)	
Leverage factor growth			−1.015**			−0.599
			(0.435)			(0.382)
FX growth	0.047	0.442	0.603			
	(0.469)	(0.391)	(0.415)			
Log(FX RV)				4.267	4.965**	4.924**
				(2.815)	(2.049)	(2.334)
GDP gap	−7.094***	−7.869***	−6.192***	−5.970***	−6.079***	−5.262***
	(2.375)	(2.340)	(1.743)	(2.195)	(2.313)	(1.779)
Call rate	4.902***	4.802***	5.129***	6.491***	6.419***	6.361***
	(1.207)	(1.152)	(1.105)	(1.601)	(1.339)	(1.291)
M2 growth	2.591	2.987*	1.269	0.462	0.827	−0.001
	(1.761)	(1.721)	(1.655)	(1.818)	(1.840)	(1.706)
CPI growth	8.375***	6.099*	3.686			
	(2.875)	(3.576)	(3.375)			
GDP deflator growth				4.982**	5.195**	4.879**
				(2.150)	(2.106)	(2.147)
Intercept	-.319***	-.976***	-.054***	−9.066*	−0.541**	−9.836*
	(4.437)	(4.676)	(4.209)	(5.267)	(5.024)	(5.420)
Adj. R^2	0.516	0.452	0.447	0.570	0.559	0.543

This table reports quarterly regression results for the determinants of the variance risk premium for Korea (sample period: 2003:Q1–2017:Q4). The dependent variable is the end-of-quarter variance risk premium. The details of the explanatory variables are described in Section 5.1. The numbers in parentheses are standard errors which are computed using Max[3,2 × horizon] Newey-West (1987) lags. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

interactions among the VRP, CV, and US macroeconomic variables through a four-variable VAR (industrial production, real federal fund rates, CV, and VRP). However, to use more macroeconomic indicators representing the state of the Korean economy, I use a FAVAR model based on Bernanke, Boivin, and Eliasz (2005), Boivin and Giannoni (2009), and Gilchrist, Yankov, and Zakrajsek (2009). The global liquidity sector is also included in the FAVAR system to reflect the features of a small open emerging market economy, which differ from the US economy. Therefore, the FAVAR model in this paper considers two broad sectors: global liquidity and macroeconomic sectors. This FAVAR model can summarize many global liquidity and macroeconomic indicators using a small number of unobservable factors.

In particular, the importance of global liquidity in analyzing the VRP in Korea has been indicated by the empirical finding in the previous section that economic variables such as capital flows are important in determining the VRP. For emerging market economies, several past studies have emphasized the importance of "supply-push" capital flows rather than country-specific "demand-pull" capital inflows. The global liquidity sector in the FAVAR is closely related to these "supply-push" capital flows.

Let X_t denote a vector of all the observable variables in the FAVAR system. X_t can be partitioned as $X_t \equiv [X_t^{GL'}\ X_t^{M'}\ CV_t\ VRP_t]'$, where the $(N^{GL} \times 1)$ vector X_t^{GL} corresponds to the measures of global liquidity; the $(N^M \times 1)$ vector $X_t^{M'}$ corresponds to the measures of the macroeconomy and financial markets in Korea; and CV_t and VRP_t are, as defined above, the conditional variance for stock index returns and the variance risk premium, respectively. The information in X_t^{GL} and X_t^M is assumed to be summarized by the $(K^{GL} \times 1)$ vector GLF_t and the $(K^M \times 1)$ vector MF_t, respectively. The number of common factors in each category is assumed to be small relative to the number of observable variables; that is, $N^{GL} \gg K^{GL}$ and $N^M \gg K^M$. Now a vector of the factors in the FAVAR system is defined as $F_t \equiv [GLF_t'\ MF_t'\ CV_t VRP_t\ ]'$. Whereas the last two factors CV_t and VRP_t are observable, both GLF_t and MF_t are latent factor vectors.

The relationship between the observed variables X_t and the factors F_t is given by the following observation equation:

$$X_t = \Lambda F_t + \nu_t, \tag{8}$$

where the factor loading matrix Λ is defined as

$$\Lambda = \begin{bmatrix} \Lambda_{11} & \Lambda_{12} & 0 & 0 \\ \Lambda_{21} & \Lambda_{22} & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

with appropriately defined conformable matrices of Λ_{11} $(N^{GL} \times K^{GL})$, Λ_{12} $(N^{GL} \times K^M)$, Λ_{21} $(N^M \times K^{GL})$, and Λ_{22} $(N^M \times K^M)$, and where $\nu_t \equiv [\nu_{tM}^{GL'}\ \nu_t^{M'}\ 0\ 0]'$ denotes the $(N^{GL} + N^M + 2) \times 1$ vector of idiosyncratic measurement errors. The measurement error vector ν_t is

