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The Variation in Variance Risk Premium and Its Predictive Power: Evidence from Option Market Sentiments

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Abstract

We show that the highly volatile variance risk premium (VRP) can be theoretically and empirically reconciled with investor sentiment captured by temporary variation in risk aversion. In an effort to understand the poor predictive power of the VRP in non-U.S. markets, we propose a new investor sentiment index, *the Variance Sentiment index (VSI)*, obtained from the trading behavior of individual investors. We show that the VSI predicts local return dynamics, in a similar way to what the VRP does in the US market. Moreover, the VSI does not lose its predictive power even in the presence of the global VRP.

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I. Introduction

While numerous studies have attempted to extract information implied in derivatives, the variance risk premium (hereafter VRP) has been one of the areas of greatest interest. The VRP is defined as the expectation of difference between risk-neutral variances and physical variances, and it is well documented as having the predictive power for future excess return dynamics in the US markets. Bollerslev et al. (2009) first show that the VRP reflects the compensation for risks which cannot be eliminated through diversification and it can predict excess returns for horizons from one to six months.[1] Drechsler and Yaron (2012) also support the predictability of the VRP by developing a model in which the VRP can capture a time-varying uncertainty premium.[2] More recent works have strived to improve the predictive power of the VRP by decomposing it. For example, Santa-Clara and Yan (2010) decompose the VRP into volatility risk premiums and jump premiums and prove that only the jump premiums predict future excess returns.[3] Du and Kapadia (2012) focus on forecasting horizons and find that model-free jump or tail index associated with the VRP can forecast mid-term excess returns. Feunou et al. (2017) sort out the VRP into up-side VRP and down-side VRP and show that only down-side VRP has a predictive power. Kilic and Shaliastovich (2017) find that the VRP can forecast bond returns as well as stock returns by decomposing it into good and bad VRPs. Bollerslev et al. (2015) show that a left-jump tail has a strong predictive power on excess returns and it is closely associated with the fear of investors. Fan et al. (2018) recently decompose the VRP into pure VRP and higher-order premium and prove that the pure component is related to short-term predictability, while the higher-order component is related to the medium-term predictability.

Although the predictive power of the VRP has been widely documented theoretically and empirically in the US markets, the question of why the VRP has a highly volatile dynamics is not fully answered. As shown in Table 1 and Figure 1, the average of the VRP in the US market is about 150 (basis points), but its standard deviation exceeds 220. Thus, the standard deviation to average ratio is about 1.5.

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[1] They extend the long run risk model pioneered by Bansal and Yaron (2004), who emphasize the importance of long-run risk of consumption to explain the predictable index returns. Based on the model of Bansal and Yaron (2004), Bollerslev et al. (2009) construct a model in which the rate of return can be explained by the variance risk factor, reflecting the long-run risk factor in the dynamics of volatility.

[2] Within the model, an investor has a utility function that prefers to resolve uncertainty quickly and dislikes economic uncertainty. In particular, the investor fears uncertainty about an economic variable that can generate uncertainty and requires a premium for the economic factor. The investor's preference on uncertainty creates a positive variance risk premium and the variance risk premium consequently predicts future returns.

[3] By assuming that volatility and jump follow independent processes and that the intensity of jumps is a second-order function of state variables, the authors guarantee the flexibility of the covariance structure of the two processes.

Previous studies have investigated the sign and magnitude of the VRP extensively. They demonstrate that the VRP should be positive if non-diversifiable variance risks exist and if investors require an additional premium for the variance risks. More specifically, Bakshi and Madan (2006) demonstrate that the VRP is positive if a physical density of returns is non-normal and investors are risk averse. Chernov (2007) also shows that given the additional risk, the risk-neutral variances in option prices are higher than physical variances.[4] However, the highly volatile movement of the VRP cannot be justified entirely by changes in risk under a reasonable size of risk aversion. Rather, the extreme volatility of the VRP is more likely to be explained by a time-varying component in preference structure or psychological fluctuation of investors. This conjecture is consistent with the extant literature, including Bollerslev et al. (2015) and Feunou et al. (2017), which examine the relationship between the VRP with the fear gauge of investors.

With all these in mind, this paper tries to examine whether the extreme variability of the VRP can be explained by the transitory component of risk aversion in preference structure. We also test if this characteristic can be a potential source of predictability on returns and volatilities in the US market. Bollerslev et al. (2014) and Londono (2015) show that no predictive power of the VRP has been observed in non-U.S. markets, even though it is a robust predictive tool in the US.[5] Only the global (i.e., US) VRP has been identified as having predictive power for non-U.S. markets: The VRP is less informative in follower economy, including Germany, England, Switzerland, Netherlands and France, than in a leader economy. Rapach et al. (2013) also support the importance of the U.S. factors in predicting international stock returns.

In this paper, in order to ensure that the poor performance of a local VRP of non-U.S. markets is attributed to investor sentiment, we propose a new sentiment index for non-U.S. markets, the *Variance Sentiment Index* (hereafter, VSI), which is calculated from the trading behavior of individual investors in their options markets. We show that this measure performs well in predicting excess return dynamics, similar to what the VRP does in the US. The VSI is defined as the ratio between individual investors' long position in volatility and short position in volatility. If investors have negative mood or have a belief in a rise in economic uncertainty, they would have a tendency for long positions in volatility. If investor sentiment really matters in predicting excess returns, the VSI might have a predictive power.

[4] An extensive literature including Benzoni (1998), Chernov and Ghysels (2002), Pan (2002), Jones (2003), and Eraker (2004) shows the existence of stochastic volatility and jumps in variance processes.

[5] Londono (2015) extends the model of Bollerslev et al. (2009) to a two-country model in order to explain why the (local) VRP could not predict the future returns except in the U.S. market.

The VSI measure is closely related to the extant market microstructure literature which examines the effect of net buying pressure or order imbalance on option prices (and volatilities) (e.g., Bollen and Whaley (2004) among others). These studies have shown that the net buying pressure can increase option prices in short terms and then in turn raise risk-neutral variances, thereby affecting the VRP. Because the VSI is defined as the long position over the short position of individual investors in option trading, this measure may also look like net demand pressure. However, our study differs fundamentally from the market microstructure literature in two aspects. First, the market microstructure studies use intraday and/or daily data and examine how option prices overreact/underreact to the short-term net demand. In other words, this sort of studies focuses on price discovery as to whether the demand-supply imbalance can deviate prices from fundamental values within a few minutes or days. Our study, however, dodges such a possibility by using monthly data. Even if price shocks occur in a few minutes or days, it is not expected that the price deviation lasts for more than one month. This is why most literature, including this paper, about investor sentiment chooses the monthly-data frequency.

Second, the VSI is calculated only from the transactions of individual investors to focus on the sentiment of unsophisticated investors. As argued by Barber and Odean (1999, 2000), individual investors are less rational and less sophisticated than institutional investors, and therefore are more vulnerable to mood, sentiment, or psychological bias. The excess demand of individual investors on volatility indicates that they have belief about a rise in economic uncertainty, not explained by fundamental risk factors. In this sense, our study is the first to focus on changes in investor sentiment using the trading behavior of individual investors in options markets. Please note that our empirical analysis has be limited to the non-US but major options markets such as the Korean and Taiwanese options markets, which are the only major markets providing option transaction data with respect to types of investors.

The results of the study are summarized as follows. First, as expected by the extant literature, the VRP is considerably volatile and predicts future excess returns, changes in volatility, and Sharpe ratios in the US markets. An increase in the VRP forecasts an increase in S&P 500 index returns and Sharpe ratios, but a decrease in volatility. Second, the standard deviation to the average ratio of the VRP is higher than 1.5. By developing a theoretical relationship between a physical density of returns and a temporary change in risk aversion through the Taylor series approximation, we prove that the temporary variation of risk aversion can explain the extremely volatile VRP. Even under the assumption that risk factors and average risk aversion do not change over time, a temporary variation of risk aversion with standard deviation of twenty percent is able to generate the average VRP of about 150 and standard deviation of higher than 50. In addition, we find that both Baker and Wurgler's (2006) Sentiment Index and the

University of Michigan Consumer Sentiment index can statistically explain the dynamics of the VRP in the US markets.

Third, the predictive power of the VRP in active, non-US markets, including Korea and Taiwan, is not as significant as in the US markets. In Korea, the VRP cannot predict excess returns for any horizons at all and in both countries the VRP cannot predict volatility changes for most horizons. This is consistent with Bollerslev et al. (2014) and Londono (2015), which show the poor predictive power of the (local) VRP in non-U.S. markets. On the other hand, the VSI, which is a sentiment index more directly calculated from the trading behaviors of individual investors, predicts excess returns, the changes in volatility, and Sharpe ratios for one to six-month horizons in both markets. All these results are comparable to the predictive power of the VRP in the US markets. An increase in the VSI represents an increase in the belief about a rise in economic uncertainty, resulting in a decrease (increase) in current stock prices (volatility), but the stock prices (volatility) would rebound after a certain period of time. In this sense, the VSI can forecast a rise in future index returns and volatilities, and such results are robust even in the presence of the U.S. (i.e., global) VRP-. This implies that the VSI in other countries than the U.S. is likely to capture the local investor sentiment, while the U.S. VRP captures the global sentiment.

This study contributes to the literature in two aspects. First, we explain that the high volatility and predictive power of the VRP can be attributed to the investor sentiment, i.e. psychological fluctuation of investors. Consistent with Bollerslev et al. (2015), which analyze the predictive power of a jump component associated with fear, we confirm the role of investor sentiment in explaining the variability and predictive power of the VRP. Second, we provide an alternative sentiment index which works well in non-U.S. markets.

The rest of the paper is organized as follows. Section II identifies the characteristics of the predictive power of the VRP in the US and in turn verifies the linkage between the VRP and major sentiment indices. Section III develops the VSI to measure the local investor sentiment from options market trading data and conducts the empirical analysis about its predictive power for future return dynamics. The analyses about the independence of the VSI from the global (i.e., US) VRP are also conducted. Section IV summarizes the results and provides conclusions.

II. Variance Risk Premium and Sentiment in the U.S.

This section examines the volatility and the predictive power of the VRP in the US for our sample period. We also develop a theoretical model to explain the effect of the investor sentiment on the

dynamics of the VRP and show that incorporating a transitory component in risk aversion generates significant variability of the VRP.

II.1 Variance Risk Premium in the US

The VRP is defined as the difference between the expected risk-neutral variances and the expected physical variances. In this paper, the risk-neutral variance is the squared VIX and the expected physical variance is calculated in three alternative ways for robustness: The first way is to adopt the historical variance of one-month daily returns (HVDR), the second is to adopt the total realized variance of one-month daily returns (TRVDR), which is proposed by Fan et al. (2018), and the third is to adopt the realized variance of five-minute intraday returns (RVIR), as in Bollerslev et al. (2009). The total realized variance by Fan et al. (2018) has internal consistency to the VIX provided by CBOE (Chicago Board of Options Exchange) in that they contain a part of higher moments than the second order (Bakshi and Madan (2000) and Kozhan et al. (2013)). In addition, the risk-neutral and physical variances are measured at the end of each month. The expectation of physical variances can be defined *ex ante* or *ex post*. To focus on predictability for future return dynamics, the expectation of physical variance is defined *ex ante* as the previous month's realized variance. No model assumption is necessary and all the information is available at time t.

