Hitotsubashi University

Global COE Hi-Stat Discussion Paper Series 214

Research Unit for Statistical and Empirical Analysis in Social Sciences (Hi-Stat)

Market Variance Risk Premiums in Japan as Predictor Variables and Indicators of Risk Aversion

Masato Ubukata
Toshiaki Watanabe

December 2011

Hi-Stat Discussion Paper

Hi-Stat
Institute of Economic Research
Hitotsubashi University
2-1 Naka, Kunitatchi Tokyo, 186-8601 Japan
http://gcoe.ier.hit-u.ac.jp

Market variance risk premiums in Japan as predictor variables and indicators of risk aversion*

Masato Ubukata[a, **] and Toshiaki Watanabe[b]

[a] *Department of Economics, Kushiro Public University of Economics*
[b] *Institute of Economic Research, Hitotsubashi University*

Abstract

This article evaluates the predictive performance of the market variance risk premium (VRP) in Japan on the Nikkei 225 returns, credit spreads, and the composite index of coincident indicators. Different measures such as expected and ex-post VRPs, which are constructed from model-free implied and realized variances, are used to verify the predictability. Moreover, the VRP is estimated by the Bollerslev, Gibson and Zhou (2011) method using Japanese macroeconomic variables to approximate the dynamics of the representative investor's relative risk aversion. The main empirical findings are: (i) the ex-post VRP, which is defined as the difference between implied and ex-post realized variances, is useful in predicting the Nikkei 225 returns, whereas the expected VRPs, which are the differences between implied and current or model-based realized variances, lose their predictive ability, (ii) the expected and ex-post VRPs provide significant predictability of credit spreads and the composite index of coincident indicators, (iii) the VRP involving Japanese macroeconomic variables contains plausible business cycle dynamics of the Japanese economy.

Keywords: variance risk premium; predictability; realized variance; implied variance; relative risk aversion
JEL classification: C22, G17

---

* The authors are grateful to Torben Andersen, Tim Bollerslev and Peter Hansen for their helpful comments and suggestions. The authors also thank the participants in the second international conference "High Frequency Data Analysis in Financial Markets" for invaluable comments. Financial support from the Ministry of Education, Culture, Sports, Science and Technology of the Japanese Government through Grant-in-Aid for Scientific Research (No.18203901; 21243018; 22243021; 23730301), the Global COE program "Research Unit for Statistical and Empirical Analysis in Social Sciences" at Hitotsubashi University and the Joint Usage and Research Center, Institute of Economic Research, Hitotsubashi University (IERPK1109) is gratefully acknowledged.

** Corresponding author. Address: Department of Economics, Kushiro Public University of Economics, 4-1-1, Ashino, Kushiro, Hokkaido 085-8585 Japan; Tel: +81 154 37 3210; Fax: +81 154 37 3287; Email: ubukata@kushiro-pu.ac.jp

1. Introduction

A well-known empirical fact that the variance or volatility of an underlying asset changes over time suggests that market participants face uncertainty risk about return variance or volatility dynamics as well as that for asset return fluctuations. The premium required for investors to accept the former risk is called the variance risk premium (VRP), which can be defined as the difference between the risk neutral and physical expectations of the forward asset return variation. The VRP is not directly observable, but the expectations in the VRP can be estimated from model-free implied and realized variances which have grown dramatically in recent years.

The risk-neutral expectation can be approximated by variance swap rate or model-free option-implied measures such as the Chicago Board Options Exchange (CBOE) Volatility Index (VIX) and Volatility Index Japan (VXJ). For a proxy of the physical expectation, there are some practical approaches using the model-free realized variance. For instance, the current realized variance as a martingale measure, the ex-post realized variance, and the model-based forecast of realized variance are often used in practice. An alternative way to estimate VRP related to macro-finance variables is proposed by Bollerslev, Gibson and Zhou (2011). In addition, we can distinguish between "market-level" and "firm-level" VRPs or between "country-specific" and "global" VRPs. In this way, many different measures of VRP are now considered.