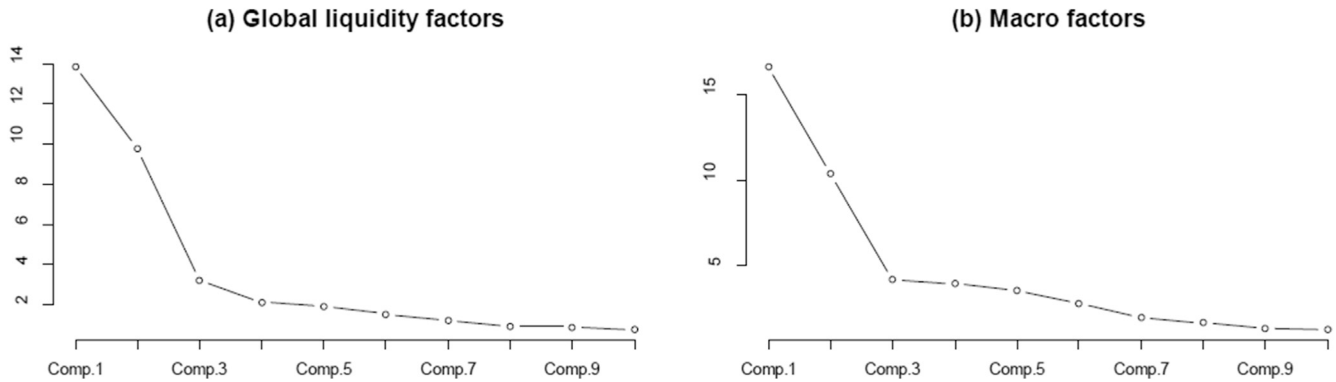


Fig. 4. Scree plots for global liquidity factors and macroeconomic factors. Each figure shows eigenvalues (variances) on the y-axis and the identification of factors on the x-axis.

Table 6
Forecast error variance decomposition.

	GLF1	GLF2	MF1	MF2	MF3	MF4	CV	VRP
(a)CV								
12-months	20.1%	19.1%	2.8%	10.9%	0.8%	0.8%	39.5%	5.9%
24-months	19.1%	20.0%	3.6%	10.9%	1.2%	0.9%	37.9%	6.4%
(b) VRP								
12-months	16.1%	18.3%	2.3%	15.4%	1.7%	0.8%	18.2%	27.1%
24-months	14.4%	18.9%	3.8%	16.0%	2.5%	1.0%	17.9%	25.5%

This table reports the results of forecast error variance decomposition for the CV and VRP for 12- and 24-month horizons. They are estimated from the reduced-form estimation of the FAVAR model in Eq. (9) in Section 5.2. The details of the FAVAR model are explained in Section 5.2.

allowed to be serially correlated and weakly correlated across different elements.

To identify the vector of macroeconomic factors MF_t, the restriction of $\Lambda_{12} = 0$ is imposed, which implies that once GLF_t is conditioned, the remaining information in X_t^M has a systematic component specific to the state of the Korean macroeconomy that is reflected in its own factor structure. This restriction is similar to what Gilchrist et al. (2009) used. They identified their credit factors using a similar restriction. The second identifying assumption is that the factors in GLF_t and MF_t are orthogonal, separating the residual information in X_t^M from GLF_t.

The dynamics of the factors F_t are described by an autoregressive process in the form

$$F_t = \Phi(L)F_{t-1} + e_t, \tag{9}$$

where $\Phi(L)$ denotes a matrix polynomial in the lag operator L of finite order p, and e_t is the $(K^{GL} + K^M + 2)$ vector of reduced-form VAR disturbances with a covariance matrix of Σ. It is assumed that the idiosyncratic measurement error vector ν_t is uncorrelated with the VAR innovation vector e_t. The impulse response analysis that follows is based on the Cholesky factorization of the covariance matrix Σ.

The number of observable variables in the global liquidity and macroeconomic sectors is set as $N^{GL} = 40$ and $N^M = 59$, respectively. The number of common factors in each sector is set as $K^{GL} = 2$ and $K^M = 4$. A full list of observable variables in each sector and the transformation method used for each variable to guarantee stationarity[8] are described in the Appendix. As noted above, I use the same data sets of global liquidity and macroeconomic variables as in Yun (2019), where bond risk premia in Korea are estimated through a factor analysis. Below, I provide descriptions of the list of variables.

Most of the underlying data for the global liquidity sector are financial data from the G4 countries (the US, the UK, Euro area, and Japan), together with some stock indexes from certain countries in the Euro area, such as DAX in Germany and CAC40 in France. To be specific, there are 9 monetary aggregates, 14 interest rates, 3 real effective exchange rates, 5 stock indexes, 5 stock realized volatilities, and 3 options-implied stock index volatilities. Among them, realized volatility is defined as the standard deviation of daily stock returns over a corresponding month.