The detailed definitions are as follows:

1) HVDR: $\mathrm{VRP_t} = VIX_t^2 - \frac{12}{30}\sum_{i=t-30}^{t}(r_i - \bar{r})^2$
2) TRVDR: $\mathrm{VRP_t} = VIX_t^2 - \frac{12}{30}\sum_{i=t-30}^{t} 2(e^{r_i} - r_i - 1)$
3) RVIR: $\mathrm{VRP_t} = VIX_t^2 - \frac{12}{N}\sum_{i=t-N}^{t}(r_i - \bar{r})^2,$

where r_i is log return, calculated using the daily closing prices for HVDR and TRVDR, and calculated using the five-minute interval prices for RVIR. N indicates the sample number of the five-minute returns for the previous one month.[6]

Table 1 shows the descriptive statistics of monthly returns of the S&P 500 index, CBOE VIX, changes in CBOE VIX, and the VRPs calculated in the three ways described above for the period from January 2009 through December 2016. The average of the VIX during the sample period is about 20 percent and it has decreased slightly over time. The average of the VRPs in the S&P 500 index is about 150 on daily basis and about 186 on intraday basis. Regardless of the calculation method, the standard

[6] Data is available from the website of Hao Zhou (https://sites.google.com/site/haozhouspersonalhomepage).

deviation of the VRP is extremely high, ranging from 220 to 245. The standard deviation to the average ratio turns out to be 1.18 to 1.63, which is very large compared to the volatility of equity index returns. For intraday returns, the skewness is more skewed and kurtosis is more leptokurtic than those for daily returns. In particular, the auto-correlation of the VRP is negative for daily returns, while positive for intraday returns.

[Insert Table 1 here]

Table 2 presents the empirical performance of the VRP in predicting S&P 500 returns and the VIX, using a conventional specification to test the predictive power of economic variables. Since Bollerslev et al. (2009), numerous studies have provided evidence of predictive power of the VRP in the US markets. We also find that during our sample period the VRP has significant predictive power for future returns. Panel A shows that the VRP predicts future index returns for , which is qualitatively consistent with results in the extant literature in that the coefficient of the VRP is statistically significant and positive for 1-month, 3-month, and 6-month horizons: An increase in the VRP suggests an increase in future returns. If an increase in the VRP captures an increase in uncertainty, the risk premium required increases. Note that the coefficient for the 2-month horizon has the right sign, but is only marginally significant.

Similarly, the VRP can predict future volatility, which is a typical measure for uncertainty or risk. Here, the sign of coefficient of the VRP in predicting future volatility is very important. For a risk-based explanation to be valid, an increase in the VRP should accompany an increase in future volatility. By contrast, if the VRP captures a temporary variation of investor sentiment, an increase in the VRP would forecast a decrease in volatility. Our empirical results are consistent with the latter explanation. As shown in Panel B, an increase in the VRP predicts a decrease in future volatility (VIX). If the VRP increases by incorrect beliefs (i.e., sentiment) about economic uncertainty, the current asset prices tend to be undervalued and current volatility tends to increase. However, after a certain period of time, the price will rebound and the volatility will revert to decrease. This conjecture is supported by with our empirical results.

[Insert Table 2 here]

II.2 Variance Risk Premium and Major Sentiment Indices in the US

Please note again that the variability of the VRP reported in Table 1 seems to be too high to be explained by reasonable changes in risk alone. Bardgett et al. (2018) show that the S&P 500 index and VIX derivatives contain conflicting information on variances. It suggests that the time series of the VIX is

too volatile compared to that of underlying index returns. We conjecture that incorporating psychological factors or investor sentiment may help explaining the high volatility of the VIX and the VRP. Given the fact that the VIX is perceived as investors' fear index, it is reasonable to assume that the VRP calculated from the VIX reflects the investor sentiment.

To test the hypothesis that the high volatility (Table 1) and the predictive power (Table 2) of the VRP are related to investor sentiment, we conduct simple regressions by regressing the VRP on the major sentiment indices, including Baker and Wurgler's (2006) Sentiment Index and the University of Michigan Consumer Sentiment Index. If the VRP contains information regarding investor sentiment, the VRP would be explained by sentiment indices.

$$\mathrm{VRP_t} = \beta_1 + \beta_2 Sent_{BW,t} + \epsilon_t \tag{1}$$

$$\mathrm{VRP_t} = \beta_1 + \beta_2 Sent_{BW_orth,t} + \epsilon_t$$

$$\mathrm{VRP_t} = \beta_1 + \beta_2 Sent_{UMCSENT,t} + \epsilon_t$$

$$\mathrm{VRP_t} = \beta_1 + \beta_2 Sent_{UMCSENT_Current,t} + \epsilon_t$$

$$\mathrm{VRP_t} = \beta_1 + \beta_2 Sent_{UMCSENT_Exp,t} + \epsilon_t$$

where $Sent_{BW,t}$ indicates the sentiment index calculated by Baker and Wurgler (2006) at time t.[7] Baker and Wurgler (2006) construct a composite sentiment index as the first principal component of six measures of investor sentiment: the closed-end fund discount, NYSE share turnover, the number and average first-day returns on IPOs, the equity share in new issues, and the dividend premium.[8] To reduce the likelihood that these proxies are connected to systemic risk, they first regress each of the raw sentiment proxies on a set of macroeconomic variables and use the residuals to build the alternative sentiment index. $Sent_{BW_orth,t}$ means this orthogonalized sentiment index with respect to macroeconomic variables.

$Sent_{UMCSENT,t}$ indicates the University of Michigan Consumer Sentiment (UMCS) at time t. This sentiment index is calculated based on the Surveys of Consumers, conducted by the Survey Research

[7] The data is available from the webpage of https://www.hbs.edu/faculty/initiatives/behavioral-finance-and-financial-stability/Pages/sentiment.aspx and https://fred.stlouisfed.org/series/UMCSENT.

[8] The selection of sentiment proxies in Baker and Wurgler (2006) is based on the following literature: Lee, Shleifer, and Thaler (1991) for the closed-end fund discount, Baker and Stein (2004) for turnover, Stigler (1964) and Ritter (1991) for the number of and first-day returns of IPOs, Baker and Wurgler (2000) for the equity share in new issues, and Baker and Wurgler (2004a, 2004b) for the dividend premium.

Center. The relative scores (percent giving favorable replies minus the percent giving unfavorable replies, plus 100) are first computed for each of the five index questions about consumer sentiment and the scores are rounded to the nearest whole number. Next, the five relative scores are summed and divided by 6.7558 (1966 base period total) and added to 2.0 (a constant to correct for sample design changes from 1950s). *UMCSENT* can be divided into Consumer Expectation Index ($Sent_{UMCSENT_Exp,t}$) and Current Economic Condition Index ($Sent_{UMCSENT_Current,t}$). The former is calculated using three questions, while the latter is calculated using the other two questions.

Table 3 presents the relationship between the VRP and the five sentiment indices, using Equation (1). The original BW index, the orthogonalized BW index, UMCSENT, and its two components are used as the sentiment indices. Panel A shows the results for the BW sentiment indices. As expected, there is an inverse relationship between the VRP and two BW indices and the coefficients are all statistically significant. An increase in the BW results in a decrease in the VRP. Regardless of the sampling frequency (daily or intradaily) in calculating the physical variances, the BW indices are statistically significant in explaining the VRP. More specifically, for the daily data, the original BW index has the adjusted R^2 of 5.83 percent and the orthogonalized BW index has the adjusted R^2 of 9.1 percent. For the intraday data, the adjusted R^2 are 5.85 and 5.67 percent, respectively. Panel B shows the results for the UMCS indices. Similar to the results in Panel A, the coefficients of the UMCSENT and its two components are statistically significant in explaining the VRP. In particular, for intraday data, the UMCSENT has the adjusted R^2 of 18.7 percent. In addition, the UMCSENT Current Economic Condition Index is more informative than UMCSENT Consumer Expectation Index for both specifications in terms of adjusted R^2. All these results are consistent with the conjecture in the previous subsection that the informativeness of the VRP is associated with investor sentiment. Given that extant studies such as Huang et al. (2015) prove the predictive power of sentiment index, the VRP may predict future excess returns because it is closely related to the sentiment.

[Insert Table 3 here]

II.3. Temporary Variation in Risk Aversion and Variability of VRP: A Theory

In this section, we investigate how the temporary change in sentiment or risk aversion affects the dynamics of the VRP theoretically. Using the Taylor series expansion technique of Bakshi and Madan (2006), we show that the temporary change in risk aversion is consistent with the empirical variability of the VRP.

The pricing kernel of a power utility class, $\mathrm{m(R)} = e^{-(\gamma+\tilde{\epsilon})R}$, can be expressed around zero as

$$\mathrm{m(R)} \approx 1 - (\gamma + \tilde{\epsilon})R + \frac{1}{2}(\gamma + \tilde{\epsilon})^2 R^2 + O(R^3). \tag{2}$$

Here, γ is the average of the risk aversion and $\tilde{\epsilon}$ is the transitory component of the risk aversion, which is affected by the sentiment of investors and is assumed to be independent from the asset returns for simplicity.

The moment-generating function of the physical density function is

$$\bar{M}(\lambda) = \int_{-\infty}^{\infty} e^{\lambda R} p(R) dR = 1 + \lambda E^P(R) + \frac{1}{2}\lambda^2 E^p(R^2) + \frac{1}{6}\lambda^3 E^P(R^3) + \frac{1}{24}\lambda^4 E^P(R^4) + O(\lambda^4), \tag{3}$$

where E^P denotes the expectation for the physical density.

If $\mathrm{m(R)} = e^{-(\gamma+\tilde{\epsilon})R}$, the moment-generating function of the risk-neutral density function is given by

$$\mathrm{M}(\lambda) = \int_{-\infty}^{\infty} e^{\lambda R} q(R) dR = \frac{\int_{-\infty}^{\infty} e^{\lambda R} e^{-(\gamma+\tilde{\epsilon})R} p(R) dR}{\int_{-\infty}^{\infty} e^{-(\gamma+\tilde{\epsilon})R} p(R) dR} = \frac{\bar{M}(\lambda-(\gamma+\tilde{\epsilon}))}{\bar{M}(-(\gamma+\tilde{\epsilon}))}. \tag{4}$$

Thus,

$$\mathrm{E}^{\mathrm{q}}(R) = \mu_q = \frac{\bar{M}(\lambda-(\gamma+\tilde{\epsilon}))'\big|_{\lambda=0}}{\bar{M}(-(\gamma+\tilde{\epsilon}))}, \tag{5}$$

where

$\bar{M}\big(-(\gamma + \tilde{\epsilon})\big) = 1 - (\gamma + \tilde{\epsilon})E^P(R) + \frac{1}{2}(\gamma + \tilde{\epsilon})^2 E^p(R^2) - \frac{1}{6}(\gamma + \tilde{\epsilon})^3 E^P(R^3) + \frac{1}{24}(\gamma + \tilde{\epsilon})^4 E^P(R^4) + O(\lambda^4)$, and

$$\bar{M}\big(\lambda - (\gamma + \tilde{\epsilon})\big)'\Big|_{\lambda=0} = E^P(R) - (\gamma + \tilde{\epsilon})E^p(R^2) + \frac{1}{2}(\gamma + \tilde{\epsilon})^2 E^P(R^3) - \frac{1}{6}(\gamma + \tilde{\epsilon})^3 E^P(R^4) + O(\lambda^4).$$

Therefore, $\mu_q = \left(1 - (\gamma + \tilde{\epsilon})E^P(R) + \frac{1}{2}(\gamma + \tilde{\epsilon})^2 E^p(R^2) + \cdots\right)^{-1} \left(E^P(R) - (\gamma + \tilde{\epsilon})E^p(R^2) + \frac{1}{2}(\gamma + \tilde{\epsilon})^2 E^P(R^3) + \cdots\right)$ (6)

Since $\left(1 + ax + bx^2\right)^{-1} \approx 1 - ax + \left(a^2 - b\right)x^2$, the risk-neutral first moment can be written as

$$\begin{aligned}\mu_q &= \left(1 + (\gamma + \tilde{\epsilon})E^P(R) + (\gamma + \tilde{\epsilon})^2\left(E^P(R)^2 - \frac{1}{2}E^p(R^2)\right)\right)\left(E^P(R) - (\gamma + \tilde{\epsilon})E^p(R^2) + \frac{1}{2}(\gamma + \tilde{\epsilon})^2 E^P(R^3) + \cdots\right) \\ &\approx \mu_p - (\gamma + \tilde{\epsilon})\sigma_p^2 + \frac{1}{2}\theta_p \sigma_p^3,\end{aligned} \tag{7}$$

because $\mathrm{E(R^2)} = \mu^2 + \sigma^2$, $\mathrm{E(R^3)} = \theta\sigma^3 + \mu^3 + 3\mu\sigma^2$.