Some previous studies have provided interesting empirical findings regarding the VRP. Many authors find that the VRP is significantly positive, that is, risk-neutral expectation of the forward return variation is larger than physical expectation. For instance, Carr and Wu (2009) find that the VRP defined as the difference between the variance swap rate and the realized variance is strongly positive. This positive VRP means that an option or volatility seller, who is exposed to unlimited loss potential, requires a premium to a buyer. Moreover, the existence of the VRP also implies that speculators may desire short volatility futures positions.

The VRP is a forward-looking variable that may provide information about future asset returns. Bollerslev, Tauchen and Zhou (2009) point out that the degree of predictability of stock returns using a market-level VRP in the US stock market is strong at the quarterly return horizon. It also outperforms all other countries' VRPs in predicting local and foreign stock returns as shown in Londono (2010). Zhou (2010) finds that it provides a significant predictability of stock returns, bond returns and credit spreads. For the firm-level VRP, Wang, Zhou and Zhou (2011) show that it has explanatory power for credit spreads. Bollerslev, Marrone, Xu and Zhou (2011) define the global VRP as the capitalization weighted-average of country-specific VRPs and show that it has stronger predictability of aggregate stock returns than country-specific ones.

However, there is little evidence of the predictive ability of the VRP in the Japanese stock market for some asset returns. For the predictability of the Nikkei 225 returns, Londono (2010) and Bollerslev et al. (2011) suggest that the market-level VRP in the US stock market and the global VRP have predictive power, whereas the market-level VRP in Japan has no predictive ability. Regarding the VRP in Japan, Sugihara (2010) finds that the VRP is positive and examines the interdependency among market-level VRPs in the US, Europe, and

Japan. Oya (2011a) investigates the relationship between the market-level VRP in Japan and the composite index of coincident indicators.

Following on from these previous studies, this article conducts a more inclusive empirical analysis of the monthly market-level VRP in the Japanese stock market. First, we reexamine the predictive performance of the VRP in Japan for the Nikkei 225 returns more carefully. We calculate the realized variance taking into account microstructure noise using high-frequency data because the classical realized variance, which is the sum of the squared high-frequency returns, is distorted by the microstructure noise induced by various market frictions such as the bid-ask spread and non-synchronous trading. For estimating the model-free implied variance, we rely on the squared VXJ obtained from the Center for the Study of Finance and Insurance at Osaka University (CSFI). After that, we construct different kinds of VRPs in Japan such as expected and ex-post VRPs to examine their predictive abilities based on multivariate forecasting regressions for the overlapping multiperiod returns with control variables appropriate for the Japanese stock market. The empirical results show that the ex-post VRP in Japan, which is defined as the difference between the implied and ex-post realized variances, is useful in predicting the Nikkei 225 returns while the expected VRPs in Japan, which are the differences between the implied and current or model-based realized variances, lose their predictive ability.

Second, this article investigates whether or not the VRP in Japan provide information about future credit spreads across different investment grade ratings in Japan's corporate bond market. Furthermore, we provide empirical evidence on the predictive ability of the VRP in predicting a composite index of coincident indicators, which is a measure of current economic conditions. We conclude that the expected and ex-post VRPs provide significant predictability of credit spreads and the composite index of coincident indicators.

Third, Bollerslev et al. (2011) describe a direct relation between the VRP and a representative investor's relative risk aversion under the square-root stochastic volatility model and the power utility function. This is based on the theoretical result that the VRP can be expressed as the covariance between the pricing kernel and quadratic variation in the underlying asset returns. Thus, we estimate an alternative VRP associated with Japanese macroeconomic variables based on the GMM procedure to capture the dynamics of relative risk aversion. The results suggest that the VRP or relative risk aversion involving Japanese macroeconomic variables contains plausible business cycle dynamics of the Japanese economy.