Second, the macroeconomic factors are extracted from a panel dataset of 59 macroeconomic and financial market variables in Korea chosen to represent broad categories of macroeconomic and financial market time series (the number of variables are in parentheses.): production (21), employment (1), monetary aggregates (4), inflation (10), exchange rates (4), housing prices (2), interest rates (7), stocks (2), and current account (8).

To estimate the common factors in each sector, I conduct a principal component analysis (PCA)[9] based on Bernanke et al. (2005), Boivin and Giannoni (2009), and so on. The estimation method for factors is based on the two-step method, reflecting the above-mentioned restrictions ($\Lambda_{12} = 0$ and the orthogonality between GLF_t and MF_t). First, global liquidity factors are extracted using a usual PCA. Next, I regress each macroeconomic variable on the global liquidity factors and take the resulting residuals. Then, I use those sets of residuals to estimate the common macroeconomic factors through a PCA.

To adequately summarize the information in each sector, there is a need to determine the number of factors for each sector, K^{GL} and K^M. Among the various methods for doing so, I take the rather informal approach of using both scree plots and cumulative variances. A scree plot shows the eigenvalues on the y-axis and the number of factors on the x-axis. One can choose the number of factors by observing the point at which the slope of the curve is clearly leveling off. The scree plots for both the global liquidity and macroeconomic sectors are illustrated in Fig. 4. Moreover, I select the number of factors for each sector so that the proportion of the cumulative variance (the sum of the eigenvalues) would reach about 60%. Therefore, I set $K^{GL} = 2$ and $K^M = 4$. For each sector, the corresponding cumulative variance ratios are 59.1% and 59.6%, respectively. However, it is worth mentioning that my separate exercises (not reported

[8] The transformation rule is based on what central banks (particularly the Bank of Korea) really monitor when they assess the global liquidity and domestic macroeconomic environment. For example, I apply a year-on-year log difference transformation to macroeconomic variables, such as industrial production, price indexes, and monetary aggregate variables, and a month-on-month difference transformation to financial market variables such as stock indexes or exchange rates.

[9] Given the number of factors r in a given sector, all the variables in that sector are standardized to a zero mean and unit variance, and the covariance matrix for those standardized variables is estimated. The largest r eigenvalues are taken from that covariance matrix, and the r factors are computed by using the corresponding eigenvectors as the weights for the variables.