The second moment of risk-neutral density is

$$\mathrm{E}^{\mathrm{q}}(R^2) = \frac{\bar{M}\big(\lambda - (\gamma + \tilde{\epsilon})\big)''\Big|_{\lambda=0}}{\bar{M}\big(-(\gamma + \tilde{\epsilon})\big)}$$

$$= \left(1-(\gamma+\tilde{\epsilon})E^P(R)+\frac{1}{2}(\gamma+\tilde{\epsilon})^2E^p(R^2)+\cdots\right)^{-1}\left(E^P(R^2)-(\gamma+\tilde{\epsilon})E^P(R^3)+\frac{1}{2}(\gamma+\tilde{\epsilon})^2E(R^4)\cdots\right)$$

$$\approx \mu_p^2+\sigma_p^2-(\gamma+\tilde{\epsilon})\left(\theta_p\sigma_p^3+2\mu_p\sigma_p^2\right)+(\gamma+\tilde{\epsilon})^2\left(\theta_p\sigma_p^3\mu_p+\tfrac{1}{2}\sigma_p^4(\kappa_p-1)\right), \tag{8}$$

since

$$\bar{M}\left(\lambda-(\gamma+\tilde{\epsilon})\right)'' = E^p(R^2)+\left(\lambda-(\gamma+\tilde{\epsilon})\right)E^P(R^3)+\frac{1}{2}(\lambda-(\gamma+\tilde{\epsilon}))^2E^P(R^4)+O(\lambda^4)$$

and

$$\mathrm{E}(\mathrm{R}^4) = 4\theta\sigma^3\mu+6\mu^2\sigma^2+\mu^4+\sigma^4\kappa.$$

Therefore,

$$\sigma_q^2 = E^q(R^2)-\mathrm{E}^q(R)^2 \approx \sigma_p^2-(\gamma+\tilde{\epsilon})\theta_p\sigma_p^3+\frac{1}{2}(\gamma+\tilde{\epsilon})^2\sigma_p^4\left(\kappa_p-3\right)$$

$$= \sigma_p^2-\gamma\theta_p\sigma_p^3+\tfrac{1}{2}\gamma^2\sigma_p^4\left(\kappa_p-3\right)+\tilde{\epsilon}\left(-\theta_p\sigma_p^3+\gamma\sigma_p^4(\kappa-3)\right)+\tilde{\epsilon}^2\left(\tfrac{1}{2}\sigma_p^4(\kappa-3)\right). \tag{9}$$

Thus,

$$\text{Variance Risk Premium} = \sigma_q^2-\sigma_p^2$$

$$\approx -\gamma\theta_p\sigma_p^3+\tfrac{1}{2}\gamma^2\sigma_p^4\left(\kappa_p-3\right)+\tilde{\epsilon}\left(-\theta_p\sigma_p^3+\gamma\sigma_p^4(\kappa-3)\right)+\tilde{\epsilon}^2\left(\tfrac{1}{2}\sigma_p^4(\kappa-3)\right). \tag{10}$$

Using Equation (10), we simulate the VRP with respect to the temporary variation in risk aversion. Panels A, B, and C in Table 4 show the average risk-neutral volatility and the average, the standard deviation, and the standard deviation to average ratio of the VRP with respect to the temporary component in risk aversion, the size of risk aversion, and the physical volatility, respectively. The average of risk aversion is set to 10, and its standard deviation is set to be 10 percent of the risk aversion. All other parameters are based on the empirical values. For example, the physical volatility, skewness, and kurtosis are set to be 15 percent, -0.05, and 3.5, respectively. Rosenberg and Engle (2002) estimate the risk aversion of 2.36 to 12.55 for the sample period from 1991 to 1995 in the S&P 5000 index options market. Bliss and Panigirtzoglou (2004) estimate the risk aversion of 4.08 for the period of 1983 to 2001 in the S&P 500 index options market and of 4.05 for the period of 1992 to 2001 in the FTSE 100 index options market. Similarly, Corrado and Miller (2006) estimate the risk aversion of 4.08 for the period of 1990 to 2003 in the S&P 500 index options market. Bakshi and Madan (2006), which use the similar approach to our study, estimate the risk aversion of 12.71 to 17.33 for the period of 1984 to 1999 in the S&P 500 index options market. Based on these earlier results in the literature, we set the constant relative risk aversion at 10 and change it from 5 to 15 in the simulation, which is shown in Panel B.

For skewness, Engle (2004) and Bollerslev and Zhou (2005) estimate the skewness on the S&P 500 returns. Although the estimate of skewness of physical densities depends on the sample period, the

length of sample, and the sampling frequency, the overall values estimated are between -0.1 and -1.5. Brandt and Kang (2004) and Brock et al. (2001) also estimate the similar values. Bakshi and Madan (2006) calculate the higher-order moments by rebalancing the estimation period periodically and find out the average skewness of -0.1 and the average kurtosis of 6.3 in the S&P 500 index returns. In our study, we set the skewness at -0.05 and the kurtosis at 3.5 to show that the temporary change in risk aversion can generate the significant variation in the VRP even with such conservative selections.

According to Equation (10), more volatile, more skewed, and more leptokurtic a physical density is, the more volatile the VRP is. In addition, the volatile risk aversion results in the volatile VRP. The important thing here is how much the change in risk aversion affects the volatility of the VRP. Panel A presents the characteristics of risk-neutral volatility and the VRP with respect the volatility of risk aversion. When the standard deviation of the risk aversion is set at 10 percent of risk aversion, the size of the VRP is similar to the empirical value of 150. The standard deviation of the simulated VRP is 27.11, which is much smaller than empirical values of about 230. As a result, the standard deviation to the average ratio is too small at 18.57 percent, compared to the empirical value of 153 percent. However, as the standard deviation of the risk aversion increases, the standard deviation of the VRP increases sharply without changing the average. The standard deviations of risk aversion of 15 and 20 percent correspond to the standard deviations of the VRP of 41 and 52 percent, respectively. Of course, the standard deviation to the average ratio is about 28 percent and 35 percent, still lower than the empirical value, but if the standard deviation of the risk aversion increases to 80 percent of average value, the standard deviation of the VRP would increase to 230, which is comparable to the empirical value. One thing to notice here is that the permanent component of risk aversion and physical distributions are assumed not to change over time. If these assumptions are relaxed, the variability of the VRP will increase even more.

Panel B shows the characteristics of the VRP by the size of the average of risk aversion. Here, the standard deviation of temporary component is set at 10 percent of the average value. When the risk aversion is set at 5, the average VRP is about 40.58 and when the risk aversion is set at 15, the average VRP is about 310. That is, the VRP increases as the risk aversion increases. Finally, Panel C show the characteristics of the VRP by physical volatility. As the physical volatility increases, all the risk-neutral volatility, the average VRP, and the volatility of the VRP increase. However, the changes in the average risk aversion or the changes in physical volatility can hardly affect the standard deviation to the average ratio of the VRP. In summary, the main factor that causes the VRP to be highly volatile is the temporary component of risk aversion (preference), which is more likely to be associated with investor sentiment.

[Insert Table 4 here]

III. Variance Risk Premium and Investor Sentiment: Evidence from Active, Non-US Options Markets

So far it is plausible to infer that the high volatility and the predictive power of the VRP can be explained by the sentiment or psychological bias of investors. The VRP is statistically and significantly correlated with the BW Sentiment Index and the UMCSENT Index, and its volatile dynamics can be explained theoretically by a transitory component in preference. In this section, we investigate why then the VRP does not predict future returns in non-U.S. markets (e.g., Bollerslev et al (2015) and Londono (2015)) Based on our empirical and theoretical results so far from the US market, we conjecture that if the VRP in non-US market does not reflect investor sentiment, it may not predict future return dynamics in their local markets. Baker et al. (2012) support this conjecture by decomposing the sentiment indices of six major countries into one global sentiment and six local sentiments using the principal component analysis. They find that the global sentiment is a contrarian predictor of country-level returns but the local sentiment is not a significant predictor.

To measure the investor sentiment more directly and more precisely for the non-US market, we propose a new sentiment index from the trading behaviors of individual investors in non-U.S. options markets, the Variance Sentiment Index (VSI). We show that this new measure has empirical performance as good as the VRP in the US market. Because the sentiment index is likely to be revealed through the trading behavior of less sophisticated investors (individual investors), we focus on the Korean and Taiwanese index options markets, which are the only major options markets that disclose the transaction data with respect to types of investors.

III.1. Variance Risk Premium in Active, Non-US Markets

The sample includes a total of eight years of monthly data from January 2009 to December 2016. The option transaction data for Korea and Taiwan are provided by the Korea Exchange and the Taiwan Futures Exchange, respectively, along with types of investors for each transaction.[9] In addition, the KOSPI index consisting of listed stocks traded on the Korea Exchange and the TAIEX index consisting of listed stocks traded on the Taiwan Stock Exchange are used to calculate the monthly returns on stock

[9] Korea Exchange is the sole securities exchange in Korea. It was established in January 2005 through the integration of former Korea Stock Exchange, Korea Futures Exchange and KOSDAQ Stock Market under the Korea Stock & Futures Exchange Act. The Taiwan Futures Exchange was established in 1998 and trades futures and options on major Taiwan stock indices, government bond futures, equity options, and interest rate futures.

indices in the two counties. The corresponding volatility indices such as VKOSPI (KOSPI VIX) and TAIEX Option VIX are adopted to estimate the dynamics of risk-neutral variances.[10]

Table 5 presents the trading volumes of major equity index options around the world during 2014-2017. According to the World Federation of Exchanges, stock index options account for about 28 percent of the equity derivatives contracts traded in 2017. The market for stock index options is highly concentrated on the Asian-Pacific region: Sixty-five percent of the trading takes place in the Asia-Pacific region. The top three exchanges (the National Stock Exchange of India, the Korea Exchange, and the Chicago Board Options Exchange) account for about 72 percent of the total volume traded during these four years and the top 5 (the top3 plus the Eurex Exchange and the Taiwan Futures Exchange) account for about 89% of total volume traded in 2017. The National Stock Exchange of India and the Korea Exchange together account for about 57 percent of the total volume traded. By contrast the CBOE Global Markets account for about 15 percent of global traded volume. Therefore, the use of stock index options data from Asian countries is expected to provide fairly meaningful results because of their relatively large trading volume and value in dollars.