The remainder of this article is organized as follows. Section 2 explains the model-free realized and implied variances used to measure the VRP and construct four types of VRPs in Japan. Section 3 presents the data and empirical results related to the dynamics of relative risk aversion estimated using Japanese macroeconomic variables and the predictive ability of the VRPs on the Nikkei 225 returns, credit spreads, and the composite index of coincident indicators. Section 4 concludes. Appendix provides a detailed description of the realized variance measure employed in this article.

2. Variance risk premium

VRP, which is defined as the difference between the risk-neutral and physical expectations of the short-term future return variation, is not directly observable. In order to measure the VRP, the risk-neutral and physical expectations are estimated from model-free implied and realized variances. In this section, we start with a brief explanation about realized and implied variance. After that, we construct three types of Japanese VRP measures to analyze whether or not their predictive power on the Nikkei 225 returns, credit spreads, and the composite index of coincident indicators is significant, and present a method of constructing an alternate VRP related to Japanese macroeconomic variables that captures the dynamics of investor's risk aversion.

2.1. Realized and implied variances

Consider the following continuous-time stochastic volatility model for the logarithmic price p_t:

$$\begin{aligned} dp_t &= \mu_t(\cdot)dt + \sqrt{V_t}dW_{1t}, \\ dV_t &= \kappa(\theta - V_t)dt + \sigma_t(\cdot)dW_{2t}, \end{aligned} \tag{1}$$

where W_{1t} and W_{2t} are two Brownian motions that have a correlation coefficient $\mathrm{corr}(dW_{1t}, dW_{2t}) = \rho$, and κ and θ are the rate at mean reversion for variance V_t and the long-term mean variance. The functions $\mu_t(\cdot)$ and $\sigma_t(\cdot)$ satisfy the regularity conditions. When $\rho < 0$, we have a leverage effect. Then the quadratic variation for an asset return from time t to $t+1$ is defined as the integral of V_s over the $[t, t+1]$ time interval, i.e.:

$$\mathcal{V}_{t,t+1} = \int_t^{t+1} V_s ds. \tag{2}$$

The realized variance is well known as an accurate estimate of the quadratic variation $\mathcal{V}_{t,t+1}$ if prices do not include any noise. If we have high-frequency return data $\left(r_{t+1/n}\ r_{t+2/n},\ \ldots,\ r_{t+1}\right)$, the realized variance over the $[t, t+1]$ time interval is computed as the sum of the squared returns, as follows:

$$RV_{t,t+1} = \sum_{i=1}^{n} r_{t+i/n}^2, \quad \operatorname*{plim}_{n\to\infty} RV_{t,t+1} = \mathcal{V}_{t,t+1}, \tag{3}$$

where n is the number of observed returns. $RV_{t,t+1}$ is usually found to provide more accurate variance estimates than those derived from lower-frequency data.

However, it fails to satisfy the consistency condition when there is microstructure noise induced by various market frictions such as the bid-ask bounces and non-synchronous trading (Campbell, Lo and MacKinlay 1997), as often exists in real high-frequency data. The literature on market microstructure provides some insights from early studies including Roll (1984), who derives a simple estimator of the bid-ask spread based on the negative autocovariance of returns. In the literature on microstructure noise, Hansen and Lunde (2006) examine the variance of microstructure noise as well as the correlation between the microstructure noise and frictionless equilibrium price. Ubukata and Oya (2009) propose test statistics for the dependence of macrostructure noise processes and capture the various dependence patterns.

There are some methods available for mitigating the effect of microstructure noise on realized variance (Bandi and Russell 2008, 2011; Barndorff-Nielsen, Hansen, Lunde and Shephard 2008; Kunitomo and Sato 2008; Oya 2011b; Zhang, Mykland and Aït-Sahalia 2005, inter alia). In order to take into account microstructure noise, we employ a modified Tukey-Hanning kernel-based estimator by Barndorff-Nielsen et al. (2008) with a finite sample optimal number of autocovariances by Bandi and Russell (2011), instead of the classical realized variance in (3). The Appendix provides a detailed description of the kernel-based realized variance.