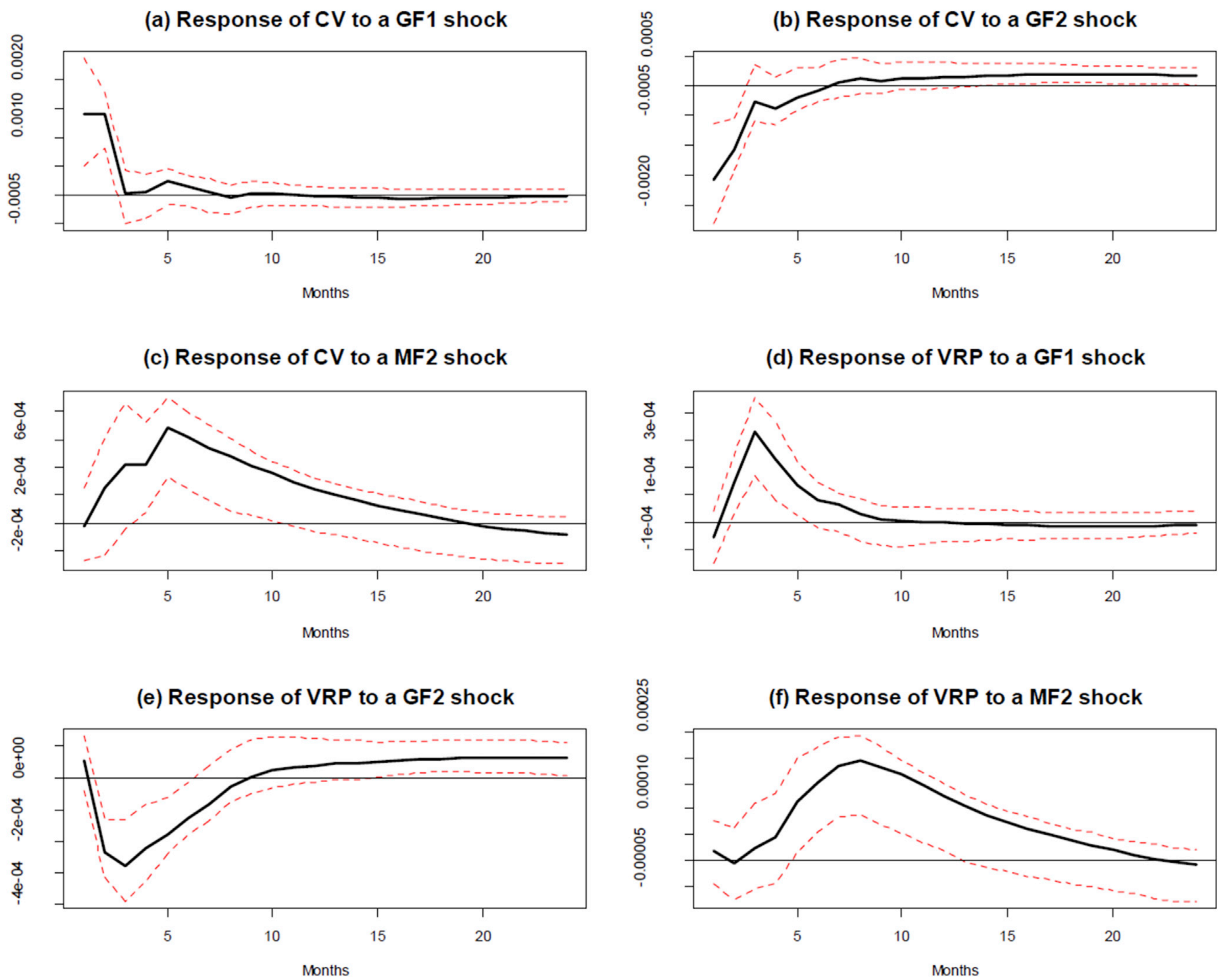
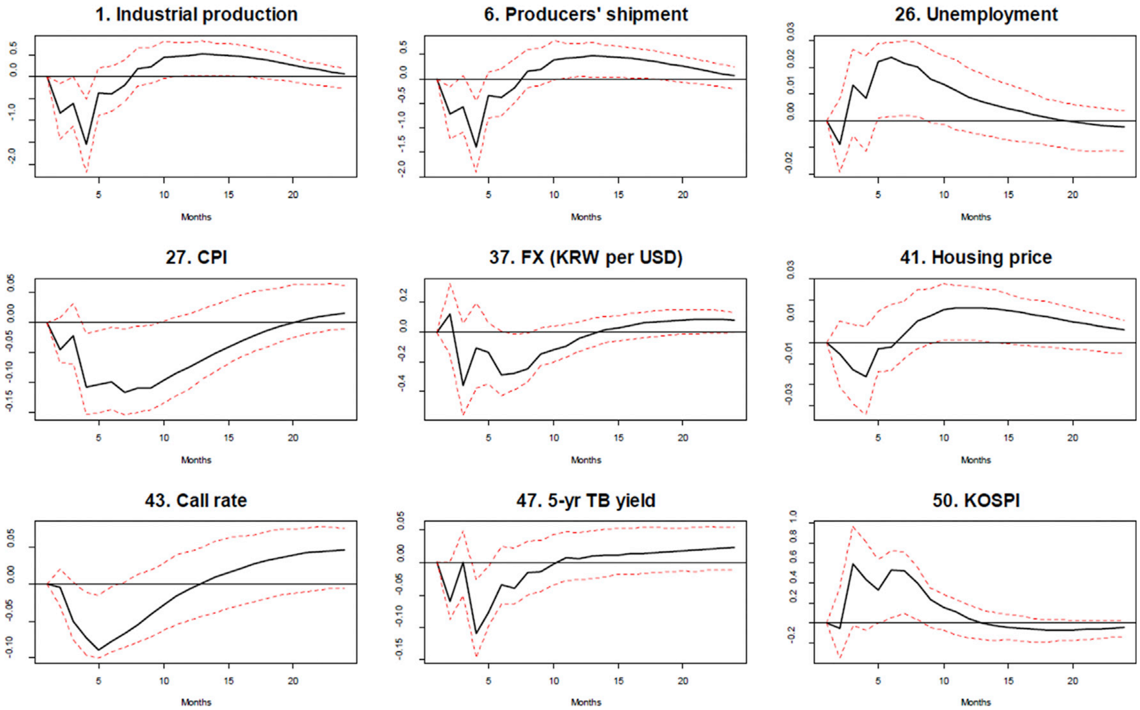


Fig. 5. Impulse responses of the conditional variance for stock index returns (CV) and variance risk premium (VRP). Given the FAVAR model described in Section 4.6, each figure depicts the effects of an orthogonalized one-standard-deviation shock to a selected global liquidity or macroeconomic factors (GF1, GF2, and MF2) on the CV or VRP. The details of the FAVAR model are explained in Section 5.2. The dotted lines represented 90-percent confidence intervals computed using a bootstrap with 500 replications.