[Insert Table 5 here]

Table 6 reports the descriptive statistics of monthly index returns, monthly volatility indices, and the monthly VRPs in the Korean and Taiwanese markets. Panel A shows the statistics of monthly index returns. The average monthly returns of KOSPI 200 and TAIEX are about 0.599% and 0.730%, respectively. For the standard deviation, the KOSPI index is 4.49% and the TAIEX index is 4.81%. The Jarque-Bera statistics show that the null hypothesis for normality cannot be rejected. Also, the ADF test supports the nonexistence of a unit root. Panels B and C show the statistics of monthly volatility indices and the log changes in volatility. The average and the standard deviation of the two volatility indices are about 18.5% and 7%, respectively. The maximum level and minimum level of the VKOSPI are 48.2% and 10.86%, and those of the TAIEX VIX are 43.58% and 8.57%, respectively. They are all negatively skewed and leptokurtic. The ADF test rejects the hypothesis that supports the existence of a unit root. Because the risk-neutral volatility is directly derived from option prices, the changes in risk-neutral volatility can be interpreted as option returns. Thus, the descriptive statistics of volatility changes are presented in Panel C. The averages of volatility changes are -1.508% for the VKOSPI, and -1.21% for

[10] The Korea Exchange started to calculate the first volatility index, VKOSPI, on April 13th, 2009 and data are available from January 2003. This index is calculated as the expected volatility of the equity index over the next thirty days using the cross-sectional prices of options, which is similar to the way for the S&P 500 VIX. Taiwan Exchange started to announce the volatility index, when TAIEX VIX and data are available from December 18th, 2006.

the TAIEX. Their standard deviations are 14.58% and 16.67%, respectively. The autocorrelation coefficients are negative for both markets, indicating that an increase in volatility changes tends to return to a decrease in the following month. The ADF test for both markets rejects the hypothesis that supports the existence of a unit root.

Panel D of Table 6 shows the summary statistics of the VRPs of Korea and Taiwan markets. Here, the reported results are based on the VRP calculated using the standard deviation of daily returns in estimation for physical variance.[11] The averages of the VRP are 76.99 for the KOSPI and 106.36 for the TAIEX, which are relatively small compared to the corresponding value (ranges from 149 to 186) for the S&P 500 in Table 1. The standard deviations are 237.49 and 173.70 for the KOSPI and the TAIEX, respectively. In particular, for the KOSPI, the standard deviation and the highest and lowest levels of the VRP are comparable for those for the S&P 500 in Table 1. The ADF test rejects the null hypothesis that a unit root exists. Figure 1 depicts the time-series of the VRPs for the S&P 500, KOSPI, and TAIEX markets.

[Insert Table 6 here]

[Insert Figure 1 here]

III.2. Relationship between Variance Risk Premium and Sentiment Indices in Active, Non-US Markets

In this subsection, we examine the predictive power of the newly-proposed sentiment index to assess the hypothesis that the poor performance of the VRP in non-US markets is due to the local VRP's failure in capturing investor sentiment.

We first conduct the predictive regression of the VRP in the KOSPI and TAIEX markets for horizons from 1 to 3 months. In this step, we confirm that the VRPs in two markets do not have the predictive power for future return dynamics. Because Ang and Bekaert (2007) demonstrate that only the short-term risk-free rate has a significant forecasting power in predicting future index returns for short horizons less than one year, we also include the 3-month CD rates for Korea and 3-month TIBOR rates for Taiwan in the regression models, respectively.

$$\mathrm{R}_{\mathrm{t,t+h}} = \beta_0 + \beta_1 VRP_t + \beta_2 r_{f,t} + \epsilon_t \tag{11}$$

[11] While the total realized variance method of Fan et al. (2018) also provides us the qualitatively same results, we do not report them to save space. Results are available upon request.

$$\Delta \mathrm{Vol}_{\mathrm{t,t+h}} = \beta_0 + \beta_1 VRP_t + \beta_2 r_{f,t} + \epsilon_t \tag{12}$$

Table 7 presents the empirical performance of the VRP in predicting future return dynamics. Panel A includes the results regarding the return while Panel B includes the results regarding the volatility changes. The VRP of the KOSPI 200 does not predict the dynamics of the KOSPI returns. It does not predict future returns as well as volatility changes for horizons from 1 to 3 months. One-month volatility change is an exception. For the TAIEX, however, the VRP performs somewhat better although the predictive power of the VRP in Taiwan is not as strong or pronounced as that in the US. Also, its predictive power for volatility changes is significant only for one-month horizon.

[Insert Table 7 here]

We now analyze the partial informativeness of the TAIEX VRP and un-informativeness of the KOSPI VRP in the following two steps. First, we estimate the relationship between the local VRP with the local, survey-based sentiment index in each country as follows.

$$\mathrm{VRP}_{\mathrm{KOSPI\ or\ TAIEX,t}} = \beta_0 + \beta_1 CCI(CSI)_t + \epsilon_t \tag{13}$$

Here, CCI is the Consumer Confidence Index, published by the National Central University Centre for Taiwan Economic Development (RCTED), which measures consumer's expectation of the economic situation in the coming six months. The index is based on a telephone survey of around 2,400 randomly selected adults over the age of 20, which is conducted nationwide during the third week of each month. The CCI survey covers six indices: domestic business condition, employment opportunities, family economic conditions, investment in stocks, inflation expectations and willingness to buy durable goods. The overall index is an unweighted average of the six sub-indices. A value between 0 and 100 indicates pessimism, while a value between 100 and 200 indicates optimism. Similar to the CCI in Taiwan, the CSI (Consumer Sentiment Index) in Korea measures the level of optimism that consumers have about the performance of the economy. The index is based on a survey of around 2200 households. The CSI is computed as a sum of six variables, including current living standards, prospective household income, and prospective spending. The CSI above 100 indicates an improving outlook and below 100 indicates a deteriorating outlook.

Table 8 reports results. The TAIEX VRP which has some forecasting power for the future excess returns (Table 7) has a statistically significant relationship with the CCI in Taiwan. In contrast, the KOSPI VRP with little forecasting power for future return dynamics (Table 7) is not significantly related to the CSI in Korea.

The second step in explaining the partial informativeness of the TAIEX VRP is to adopt the following predictive regression models. These specifications are designed to test if the informativeness of the TAIEX VRP is dominated by the survey-based sentiment measure, CCI. If it is, the coefficient of the TAIEX VRP would not be statistically significant in the presence of the CCI in the following regression specifications.

$$\mathrm{R}_{\mathrm{t,t+h}} = \beta_0 + \beta_1 CCI_t + \beta_2 VRP_t + \beta_3 r_{f,t} + \epsilon_t \tag{14}$$

$$\Delta\mathrm{Vol}_{\mathrm{t,t+h}} = \beta_0 + \beta_1 CCI_t + \beta_2 VRP_t + \beta_3 r_{f,t} + \epsilon_t \tag{15}$$

$$Sharpe_{t,t+h} = \beta_0 + \beta_1 CCI_t + \beta_2 VRP_t + \beta_3 r_{f,t} + \epsilon_t \text{ [12]} \tag{16}$$

Table 9 reports the results for the forecasting regressions (14)-(16) on future excess returns, change in volatility, and the Sharpe ratios. Interestingly, most coefficients of the VRP almost completely lose the statistical significance (that Table 7 demonstrates) in the presence of the CCI. The coefficients of the CCI are statistically significant in all models, except for the one-month change in volatility forecasting. This result suggests that the partial informativeness of the TAIEX VRP is attributed to the observation that it reflects the sentiment.

[Insert Tables 8 and 9 here]

III.3. Variance Sentiment Index and its Predictive Power

To further examine that the dynamics of the VRP is associated with investor sentiment, we construct the new sentiment index directly extracted from the trading behaviors of individual investors. An option is a non-linear financial instrument whose prices depend on volatility of an underlying asset. Thus, the volatility implied in option prices represents investors' forecast for future uncertainty. Also, investors' belief on economic uncertainty can be reflected on the trading behaviors. For example, if investors have negative mood, they are likely to increase long position in volatility (options). In particular, because individual investors are presumably more irrational and more unsophisticated, their trading behaviors are more sensitive to the sentiment. With these in mind, we define the Variance Sentiment Index (VSI) as the ratio between long position and short position of individual investors in volatility per month:

[12] The Sharpe ratio is defined as $(\mathrm{E_t}(\mathrm{R_i}) - r_{f,t})/VIX_{\mathrm{t}}$, where volatility is approximated by implied volatility (VIX) instead of realized volatility. As such, this Sharpe ratio is an ex ante measure.

$$\mathrm{VSI_t(Variance\ Sentiment\ Iindex)} = \frac{Long\ Position\ in\ Volatility_{ind,t}}{Short\ Position\ in\ Volatility_{ind,t}} = \frac{Long\ in\ Calls_{ind,t} + Long\ in\ Puts_{ind,t}}{Short\ in\ Calls_{ind,t} + Short\ in\ Puts_{ind,t}}.$$

One thing to notice here is that the directional trades on options may reflect the market sentiment of investors as well. For example, a positive mood of investors may result in long position in calls or short position in puts. However, such a definition cannot distinguish sentiment-based trading from informed trading. If a sophisticated investor with private information takes long position in calls, an uninformed investor tends to have short position in calls. In this study, therefore, we focus on the volatility trading rather than the directional trading.

To construct the VSI, we use option transaction data with respect to types of investors, including institutional investors, foreign investors, and individual investors. The Korea Exchange and the Taiwan Futures Exchange are the only major options markets that provide trading volume data by types of investors. This is the main reason for why we select these two options markets as our test bed. Table 10 presents the trading volumes and transaction ratios with regard to types of investors from January 2009 to December 2016 in the two options markets. An investor will have long position (short position) in volatility when he/she expects economic uncertainty to increase (decrease). Thus, a long position of individual investors in volatility is equivalent to buying a fear (uncertainty) index.

For the sample period, the trading volumes of individual investors are relatively high for both options markets. The trading ratio of individual investors is about 32% in Korea and 44% in Taiwan for both long and short positions. For other developed options markets, by comparison, it is documented that the ratios of individual investors are less than 10%. Barber et al. (2009) show that individual investors are more susceptible to psychological bias than institutional investors. If individual investors want to take option positions with irrational beliefs, the institutional investors respond to the irrational demand from individual investors and as a result, the investor sentiment can be partially reflected in the price.

The participation ratios of foreign investors are, however, very different between the two options markets. About 37% of the option transactions is made by foreign investors in Korea, but only 7-8% is made by foreign investors in Taiwan.

[Insert Table 10 here]

Table 11 shows the descriptive statistics of the VSI in Korea and Taiwan. For the sample period, the average VSI in Korea is greater than one, indicating that individual investors in the KOSI index options market are more likely to expect the increase in volatility. In contrast, the average VSI in Taiwan

is less than one. The autocorrelation of the VSI is positive and persistent, similar to the BW sentiment index or the University of Michigan Consumer Sentiment Index is. In addition, Jarque-Bera statistics suggest that the distribution of the VSI is normal in Korea, while it is non-normal in Taiwan.

[Insert Table 11 here]

We now test whether the VSI predicts future index returns, changes in volatility, and the Sharpe ratios. Our main focus is to see if such predictive regressions produce results that are consistent with those expected by the investor sentiment story. When investor sentiment is positive, an asset price can be overvalued than its fundamental value, and returns to the fundamental value after a certain period of time (Baker and Wurgler (2006) and Stambaugh et al. (2012)). In this process, the investor sentiment negatively predicts excess returns. In contrast, the negative investor sentiment increases the long position in volatility, increasing the VSI. Thus, the VSI can positively predict excess returns and negatively predict changes in volatility, thereby positively predicting the Sharpe ratios.