(a) CV shock



(b) VRP shock

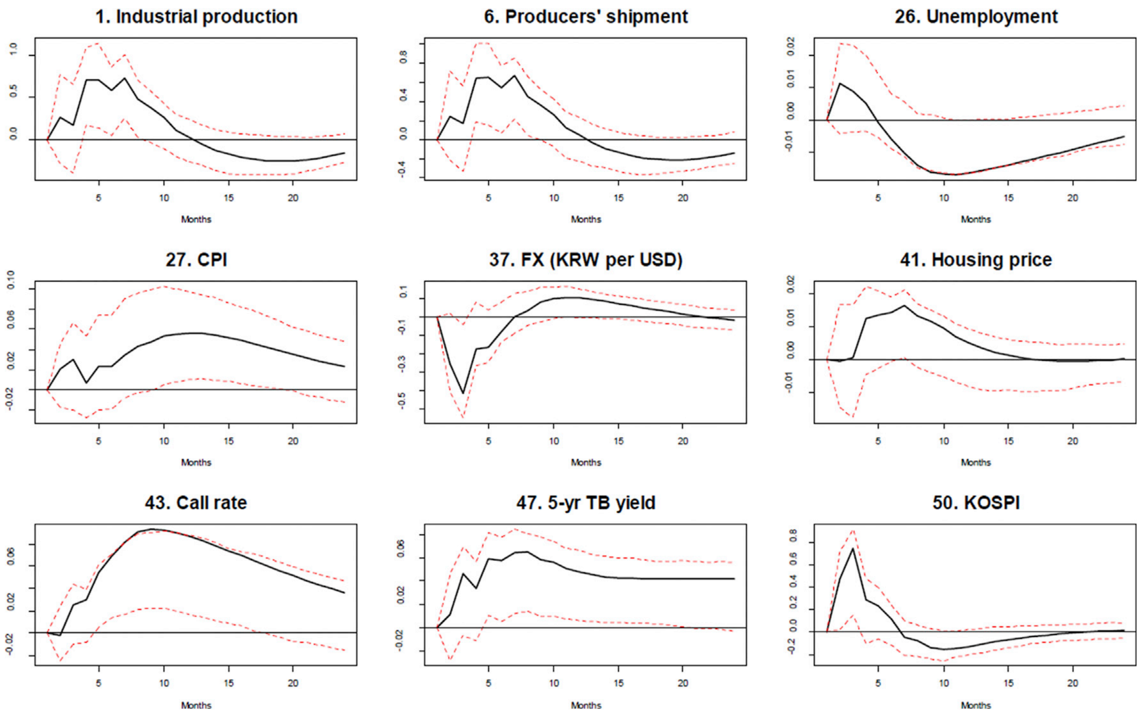


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Fig. 6. Impulse response of selected macroeconomic variables to a conditional variance for stock index returns (CV) or variance risk premium (VRP) shock. Given the FAVAR model described in Section 4.6, each figure depicts the effects of an orthogonalized one-standard-deviation shock to either the CV (Panel (a)) or VRP (Panel (B)) on a selected macroeconomic or financial market variable. The dotted lines represented 90-percent confidence intervals computed using a bootstrap with 500 replications.

here) shows that the empirical results in this paper do not change much from selecting different numbers of factors.

Next, I conduct the economic interpretations of the factors obtained through the PCA. First, the three variables most highly correlated with the first element of GLF_t, say $GLF_t^{(1)}$, are the UK 3-month LIBOR (0.958), Japan's M3 growth (−0.930) and the US 5-year T-bond yield (0.913). Therefore, $GLF_t^{(1)}$ can be interpreted as having an inverse relationship with global funding conditions. On the other hand, the second global liquidity factor, $GLF_t^{(2)}$, is most highly correlated with the FTSE realized volatility (−0.925), CAC realized volatility (−0.920), and S&P 500 realized volatility (−0.917)). Thus, $GLF_t^{(2)}$ likely reflects financial market uncertainty.

Among the macroeconomic factors, the forecasting error variance decomposition results below show that the second element of MF_t is the only factor that is significantly related to the VRP and CV. $MF_t^{(2)}$ is most highly correlated with the variables related to economic activity and the business cycle, such as the shipment index for non-durable consumer goods (−0.614), shipment index for durable consumer goods (−0.559), and industrial production for non-durable consumer goods (−0.556).

After estimating GLF_t and MF_t, the reduced form of the dynamic factor model in Eq. (9) can be estimated. The lag order of this VAR model is set to 3 based on the AIC criterion. Orthogonalized shocks are identified through the usual Cholesky factorization and the estimation results of Eq. (9). Table 6 shows the results from the forecast error variance decomposition for the CV and VRP for 12- and 24-month horizons. The results for the CV and VRP are very similar to each other, so I will focus on the VRP. As can be seen from Table 6, the global liquidity factors are important determinants of variations in the VRP. Shocks to $GLF_t^{(1)}$ and $GLF_t^{(2)}$ account for 16.1% and 18.3% of the variations in the VRP, respectively, at the 12-month horizon. Thus, in total, the global liquidity factors explain about 34% of the variations in the VRP. In contrast, macroeconomic shocks are less important drivers of the variations in the VRP. Shocks to $MF_t^{(2)}$ account for 15.4% of the variations in the VRP. Among the four macroeconomic factors, $MF_t^{(2)}$ is the only factor with a significant interaction with the VRP and CV, justifying my focus on $MF_t^{(2)}$. In sum, the variance decomposition results indicate a considerable degree of interactions between the VRP and global liquidity variables.

I now turn to the results from the impulse response analysis. Fig. 5 depicts the responses of the CV and VRP to a one-standard-deviation orthogonalized shock to $GF_t^{(1)}$, $GF_t^{(2)}$, and $MF_t^{(2)}$. An increasing shock to $GF_t^{(1)}$ (interpreted as a deterioration in global funding conditions) significantly increases the CV and VRP. The responses of the CV and VRP to an increasing $GF_t^{(2)}$ shock (interpreted as a decrease in financial market uncertainty) are significantly negative. In response to a shock to $MF_t^{(2)}$ (a contractionary shock to the business cycle), both the CV and VRP rise significantly. For most impulse responses, the CV and VRP respond in the same direction, though the VRP appears to respond more slowly and persistently than the CV in most cases.

The results from this impulse response analysis are consistent with the results from Section 5.1. The quarterly regressions in Section 5.1 show that an increase in capital flows or leverage, each of which reflects a favorable development in global funding conditions, tends to lower the VRP. Moreover, the quarterly regressions also indicate that an increase in the output gap tends to lower the VRP.

Next, I consider the effects of VRP and CV shocks on domestic macroeconomic variables. The effects of a CV or VRP shock on selected macroeconomic variables are shown in Panels (a) and (b) of Fig. 6. One of the advantages of a FAVAR analysis is that it can obtain the impulse responses of the many individual variables used for factor estimation.

The responses of many individual macroeconomic variables turn out to be statistically significant. In particular, an orthogonalized CV shock seems to have a contractionary effect on the economy: this CV shock (interpreted as an increase in economic uncertainty) leads to a contraction in industrial production, producers' shipments and employment. In addition, CPI and other price indexes declines in response to a contractionary CV shock, indicating that a CV shock can be interpreted as a shock to the aggregate demand curve in the economy. Furthermore, a CV shock leads to a decline in the call rate, implying that the central bank responds actively to uncertainty shocks, and the interest rate on 5-year government bonds falls in response to a CV shock.

On the other hand, the dynamic effects of an orthogonalized VRP shock on selected macroeconomic variables are often the opposite of those from a CV shock. For example, a VRP shock increases industrial production and producer shipments. Thus, it is difficult to directly link the VRP to business-cycle theories. Recall that the horizons in which the VRP predicts stock returns well are one to three months, far shorter than normal business cycle frequency. In fact, the relationship between the VRP and economic activity was unclear even in past empirical analyses of the US economy. In Bekaert et al. (2013), for example, a positive CV shock appears to significantly shrink the economy (represented by industrial production), whereas a VRP shock is statistically insignificant to the economy.

The effects of both CV and VRP shocks on the KOSPI index seem to be related to the stock return predictability of the CV and VRP. In particular, KOSPI responds to a CV shock more slowly than it does to a VRP shock. This difference in timing is consistent with my empirical finding that the VRP predicts stock returns well in a shorter horizon than CV does.

The impulse response results in this paper are similar to those of Bloom (2009) and Bloom, Floetotto, and Jaimovich (2012). They argued that economic uncertainty shocks generate significant business cycle effects, and that a central bank needs to respond actively to changes in economic uncertainty. Their empirical analysis used the VIX index as a proxy for economic uncertainty.

6. Conclusions

In this paper, I have analyzed the VRP in Korea. Unlike the US economy, the Korean economy is a small open economy with high volatility in capital flows. Thus, in contrast to past studies, I here linked global liquidity and capital flows to the determinants of the VRP. My empirical analysis has provided the following results.

First, I use a "general-to-specific" version (HAR-Gets) of the HAR-RV-IV model of Corsi (2009) for monthly volatility forecasting of the KOSPI 200 to estimate the VRP in Korea. Similar to the S&P 500, option-market information is useful in forecasting stock return variances.