We add the local VRP in the all regression model specifications to examine whether the VSI holds its predictive power independent of the VRP. We also add the three-month risk-free rate as a regressor.

$$\mathrm{R}_{\mathrm{t,t+h}} = \beta_0 + \beta_1 VSI_t + \beta_2 VRP_t + \beta_3 r_{f,t} + \epsilon_t \tag{17}$$

$$\Delta\mathrm{Vol}_{\mathrm{t,t+h}} = \beta_0 + \beta_1 VSI_t + \beta_2 VRP_t + \beta_3 r_{f,t} + \epsilon_t \tag{18}$$

$$Sharpe_{t,t+h} = \beta_0 + \beta_1 VSI_t + \beta_2 VRP_t + \beta_3 r_{f,t} + \epsilon_t \tag{19}$$

Table 12 reports the results. Panels A, B, and C include the results for future excess returns, changes in volatility, and the Sharpe ratios, respectively. The VSI has significant predictive power even in the presence of the VRP and short-term interest rates in both markets. The VSI positively predicts excess returns, negatively predicts volatilities, and positively predicts Sharpe ratios, which are completely consistent with the expectation based on the investor sentiment conjecture. In Panel A, the adjusted R^2 for the KOSPI market increases from 10.7 percent for one-month horizon to 51.5 percent for six months. For the TAIEX market, the adjusted R^2 also increases from 14.8 percent for one month to 37.1 percent for six months. Huang et al. (2015) confirm that the predictive power of a regressor can be guaranteed if the

adjusted R^2 of the univariate predictive regression is greater than 1.3 percent for one-month horizon. The VSI has the adjusted R^2 of greater than 5 percent in the univariate predictive regression.[13] The coefficients of three-month risk-free rate are significant in the predictive models for excess returns in Panel A, confirming the result in Ang and Bekaert (2007). For both markets, the coefficients are all negative, implying that an increase in short-term interest rate causes a fall in stock prices.

There are some interesting differences and similarities in predictive power between the two markets. For the TAIEX market, the VSI has the significant predictive power for future excess returns, but the magnitude of the coefficient is about one-fifth of the KOSPI market's, indicating that the VSI's predictive power in the TAIEX market is significantly weaker than in the KOSPI market. In addition, for the TAIEX market, the VRP is still significant in predicting excess returns in the presence of the VSI, while for the KOSPI market, the VRP is not significant in predicting excess returns.

[Insert Table 12 here]

Panel B of Table 12 reports the empirical performance of the VSI in predicting changes in risk-neutral volatility. For both markets and for most horizons, the VSI negatively and significantly predicts changes in volatility, except for the one-month horizon in Taiwan. An increase in long position of individual investors in volatility results in a decrease in future volatility. The adjusted R^2 ranges from 4.1 percent at one-month horizon to 15.1 percent at six-month horizon for the KOSPI market. Similarly, the adjusted R^2 increases from 4.2 percent to 16.7 percent for the TAIEX market. In contrast, the VRP does not predict changes in volatility for most horizons. For the KOSPI market, the VRP does not predict volatility changes except for one-month horizon, and for the TAIEX market, the VRP does not predict volatility changes for horizons of two and three months.

Based on these results, we confirm that the VSI is superior to the local VRP in predicting excess returns and changes in future volatility in the both markets. In Panel C, the predictive power for the Sharpe ratios is also reported for robustness. For all horizons, the VSI predicts the Sharpe ratios significantly. The VRP is also significant in Taiwan, but not in Korea. The short-term risk-free rate also predicts the Sharpe ratio significantly. The adjusted R^2 increases sharply from 7.7 (4.5) percent at one-month horizon to 38.5 (18.2) percent at six-month horizon in the KOSPI (TAIEX) market.

III.4. Local Variance Sentiment Index and the Global Variance Risk Premium

[13] Results are available upon request.

We hypothesize that the local VRP in non-U.S. markets, in particular the KOSPI VRP, does not capture investor sentiment and therefore its predictive power for future return dynamics is poor. In this section, we first examine the relationships among the VRPs of the S&P 500, KOSPI 200, and the TAIEX indices. Here, the S&P 500 VRP is thought to be as the global VRP and it is well known to exhibit the predictive power for excess returns of non-U.S. markets (Bollerslev et al. (2014) and Londono (2015)). We hope to figure out why some countries' VRPs are informatively inferior. We adopt the regression models as follows:

$$\mathrm{VRP}_{S\&P500,t} = \beta_0 + \beta_1 \mathrm{VRP}_{\mathrm{KOSPI,t-1}} + \epsilon_t \tag{20}$$

$$\mathrm{VRP}_{\mathrm{KOSPI,t}} = \beta_0 + \beta_1 \mathrm{VRP}_{S\&P500,t-1} + \epsilon_t \tag{21}$$

$$\mathrm{VRP}_{S\&P500,t} = \beta_0 + \beta_1 \mathrm{VRP}_{\mathrm{TAIEX,t-1}} + \epsilon_t \tag{22}$$

$$\mathrm{VRP}_{\mathrm{TAIEX,t}} = \beta_0 + \beta_1 \mathrm{VRP}_{S\&P500,t-1} + \epsilon_t \tag{23}$$

Panel A of Table 13 reports the contemporaneous correlations across the VRPs of the S&P 500, the KOSPI 200, and the TAIEX indices. The correlations are very high and statistically significant. The correlation between the S&P 500 VRP and the KOSPI 200 VRP is 0.577 and the correlation between the S&P 500 VRP and the TAIEX VRP is 0.605. The correlation between the KOSPI VRP and the TAIEX VARP is 0.638. These results suggest that much of information inherent in the VRPs is shared with each other, suggesting the existence of common factors in dynamics of the VRPs. Their predictive powers are, however, very different as shown in Table 2 and Table 7: The KOSPI VRP in particular does not predict the local future excess returns as well as changes in volatility. One plausible explanation is the information cascade among the VRPs. If the VRP of a non-US market follows that of the US market, it would not predict its local future return dynamics. Panel B reports the results of the above regression models (Eqs. (20) through (23)) to test this conjecture. Interestingly, the S&P 500 VRP significantly precedes the KOSPI 200 VRP, which does not predict future KOSPI returns as shown in Table 7. In contrast, the TAIEX VRP is not preceded by the S&P 500 VRP. In other words, the poor predictive power of the KOSPI 200 VRP can be interpreted as informatively lagging the S&P 500 VRP.

[Insert Table 13 here]

Next, we examine the relationship between the local VSI and the (global) S&P 500 VRP, both of which demonstrate predictive power for excess returns in local markets. We adopt the following predictive regression specifications.

$$\mathrm{R}_{\mathrm{t,t+h}} = \beta_0 + \beta_2 VRP_{S\&P500,t} + \beta_3 R_{f,t} + \epsilon_t \tag{24}$$

$$R_{t,t+h} = \beta_0 + \beta_1 VSI_t + \beta_2 VRP_{S\&P500,t} + \beta_3 R_{f,t} + \epsilon_t \quad (25)$$

$$\Delta Vol_{t,t+h} = \beta_0 + \beta_2 VRP_{S\&P500_t} + \beta_3 R_{f_t} + \epsilon_t \quad (26)$$

$$\Delta Vol_{t,t+h} = \beta_0 + \beta_1 VSI_t + \beta_2 VRP_{S\&P500,t} + \beta_3 R_{f,t} + \epsilon_t \quad (27)$$

$$Sharpe_{t,t+h} = \beta_0 + \beta_2 VRP_{S\&P500,t} + \beta_3 R_{f_t} + \epsilon_t \quad (28)$$

$$\text{Sharpe}_{t+t+h} = \beta_0 + \beta_1 VSI_t + \beta_2 VRP_{S\&P500,t} + \beta_3 R_{f,t} + \epsilon_t \quad (29)$$

Panel A of Table 14 reports the results for the one-month[14]-horizon. Most interestingly, the coefficients of the VSI are statistically significant for all models even in the presence of the S&P 500 (i.e., global) VRP. Consistent with the results in the literature, the S&P 500 VRP has significant predictive power on future returns, volatility changes, and the Sharpe ratios, highlighting the importance of the global VRP. However, the adjusted R^2s for the models without the VSI as a regressor are significantly different between the KOSPI 200 and the TAIEX. For the predictive models without the VSI, the adjusted R^2 is only 1.3% for KOSPI 200 excess returns, but 8.6% for TAIEX excess returns. The inclusion of the VSI, significantly improves the predictive power of the models. The coefficients of the VSI are statistically significant at the one percent significance level in both markets. The adjusted R^2s rise to 11.5% and 15.7%, respectively. Please also note that the S&P 500 VRP does not lose its significance in the presence of the TAIEX VSI but it does in the presence of the KOSPI 200 VSI.

Panels B and C report the results for the changes in volatility and the Sharpe ratios. For all model specifications, the VSI has the predictive power even in the presence of the S&P 500 VRP, as is the case in Panel A for excess returns. The inclusion of the VSI improves the model performance in predicting future volatility changes and the Sharpe ratios. For the Sharp ratios, the S&P 500 VRP does not lose its significance in the presence of the TAIEX VSI but it does in the presence of the KOSPI 200 VSI.

Overall, these results suggest that information in the VSIs of active, non-US markets may be different from that in the S&P 500 VRP. While the S&P 500 VRP may capture the global sentiment, the VSI is likely to capture the local sentiment.

[Insert Table 14 here]

[14] Results are qualitatively similar for longer horizons but are not reported to save space. They are available upon request.

IV. Conclusion

This study conducts theoretical and empirical analyses to identify the sources of the VRP's high volatility and predictive power. The highly volatile movement of the VRP is difficult to be explained by the constant risk version. The incorporation of the time-varying component in risk aversion seems to generate the volatility of the VRP comparable to the empirical value. The coefficients of the VRP in the predictive regression for excess returns and volatility in this paper are consistent with those in the extant literature on investor sentiment. We first document the close relationship between the VRP and the major sentiment indices in the US. We then show that the poor predictive power of the local VRP in non-U.S. markets can be explained by the failure of the local VRP in capturing the investor sentiment in the local markets. We propose a new local sentiment index, the VSI. Results show that the VSI significantly predicts the future excess return, volatility changes, and the Sharpe ratios in the KOSPI 200 and TAIEX markets, in the manner which is comparable to the performance of the VRP in the US market. These results are robust even in the presence of the -US VRP, which is considered as a global VRP. We interpret the results as suggesting while the US VRP represents the global investor sentiment, the VSI represents the local sentiment.

In this paper, we document an important source of the predictive power for future return dynamics and the variability of the VRP. However, it is empirically difficult to generalize these results into the other major options markets. Only a few East Asian countries provide transaction data with respect to types of investors for their respective options markets. In addition, the trading volume (and value) ratio of individual investors in most of other options markets is much smaller than those of these East Asian options markets. We believe that it should be studied empirically, although challenging, whether the VSI measures the local sentient and predict return dynamics even in options markets in which individual investors participate much less. Further analyses are warranted upon more data available for other major markets.

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Table 1. Variance Risk Premium (VRP) and the S&P 500 Index Returns

This table presents the summary statistics of S&P 500 index returns, VIX, ΔVIX, and the variance risk premiums calculated in three different ways, including Jarque-Bera statistic and Augmented Dickey–Fuller (ADF) statistic. Detailed definitions for the three ways are in Section II.1. Our sample is monthly from January 2009 to December 2016.