Second, the results from both the Granger-causality and bivariate VAR analyses indicate that there is a close dynamic relationship between the VRPs of Korea and the US, implying the possibility that risk aversion is globally propagated and suggesting the need to consider global sources when investigating the VRP in Korea.

Third, in forecasting future KOSPI 200 returns, the VRP has short-term stock return forecasting ability, such as monthly or quarterly returns. Thus, as in the US, the VRP in Korea likely reflects the level of risk aversion in the economy. The VRP's short-term forecasting ability is comparable to that of other popular predictor variables such as the dividend yield and output gap.

Finally, the FAVAR analysis shows that the global liquidity sector is more important than the domestic macroeconomic sector in determining both the VRP and CV. Specifically, an increase in global liquidity reduces both the VRP and CV. However, uncertainty shocks (measured by the CV) affect the domestic macroeconomy more significantly than the VRP does.

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Appendix

Table A1
Panel data set for macroeconomic and financial market variables in Korea by broad categories

	Variable	Transformation	Source
(a) Real output and income (21 variables)			
1	Industrial Production Index: Manufacturing	3	Statistics Korea
2	Industrial Production Index: Capital Goods	3	Statistics Korea
3	Industrial Production Index: Intermediate Goods	3	Statistics Korea
4	Industrial Production Index: Durable Consumer Goods	3	Statistics Korea
5	Industrial Production Index: Non-Durable Consumer Goods	3	Statistics Korea
6	Producers' Shipment Index: Manufacturing	3	Statistics Korea
7	Producers' Shipment Index: Capital Goods	3	Statistics Korea
8	Producers' Shipment Index: Intermediate Goods	3	Statistics Korea
9	Producers' Shipment Index: Durable Consumer Goods	3	Statistics Korea
10	Producers' Shipment Index: Non-Durable Consumer Goods	3	Statistics Korea
11	Producers' Inventory Index: Manufacturing	3	Statistics Korea
12	Producers' Inventory Index: Capital Goods	3	Statistics Korea
13	Producers' Inventory Index: Intermediate Goods	3	Statistics Korea
14	Producers' Inventory Index: Durable Consumer Goods	3	Statistics Korea
15	Producers' Inventory Index: Non-Durable Consumer Goods	3	Statistics Korea
16	Shipment Index for Domestic Market: Durable Consumer Goods	3	Statistics Korea
17	Shipment Index for Domestic Market: Non-Durable Consumer Goods	3	Statistics Korea
18	Shipment Index for Domestic Market: Machinery	3	Statistics Korea
19	Shipment Index for Domestic Market: Machinery (excluding Vessels)	3	Statistics Korea
20	Industrial Production: Machinery Orders Received (excluding Vessels)	3	Statistics Korea
21	Industrial Production: Construction Orders Received	3	Statistics Korea
(b) Monetary aggregates (4 variables)			
22	Money Supply (Average): Monetary Base	3	The Bank of Korea
23	Money Supply (Average): M1	3	The Bank of Korea
24	Money Supply (Average): M2	3	The Bank of Korea
25	Money Supply (Average): Lf	3	The Bank of Korea
(c) Employment (1 variable)			
26	Employment: Unemployment rate	1	Statistics Korea
(d) Price indexes (10 variables)			
27	Price Index: Consumer Price Index	3	Statistics Korea
28	Price Index: Producer Price Index	3	The Bank of Korea
29	Price Index: Export	3	The Bank of Korea

(continued on next page)

Table A1 (*continued*)

	Variable	Transformation	Source
(a) Real output and income (21 variables)			
30	Price Index: Import	3	The Bank of Korea
31	Price Index: Core (excluding Agricultural Product & Oils)	3	Statistics Korea
32	Price Index: Consumer Commodities	3	Statistics Korea
33	Price Index: Consumer Services	3	Statistics Korea
34	Price Index: Domestic Supply Raw Materials	3	The Bank of Korea
35	Price Index: Domestic Supply Intermediate Goods	3	The Bank of Korea
36	Price Index: Domestic Supply Final Goods	3	The Bank of Korea
(e) Foreign exchange rates (4 variables)			
37	Foreign Exchange Rate: KRW per USD	2	The Bank of Korea
38	Foreign Exchange Rate: KRW per JPY	2	The Bank of Korea
39	Foreign Exchange Rate: KRW per EUR	2	The Bank of Korea
40	Foreign Exchange Rate: KRW per CNY	2	The Bank of Korea
(f) Housing prices (2 variables)			
41	Housing Price: House Purchase Price	2	KB Bank
42	Housing Price: House Rentals	2	KB Bank
(g) Interest rates (6 variables)			
43	Call Rate (Overnight, Uncollateraized)	1	The Bank of Korea
44	Interest Rates: CD (91-days)	1	The Bank of Korea
45	Interest Rates: CP (91-days)	1	The Bank of Korea
46	Interest Rates: Treasury Bonds (3-year)	1	The Bank of Korea
47	Interest Rates: Treasury Bonds(5-year)	1	The Bank of Korea
48	Interest Rates: Monetary Stabilization Bonds (364-day)	1	The Bank of Korea
49	Interest Rates: Corporate Bonds (AA-)	1	The Bank of Korea
(h) Stock indexes (2 variables)			
50	Stock Index: KOSPI	2	Korea Exchange
51	Stock Index: KOSDAQ	2	Korea Exchange
(i) Current account (8 variables)			
52	Current Account: Exports of Goods	3	The Bank of Korea
53	Current Account: Imports of Goods	3	The Bank of Korea
54	Current Account: Services, Credit	3	The Bank of Korea
55	Current Account: Services, Debit	3	The Bank of Korea
56	Current Account: Primary Income, Credit	3	The Bank of Korea
57	Current Account: Primary Income, Debit	3	The Bank of Korea
58	Current Account: Secondary Income, Credit	3	The Bank of Korea
59	Current Account: Secondary Income, Debit	3	The Bank of Korea

The variables listed here are used to retrieve the macroeconomic factors. The transformation codes are 1. No transformation (level); 2. A month-on-month log difference (used for financial market variables); and 3. A year-on-year log difference (used for macro and monetary variables). The same data set has been also used in Yun (2019).

Table A2
Panel data set for global liquidity variables by broad categories

	Variable	Country	Transformation	Source
(a) Monetary aggregates (9 variables)				
1	Monetary Base	US	3	IFS/IMF
2	Monetary Base	Japan	3	IFS/IMF
3	M1	US	3	IFS/IMF
4	M1	Euro	3	IFS/IMF
5	M1	UK	3	IFS/IMF
6	M3	US	3	IFS/IMF
7	M3	Euro	3	IFS/IMF
8	M3	UK	3	IFS/IMF
9	M3	Japan	3	IFS/IMF
(b) Interest rates (14 variables)				
10	Federal Fund Rate	US	1	FRED
11	Official Rate	Euro	1	ECB
12	Call	Japan	1	BOJ
13	6-month T-bill Rate	US	1	Bloomberg
14	5-year T-bond Yield	US	1	Bloomberg
15	T-bond (10 years)	US	1	Bloomberg
16	T-bond (30 years)	US	1	Bloomberg

(*continued on next page*)

Table A2 (*continued*)

	Variable	Country	Transformation	Source
(a) Monetary aggregates (9 variables)				
17	T-bond (10 years)	Germany	1	Bloomberg
18	T-bond (10 years)	Japan	1	Bloomberg
19	T-bond (10 years)	UK	1	Bloomberg
20	3-month LIBOR Rate	US	1	Bloomberg
21	3-month LIBOR Rate	Euro	1	Bloomberg
22	3-month LIBOR Rate	UK	1	Bloomberg
23	3-month LIBOR Rate	Japan	1	Bloomberg
(c) Exchange rates (4 variables)				
24	Real Effective Exchange Rate	US	2	IFS/IMF
25	Real Effective Exchange Rate	Euro	2	IFS/IMF
26	Real Effective Exchange Rate	UK	2	IFS/IMF
27	Real Effective Exchange Rate	Japan	2	IFS/IMF
(d) Stock indexes (5 variables)				
28	S&P 500 Stock Index	US	2	Bloomberg
29	DAX Stock Index	Germany	2	Bloomberg
30	CAC40 Stock Index	France	2	Bloomberg
31	NIKKEI225 Stock Index	Japan	2	Bloomberg
32	FTSE100 Stock Index	UK	2	Bloomberg
(e) Realized volatilities for stock indexes (5 variables)				
33	S&P 500 Realized Volatility	US	1	–
34	DAX Realized Volatility	Germany	1	–
35	CAC40 Realized Volatility	France	1	–
36	NIKKEI225 Realized Volatility	Japan	1	–
37	FTSE100 realized volatility	UK	1	–
(f) Option-implied volatilities for stock indexes (3 variables)				
38	S&P 500 Option-implied Volatility (VIX)	US	1	Bloomberg
39	DAX Option-implied Volatility (VDAX New)	Germany	1	Bloomberg
40	NIKKEI Option-implied Volatility (VXJ)	Japan	1	Bloomberg

The variables listed here are used to retrieve the global liquidity factors. The transformation codes are 1. No transformation (level); 2. A month-on-month log difference (used for financial market variables); and 3. A year-on-year log difference (used for monetary variables). Realized volatilities are the square root of the average of the daily squared stock index returns over a month. The same data set has been also used in Yun (2019).

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