Statistics	Index Returns (monthly)	VIX	ΔVIX	VRP (HVDR)	VRP (TRVDR)	VRP (RVIR)
Average	0.009455	19.92729	-0.0109	149.1660	152.5655	186.087
Stdev.	0.040705	7.610237	0.2198	244.1474	233.8332	220.2428
Max	0.102307	46.35000	0.8525	997.5094	1009.417	1022.966
Min	-0.116457	11.40000	-0.4859	-1376.378	-1253.410	-132.4284
Skewness	-0.449144	1.635084	0.5080	-1.814047	-1.485093	1.8727
Kurtosis	3.486953	5.608019	4.3855	18.90247	16.82459	6.586
Auto-corr.	-0.006	0.761	-0.296	-0.252	-0.257	0.333
Jarque-Bera Stat. (p-value)	4.176174 (0.123)	69.983*** (0.00)	11.810*** (0.0027)	1064.207*** (0.000)	799.7654*** (0.000)	107.574*** (0.000)
ADF Stat. (p-value)	-10.0232*** (0.000)	4.085*** (0.001)	-13.107*** (0.0001)	-12.619*** (-0.001)	-2.913** (-0.047)	-7.144*** (-0.000)

* Statistical significance at 10 percent level.
** Statistical significance at 5 percent level.
*** Statistical significance at 1 percent level.

Table 2. Forecasting Regression for S&P 500 Index Returns and Changes in Return Volatility

This table shows the results of predictive regressions for the variance risk premium estimated from S&P 500 index options for horizons from one month to six months. The values in parentheses are t-values obtained using Newey and West (1987) covariance method, which proposes a general covariance estimator that is consistent in the presence of both heteroskedasticity and autocorrelation of unknown form. The independent variables include the risk-free rate as well as the variance risk premium. The dependent variables are cumulative excess return in Panel A and cumulative log-change in volatility in Panel B, respectively. Our sample is monthly from January 2009 to December 2016.

Panel A: Cumulative S&P 500 Excess Returns

Horizon (N-months)	Independent Variables			Adj. R-squared
	Const. (t-value)	VRP (t-value)	Risk-Free (t-value)	
N=1	-0.0004	5.32E-05***	0.027	0.0966
	(-0.099)	(3.914)	(0.841)	
N=2	0.0079	2.84E-05	0.0977	0.0269
	(0.907)	(1.505)	(1.239)	
N=3	0.0098	6.02E-05***	0.142	0.087
	(0.736)	(2.140)	(1.363)	
N=6	0.0204	6.64E-05**	0.350***	0.139
	(1.512)	(2.033)	(3.213)	

Panel B: Cumulative Log-Changes in Volatility

Horizon (N-months)	Independent Variables			Adj. R-squared
	Const.	VRP	Risk-Free	
N=1	0.025	-0.000237***	-0.0236	0.0499
	(0.924)	(-4.214)	(-0.144)	
N=2	0.021	-0.0001	-0.290	0.0005
	(0.443)	(-1.590)	(-0.909)	
N=3	0.0406	-0.000213***	-0.447	0.0314
	(0.589)	(-2.053)	(-0.999)	
N=6	0.057	-0.000215	-0.966*	0.0604
	(0.648)	(-1.241)	(-1.895)	

* Statistical significance at 10 percent level.
** Statistical significance at 5 percent level.
*** Statistical significance at 1 percent level.

Table 3. Sentiment Index and the VRP in the US

This table shows the results of linear regression for sentiment indices and the variance risk premiums in the US. The dependent variable is variance risk premium calculated from S&P 500 daily returns or from S&P 500 intraday returns. The independent variables are Baker and Wurgler sentiment index or its orthogonalized index in Panel A, and University of Michigan Consumer Sentiment Index or its components in Panel B. The values in parentheses are t-values obtained using Newey and West (1987) covariance method, which proposes a general covariance estimator that is consistent in the presence of both heteroskedasticity and autocorrelation of unknown form. Our sample is from January 2009 to December 2016.

Panel A: Baker and Wurgler Sentiment Index

Independent Variables	Dependent Variable			
	VRP estimated using daily returns		VRP estimated using intraday returns	
Const.	78.32***	123.687***	128.02***	175.323***
	(3.155)	(6.14)	(3.753)	(6.384)
$\mathrm{Sent}_{\mathrm{BW}}$	-286.13***		-255.048**	
	(-4.228)		(-2.232)	
$\mathrm{Sent}_{\mathrm{BW,orth}}$		-266.756***		-193.98*
		(-3.546)		(-1.744)
Adjusted R^2	0.0583	0.091	0.0585	0.0567

Panel B: University of Michigan Consumer Sentiment Index

Independent Variables	Dependent Variable					
	VRP estimated using daily returns			VRP estimated using intraday returns		
Const.	499.25***	557.90***	393.28**	914.95***	853.58***	869.82***
	(2.67)	(3.28)	(2.08)	(5.94)	(6.01)	(5.55)
UMCSENT	-4.44*			-9.25***		
	(-1.89)			(-4.77)		
UMCSENT_ Current		-4.59**			-7.42***	
		(-2.42)			(-4.75)	
UMCSENT_ Expec			-3.40			-9.54***
			(-1.30)			(-4.40)
Adjusted R^2	0.0264	0.049	0.007	0.187	0.185	0.162

* Statistical significance at 10 percent level.
** Statistical significance at 5 percent level.
*** Statistical significance at 1 percent level.

Table 4. Temporary Variation in Risk Aversion and Dynamics of VRP

This table shows the characteristics of the simulated variance risk premium with respect to the standard deviation of risk aversion, the level of risk aversion, and the physical volatility of underlying stock index. The baseline parameters used are as follows: the standard deviation of risk aversion (temporary component) is 15% for Panel A, the level of risk aversion is 10 for Panel B, and the physical volatility, skewness, and kurtosis of the distribution are 15 percent, -0.05, and 3.5 for Panel C, respectively.

Panel A: The standard deviation of temporary component and dynamics of the VRP

SD of Risk Aversion	Average Risk-Neutral Vol.	Average VRP	SD of VRP	SD/Average Ratio
10%	19.24%	146.01	27.11	18.57%
15%	19.24%	146.58	41.21	28.11%
20%	19.24%	147.79	52.32	35.39%

Panel B: The average risk aversion and the dynamics of the VRP

Risk Aversion	Average Risk-Neutral Vol.	Average VRP	SD of VRP	SD/Average Ratio
5	16.29%	40.58	7.17	17.86%
10	19.24%	146.01	27.11	18.57%
15	23.11%	310.74	58.78	18.91%

Panel C: Physical volatility and the dynamics of the VRP

Physical Volatility	Average Risk-Neutral Vol.	Average VRP	SD of VRP	SD/Average Ratio
10%	11.41%	30.28	5.65	18.50%
15%	19.24%	146.01	27.11	18.57%
20%	29.14%	451.58	85.32	18.89%

Table 5. Trading Volumes of Major Stock Index Options Exchanges

This table shows the trading volumes, trading values, and open interests of major stock index options exchanges for 2014 through 2017. Panel A presents the trading volume in terms of number of contracts while Panel B presents the notional value (i.e., trading value) in terms of the US dollars. Open Interest in Panel C is in terms of contracts.

Panel A: Trading Volume (Number of Contracts)

	Exchange	Volume			
		2017	2016	2015	2014
1	National Stock Exchange of India	1,362,724,693	1,034,997,570	1,893,555,261	1,057,000,000
2	Korea Exchange	554,765,334	359,036,315	483,597,487	462,000,000
3	CBOE	496,337,160	433,316,741	263,813,550	247,000,000
4	Eurex	372,741,102	388,839,391	401,387,669	340,000,000
5	TAIFEX	186,736,963	167,732,568	192,190,964	152,000,000

Panel B: Trading Value (Million US Dollars)

	Exchange	Notional Value			
		2017	2016	2015	2014
1	National Stock Exchange of India	18,124,076	9,637,063	7,135,078	5,560,000
2	Korea Exchange	43,699,884	34,474,994	51,222,020	56,155,000
3	CBOE	NA	NA	52,445,700	47,097,000
4	Eurex	15,743,394	13,369,947	17,100,750	16,018,000
5	TAIFEX	3,224,524	2,261,601	2,605,524	2,258,000

Panel C: Trading Volumes, Notional Values, and Open Interests in 2017

Ranking	Exchange	Volume	Notional Value	Open Interest
1	National Stock Exchange of India	1,362,724,693	18,124,076	1,778,350
2	Korea Exchange	554,765,334	43,699,884	2,757,470
3	CBOE Global Markets	496,337,160	NA	25,896,900
4	Eurex	372,741,102	15,743,394	35,138,231
5	TAIEX	186,736,963	3,224,524	1,201,209
6	CME Group	168,773,253	27,345,300	4,541,650
7	Moscow Exchange	38,061,837	77,081	1,606,300
8	Japan Exchange Group	33,347,953	NA	2,163,030
9	Tel-Aviv Stock Exchange	32,388,214	1,335,027	281,821
10	Hong Kong Exchanges and Clearing	31,935,369	299,515	24,649,600

	others	89,798,705	NA	NA
	Total	3,367,610,583		

Source: World Federation of Exchanges

Table 6. Descriptive Statistics of Korean and Taiwanese Markets

Panels A, B, C, and D show the summary statistics of monthly stock index returns, option-implied volatility indices, the changes in option volatility indices, and the variance risk premiums, respectively, in Korea and Taiwan. The sample mean, standard deviation, max, min, skewness, kurtosis, autocorrelation, Jarque-Bera statistic, and Augmented Dickey–Fuller statistic are reported. The values in parentheses are the p-values of Jarque-Bera test for normality and of ADF for unit-root. Our sample is monthly from January 2009 to December 2016.

Panel A: Monthly Returns

Statistic	Monthly Returns	
	KOSPI 200	TAIEX
Average	0.005987	0.007301
Stdev.	0.044907	0.048079
Max	0.128549	0.139779
Min	-0.134818	-0.110309
Skewness	0.083269	0.224905
Kurtosis	3.915228	3.655915
Auto-corr.	-0.048	0.109
Jarque-Bera Stat. (p-value)	3.46151(0.177)	2.53022(0.282)
ADF (p-value)	-8.4891***(0.000)	-9.3352***(0.000)

Panel B: Monthly Volatility Index

Statistic	Monthly Volatility Indices	
	KOSPI 200	TAIEX
Average	18.59781	18.53854
Stdev.	7.425515	7.037285
Max	48.21000	43.58000
Min	10.86000	8.570000
Skewness	1.951837	1.380705
Kurtosis	7.359502	4.696538
Auto-corr.	-0.048	0.049
Jarque-Bera Stat. (p-value)	136.9757***(0.000)	42.01452***(0.000)
ADF (p-value)	-8.489***(0.000)	-9.335***(0.000)

Panel C: Monthly Changes in Volatility Index

Statistic	Monthly Changes in Volatility Indices	
	KOSPI 200	TAIEX
Average	-0.015077	-0.012172
Stdev.	0.145830	0.166738
Max	0.377505	0.603898
Min	-0.364799	-0.424680
Skewness	0.243087	0.498624

Kurtosis	3.399383	4.369878
Auto-corr.	-0.109	-0.209
Jarque-Bera Stat. (p-value)	1.56700(0.4568)	11.48427*** (0.003)
ADF (p-value)	-8.8368*** (0.000)	-11.95002***(0.000)

Panel D: Variance Risk Premium

Statistic	Variance Risk Premium	
	KOSPI 200	TAIEX
Average	76.99404	106.3600
Stdev.	237.4936	173.7036
Max	1156.407	821.8389
Min	-1268.231	-490.4168
Skewness	-0.556079	1.149633
Kurtosis	17.60352	7.733681
Auto-corr.	0.455	0.394
Jarque-Bera Stat. (p-value)	857.9983***(0.000)	110.7774***(0.000)
ADF (p-value)	-5.19***(0.000)	-7.158***(0.000)

* Statistical significance at 10 percent level.
** Statistical significance at 5 percent level.
*** Statistical significance at 1 percent level.

Table 7. Forecasting Performance of the VRP in Korea and Taiwan

This table shows the results of predictive regressions for the variance risk premiums estimated from KOSPI 200 and TAIEX options for horizons from one month to three months. The values in parentheses are t-values obtained using Newey and West (1987) covariance method, which proposes a general covariance estimator that is consistent in the presence of both heteroscedasticity and autocorrelation of unknown form. The forecasting variables include the risk-free rate as well as the local variance risk premium. The dependent variables are cumulative excess return in Panel A and cumulative log-change in volatility in Panel B. Our sample is monthly from January 2009 to December 2016.

Panel A: Excess Returns

Dependent Variable		Future N-month Cumulative Return	
		KOSPI 200	TAIEX
Horizon (month)	Independent Variables	Coeff. (t-value)	Coeff. (t-value)
N=1	Const.	0.0091	0.043*
		(0.614)	(1.700)
	VRP	3.50E-05	7.71E-05**
		(1.277)	(2.164)
	Risk-Free Fate	-0.0095	-0.221*
		(-0.399)	(-1.676)
	Adjusted R^2	0.0160	0.109
N=2	Const.	0.0149	0.0825
		(0.4981)	(1.847)
	VRP	5.90E-05	0.00014*
		(0.962)	(1.726)
	Risk-Free Fate	-0.011	-0.420*
		(-0.242)	(-1.798)
	Adjusted R^2	0.0335	0.184
N=3	Const.	0.0178	0.0884*
		(0.461)	(1.643)
	VRP	9.86E-05	0.00023***
		(1.627)	(2.463)
	Risk-Free Rate	-0.0122	-0.467*
		(-0.1957)	(-1.642)
	Adjusted R^2	0.0969	0.2789

Panel B: Changes in Volatility

Dependent Variable		Future N-month Cumulative Change in Volatility	
		KOSPI 200	TAIEX
Horizon (month)	Independent Variables	Coeff. (t-value)	Coeff. (t-value)
N=1	Const.	0.0065	-0.011

		(0.118)	(-0.154)
	VRP	-0.000145***	-0.000233**
		(-3.629)	(-2.230)
	Risk-Free Rate	-0.016	0.119
		(-0.183)	(0.307)
	Adjusted R^2	0.0348	0.0429
N=2	Const.	-0.0077	-0.159
		(-0.072)	(-1.256)
	VRP	-0.00012	-0.000105
		(-1.357)	(-0.977)
	Risk-Free Rate	-0.018	0.755
		(-0.106)	(1.098)
	Adjusted R^2	-0.0003	0.005
N=3	Const.	0.000158	-0.176
		(0.001)	(-1.020)
	VRP	-0.000158	-0.000202
		(-1.200)	(-1.592)
	Risk-Free Rate	-0.043	0.844
		(-0.179)	(0.920)
	Adjusted R^2	0.0094	0.029

* Statistical significance at 10 percent level.
** Statistical significance at 5 percent level.
*** Statistical significance at 1 percent level.

Table 8. Variance Risk Premium and Local Survey-based Sentiment Indices in Korea and Taiwan

This table shows the results of contemporaneous linear regressions for the traditional sentiment indices estimated from the survey data in Korea and Taiwan (Consumer Sentiment Index in Korea and Consumer Confidence Index in Taiwan). The values in parentheses are t-values obtained using Newey and West (1987) covariance method, which proposes a general covariance estimator that is consistent in the presence of both heteroscedasticity and autocorrelation of unknown form. The dependent variable is the local variance risk premium for each country. Our sample is monthly from January 2009 to December 2016.

Independent Variables	Dependent Variable	
	KOSPI VRP	TAIEX VRP
Const.	714.21	885.383***
	(0.763)	(4.331)
Consumer Sentiment	-6.174	-10.042***
(Confidence) Index	(-0.696)	(-3.983)
Adjusted R^2	0.0299	0.342

* Statistical significance at 10 percent level.
** Statistical significance at 5 percent level.
*** Statistical significance at 1 percent level.

Table 9. Predictive Power of the Variance Risk Premium in Taiwan in the Presence of the Local Survey-based Sentiment Index

This table shows the results of forecasting regressions on excess returns, change in volatilities, and the Sharpe ratios in Taiwan for horizons from one month to six months. The values in parentheses are t-values obtained using Newey and West (1987) covariance method, which proposes a general covariance estimator that is consistent in the presence of both heteroscedasticity and autocorrelation of unknown form. The forecasting variables include the survey-based sentiment index, the TAIEX variance risk premium, and the risk-free rate. The dependent variables are the cumulative excess return, cumulative log-change in volatilities, and cumulative Sharpe ratio, respectively. Our sample is monthly from January 2009 to December 2016.

Dependent Variables		Excess return	Change in Volatilities	Sharpe Ratio
Horizon (month)	Independent Variables	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)
N=1	Const.	0.13***	-0.072	1.70***
		(3.35)	(-0.57)	(2.79)
	CCI	-0.002***	0.001	-0.012**
		(-3.24)	(0.74)	(-2.39)
	Local VRP (TAIEX)	3.20E-05	-0.0002*	0.0001
		(0.96)	(-1.70)	(0.30)
	Risk-Free Rate	-0.005	-0.02	-0.19
		(-0.043)	(-0.06)	(-0.08)
	Adjusted R^2	0.171	0.034	0.050
N=2	Const.	0.26***	-0.536***	2.55***
		(3.16)	(-2.58)	(2.71)
	CCI	-0.0033***	0.006***	-0.03***
		(-3.27)	(2.63)	(-2.55)
	Local VRP (TAIEX)	4.93E-05	7.87E-05	-2.11E-05
		(0.73)	(0.59)	(-0.038)
	Risk-Free Rate	-0.002	-0.09	-0.16
		(-0.008)	(-0.14)	(-0.05)
	Adjusted R^2	0.306	0.052	0.139
N=3	Const.	0.32***	-0.67**	2.52***
		(3.50)	(-2.49)	(2.73)
	CCI	-0.004***	0.009***	-0.03***
		(-3.71)	(2.61)	(-2.69)
	Local VRP (TAIEX)	0.0001	4.37E-05	0.0003
		(1.65)	(0.25)	(0.82)
	Risk-Free Rate	0.067	-0.31	0.55
		(0.20)	(-0.32)	(0.15)
	Adjusted R^2	0.402	0.109	0.213
N=6	Const.	0.53***	-1.09***	3.22***
		(3.78)	(-3.16)	(3.19)
	CCI	-0.0067***	0.016***	-0.039***
		(-3.83)	(3.11)	(-2.97)

	Local VRP (TAIEX)	7.39E-05	4.12E-05	-0.0001
		(0.70)	(0.23)	(-0.21)
	Risk-Free Rate	0.082	-1.03	0.64
		(0.150)	(-0.64)	(0.15)
	Adjusted R^2	0.420	0.207	0.266

Table 10. Volatility Trading Activities in Korea and Taiwan

This table reports the volatility trading activities with respect to types of investors in the KOSPI 200 and TAIEX options markets during the sample period. The long position in volatility corresponds to long position in calls or puts while the short position in volatility corresponds to short position in calls or puts. Our sample is monthly from January 2009 to December 2016.

Panel A: Korea (KOSPI 200 Index Options Market)

	Long Position in Volatility (long position on calls or puts)		Short Position in Volatility (short position on calls or puts)	
	Contracts	Ratio	Contracts	Ratio
Individuals	4,355,370,811	0.32327	4,281,539,955	0.31781
Institutions	4,087,433,073	0.30338	4,188,609,063	0.31092
Foreign Investors	5,030,078,790	0.37335	5,001,718,053	0.37127
Total	13,472,882,674	1	13,471,867,071	1

Panel B: Taiwan (TAIEX Options Market)

	Long Position on Volatility (long position on calls or puts)		Short Position on Volatility (short position on calls or puts)	
	Contracts	Ratio	Contracts	Ratio
Individuals	456,033,855	0.44264	456,226,595	0.44283
Institutions	487,556,246	0.47324	502,495,458	0.48774
Foreign Investors	86,654,428	0.08411	71,522,475	0.06942
Total	1,030,244,529	1	1,030,244,529	1

Table 11. Descriptive Statistics of the Variance Sentiment Index (VSI)

This table reports the summary statistics for the Variance Sentiment Index (VSI) calculated from the trading volume of individual investors in the KOSPI 200 and TAIEX options markets. Our sample is monthly from January 2009 to December 2016. The values in parentheses are the p-values of Jarque-Bera test for normality and of ADF for unit-root.

Statistic	VSI in Korea	VSI in Taiwan
Average	1.012234	0.996929
Stdev.	0.010172	0.03046
Max	1.034096	1.098499
Min	0.989668	0.910591
Skewness	-0.249151	0.174838
Kurtosis	2.475161	4.276117
Auto-corr.	0.848	0.348
Jarque-Bera Stat. (p-value)	2.095041 (0.3508)	7.002996** (0.0302)
ADF (p-value)	-4.748903*** (0.001)	-7.145940*** (0.000)

* Statistical significance at 10 percent level.
** Statistical significance at 5 percent level.
*** Statistical significance at 1 percent level.

Table 12. Forecasting Performance of the Variance Sentiment Index (VSI)

This table reports the results of predictive regressions for the Variance Sentiment Index (VSI), along with the variance risk premium and the risk-free rate, for horizons from one month to three months in Korea and Taiwan. The dependent variables are excess returns, changes in volatility, and Sharpe ratios in Panels A, B, and C, respectively. The values in parentheses are t-values obtained using Newey and West (1987) covariance method, which proposes a general covariance estimator that is consistent in the presence of both heteroscedasticity and autocorrelation of unknown form. Our sample is monthly from January 2009 to December 2016.

Panel A: Excess Returns

		KOSPI 200	TAIEX
Horizon (month)	Independent Variables	Coeff. (t-value)	Coeff. (t-value)
N=1	Const.	-2.05***	-0.30**
		(-3.26)	(-2.18)
	VSI	2.10***	0.37***
		(3.26)	(2.53)
	VRP	2.47E-06	8.03E-05**
		(0.107)	(2.39)
	Risk-Free Rate	-0.10***	-0.38***
		(-2.54)	(-2.65)
	Adjusted R^2	0.107	0.148
N=2	Const.	-4.35***	-0.72***
		(-4.23)	(-3.37)
	VSI	4.44***	0.88***
		(4.22)	(3.78)
	VRP	-9.18E-06	0.000145**
		(-0.20)	(2.35)
	Risk-Free Rate	-0.20***	-0.80***
		(-3.00)	(-3.17)
	Adjusted R^2	0.263	0.301
N=3	Const.	-5.45***	-0.72***
		(-4.68)	(-2.90)
	VSI	5.55***	0.88***
		(4.70)	(3.40)
	VRP	1.35E-05	0.000236***
		(0.37)	(3.07)
	Risk-Free Rate	-0.24***	-0.84***
		(-3.42)	(-2.89)
	Adjusted R^2	0.382	0.352
N=6	Const.	-8.62***	-1.25***
		(-6.35)	(-2.55)
	VSI	8.79***	1.55***
		(6.45)	(2.95)
	VRP	2.28	0.00026***
		(0.28)	(2.43)
	Risk-Free Rate	-0.40***	-1.52***
		(-5.28)	(-3.08)
	Adjusted R^2	0.515	0.371

Panel B: Changes in Volatility

		KOSPI 200	TAIEX
Horizon (month)	Independent Variables	Coeff. (t-value)	Coeff. (t-value)
N=1	Const.	2.79**	0.52
		(1.96)	(1.27)
	VSI	-2.84*	-0.58
		(-1.94)	(-1.33)
	VRP	-0.000101**	-0.000238**
		(-1.96)	(-2.07)
	Risk-Free Rate	0.10	0.36
		(0.88)	(0.85)
	Adjusted R^2	0.041	0.042
N=2	Const.	8.28***	1.96***
		(2.52)	(2.44)
	VSI	-8.42***	-2.32***
		(-2.50)	(-2.63)
	VRP	9.67E-06	-0.000119
		(0.12)	(-0.96)
	Risk-Free Rate	0.34	1.76**
		(1.33)	(2.22)
	Adjusted R^2	0.075	0.088
N=3	Const.	11.04**	2.07***
		(2.41)	(2.71)
	VSI	-11.2**	-2.45***
		(-2.39)	(-2.95)
	VRP	1.41E-05	-0.000217
		(0.13)	(-1.27)
	Risk-Free Rate	0.43	1.89*
		(1.30)	(1.91)
	Adjusted R^2	0.128	0.110
N=6	Const.	15.67***	3.13***
		(3.01)	(2.80)
	VSI	-15.89***	-3.69***
		(-2.98)	(-2.91)
	VRP	5.45E-05	-0.00040**
		(0.27)	(-2.27)
	Risk-Free Rate	0.55	2.76*
		(1.26)	(1.81)
	Adjusted R^2	0.151	0.167

Panel C: Sharpe Ratios

		KOSPI 200	TAIEX
Horizon (month)	Independent Variables	Coeff. (t-value)	Coeff. (t-value)
N=1	Const.	-34.55***	-3.89

		(-3.88)	(-1.59)
	VSI	35.29***	4.92*
		(3.90)	(1.94)
	VRP	-0.000281	0.000707*
		(-1.03)	(1.81)
	Risk-Free Rate	-1.68***	-4.77**
		(-2.95)	(-2.24)
	Adjusted R^2	0.077	0.045
N=2	Const.	-46.66***	-6.34***
		(-4.83)	(-2.61)
	VSI	47.61***	7.90***
		(4.88)	(3.13)
	VRP	-0.00034	0.000841**
		(-1.25)	(2.09)
	Risk-Free Rate	-2.23***	-7.36***
		(-3.68)	(-2.56)
	Adjusted R^2	0.178	0.134
N=3	Const.	-47.11***	-5.17**
		(-4.61)	(-2.23)
	VSI	48.08***	6.49***
		(4.69)	(2.73)
	VRP	-0.000167	0.001276***
		(-0.84)	(3.29)
	Risk-Free Rate	-2.28***	-6.28**
		(-3.98)	(-2.01)
	Adjusted R^2	0.241	0.168
N=6	Const.	-51.62***	-5.85*
		(-6.15)	(-1.87)
	VSI	52.75***	7.61**
		(6.32)	(2.25)
	VRP	-5.78E-05	0.000997**
		(-0.16)	(2.17)
	Risk-Free Rate	-2.63***	-8.14**
		(-5.21)	(-2.10)
	Adjusted R^2	0.385	0.182

* Statistical significance at 10 percent level.
** Statistical significance at 5 percent level.
*** Statistical significance at 1 percent level.

Table 13. Relationship among the VRPs of Korea, Taiwan and the U.S.

This table shows the contemporaneous correlations and lead-lag relationships among the variance risk premiums of three countries. The S&P 500 variance risk premium is considered to represent the global variance risk premium. Panel A reports the correlations among three variance risk premiums, and Panels B and C report the lead-lag regression results between the variance risk premiums of Korea and the U.S. and Taiwan and the U.S., respectively. The values in parentheses in Panel A are p-values and the values in parentheses in Panels B and C are t-values. Our sample is monthly from January 2009 to December 2016.

Panel A: Correlations

	S&P VRP	KOSPI VRP
KOSPI VRP	0.577	1.00
	(0.00)	
TAIEX VRP	0.605	0.638
	(0.00)	(0.00)

Panel B: Lead-Lag Regression between the Global (i.e., S&P) VRP and the Korean VRP

	KOSPI VRP	S&P VRP
Const.	24.04*	156.39***
	(1.85)	(7.02)
KOSPI VRP(-1)		-0.13
		(-0.698)
S&P VRP(-1)	0.32**	
	(2.28)	
Adjusted R^2	0.106	0.008

Panel C: Lead-Lag Regression between the Global (i.e., S&P) VRP and the Taiwanese VRP

	TIIEX VRP	S&P VRP
Const.	88.94***	131.17***
	(4.05)	(4.75)
TAIEX VRP(-1)		0.13
		(0.49)
S&P VRP(-1)	0.066	
	(0.446)	
Adjusted R^2	-0.0007	-0.001

* Statistical significance at 10 percent level.
** Statistical significance at 5 percent level.
*** Statistical significance at 1 percent level.

Table 14. Forecasting Performance of the VSI in the Presence of the U.S. VRP

This table shows the results of predictive regressions for the Variance Sentiment Index (VSI) in the presence of the U.S. (i.e., global) variance risk premium, for the one-month horizon in Korea and Taiwan. The risk-free rate is also included as an explanatory variable in all models. The dependent variables are excess returns, changes in volatility, and Sharpe ratios in Panels A, B, and C, respectively. The values in parentheses are t-values obtained using Newey and West (1987) covariance method, which proposes a general covariance estimator that is consistent in the presence of both heteroscedasticity and autocorrelation of unknown form. Our sample is monthly from January 2009 to December 2016.

Panel A: Excess Returns

		KOSPI 200		TAIEX	
Horizon (month)	Independent Variables	Coeff. (t-value)		Coeff. (t-value)	
N=1	Const.	0.013	-1.96***	0.055	-0.417***
		(0.892)	(-3.224)	(1.408)	(-2.672)
	VSI		2.006***		0.507***
			(3.225)		(2.914)
	VRP_US	3.23E-05***	1.67E-05	4.39E-05***	6.17E-05***
		(2.503)	(0.953)	(3.303)	(4.712)
	Risk-Free Rate	-0.019	-0.099***	-0.276	-0.457**
		(-0.83)	(-2.645)	(-1.434)	(-2.28)
	Adjusted R^2	0.013	0.115	0.086	0.157

Panel B: Changes in Volatility

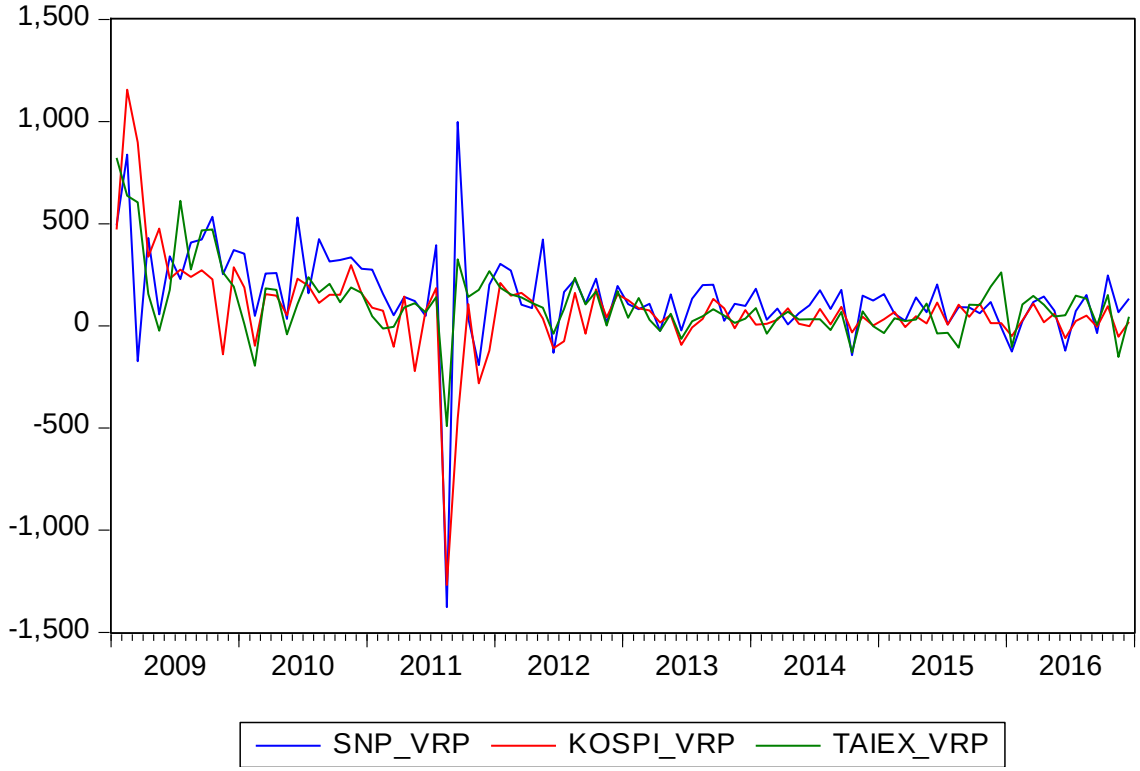
		KOSPI 200		TAIEX	
Horizon (month)	Independent Variables	Coeff. (t-value)		Coeff. (t-value)	
N=1	Const.	-0.009	3.110**	-0.014	1.004*
		(-0.177)	(2.397)	(-0.192)	(1.870)
	VSI		-3.164**		-1.092*
			(-2.383)		(-1.936)
	VRP	-1.72E-04***	-1.47E-04***	-1.91E-04***	-2.29E-04***
		(-4.000)	(-2.673)	(-4.116)	(-4.412)
	Risk-Free Rate	0.0312	0.156	0.151	0.540
		(0.361)	(1.395)	(0.382)	(1.274)
	Adjusted R^2	0.063	0.079	0.064	0.084

Panel C: Sharpe Ratios

		KOSPI 200	TAIEX
Horizon (month)	Independent Variables	Coeff. (t-value)	Coeff. (t-value)

N=1	Const.	0.193	-29.969***	0.662	-5.393**
		(0.719)	(-3.821)	(1.383)	(-2.019)
	VSI		30.593***		6.490**
			(3.851)		(2.345)
	VRP	3.05E-04*	6.66E-05	4.74E-04**	7.00E-04***
		(1.644)	(0.269)	(2.426)	(3.609)
	Risk-Free Rate	-0.252	-1.459***	-2.972	-5.283**
		(-0.630)	(-2.911)	(-1.192)	(-2.118)
	Adjusted R^2	-0.009	0.071	0.026	0.065

* Statistical significance at 10 percent level.
** Statistical significance at 5 percent level.
*** Statistical significance at 1 percent level.

Figure 1. Variance Risk Premiums in the U.S, Korea, and Taiwan

This figure shows the time-series of the variance risk premiums in the S&P 500, KOSPI, and TAIEX markets during our monthly sample period, January 2009 through December 2016.