Model-free option-implied variance is employed for approximating the risk-neutral expectation of the forward quadratic variation of an asset based on its option prices. It is model-free in the sense that it does not rely on a particular option pricing model such as the Black-Scholes model. Let $P_t(t+1, K)$ and $C_t(t+1, K)$ denote the European put and call option prices at time t with strike K and maturity $t+1$, and $B(t, t+1)$ and $F(t, t+1)$ denote risk-free zero-coupon bond and forward prices at time t with maturity $t+1$. As shown by Demeterfi, Derman, Kamal and Zou (1999), Britten-Jones and Neuberger (2000) and Jian and Tian (2005, 2007), the model-free implied variance, termed $IV_{t,t+1}$, is constructed from the portfolio of European options and equal to the expectation of $\mathcal{V}_{t,t+1}$ conditional on time t information under the risk-neutral measure Q, i.e.:

$$
\begin{aligned}
IV_{t,t+1} &= \frac{2}{B(t,t+1)}\Big[\int_0^{F(t,t+1)} \frac{P_t\big(t+1,K\big)}{K^2}dK + \int_{F(t,t+1)}^{\infty} \frac{C_t\big(t+1,K\big)}{K^2}dK\Big] \qquad (4) \\
&= E_t^Q[\mathcal{V}_{t,t+1}], \qquad (5)
\end{aligned}
$$

where K represents the strike price.

However, the number of available strike prices is finite in practice. Thus, many authors propose the implied variance calculation methods to approximate the integrals on the right-hand side of (4) (See CBOE 2009, Fukasawa, Ishida, Maghrebi, Oya, Ubukata and Yamazaki 2011 and Jiang and Tian 2007, for details). For example, the VIX index in the US and VXJ have attracted much attention as a model-free option-implied variance measure in each financial market. These indexes are usually measured as annualized 30-day square roots of quadratic variation in percentage points. This article depends on the squared VXJ computed following the Fukasawa et al. (2011) approach, which is based on a formula induced by the model-free link introduced in the context of pricing variance swaps in order to reduce approximation errors.

2.2. Measurement of variance risk premium

Variance risk premium at time t, termed VRP_t, can be defined as the difference between the expectations of $\mathcal{V}_{t,t+1}$ under the risk neutral measure Q and the physical measure P, i.e.:

$$
VRP_t \equiv E_t^Q[\mathcal{V}_{t,t+1}] - E_t^P[\mathcal{V}_{t,t+1}]. \qquad (6)
$$

$E_t^Q[\mathcal{V}_{t,t+1}]$ can be replaced by the model-free option-implied variance where we use the squares of VXJ. For a proxy of $E_t^P[\mathcal{V}_{t,t+1}]$, some practical approaches are possibly considered. For investigating the predictability of the Nikkei 225 returns, credit spreads, and the composite index of coincident indicators, we construct three types of monthly VRPs, which are distinguished by the methods to approximate the quantity of $E_t^P[\mathcal{V}_{t,t+1}]$ as explained below.

The first VRP involves using the lagged realized variance over the $[t-1,t]$ time period, that is:

$$VRP_t^{(1)} \quad = \quad IV_{t,t+1} - RV_{t-1,t}, \tag{7}$$

which is based on the assumption that $RV_{t,t+1}$ follows a martingale difference sequence $E_t[RV_{t,t+1}] = RV_{t-1,t}$.

The second VRP is to use ex-post realized variance estimates of the true quadratic variation $\mathcal{V}_{t,t+1}$ over the $[t,t+1]$ time interval.

$$VRP_t^{(2)} \quad = \quad IV_{t,t+1} - RV_{t,t+1}. \tag{8}$$

$RV_{t,t+1}$ is not observed at time t and so $VRP_t^{(2)}$ is called the ex-post VRP. It is not available for the one-period-ahead forecast of some asset returns, but may be useful for their predictability over multiple periods.

The third VRP uses a one-period-ahead forecast of realized variance based on its time-series model. We employ the heterogeneous interval autoregressive (HAR) model of Corsi (2009) to describe the dynamics of realized variance. Then the third VRP is measured by:

$$VRP_t^{(3)} \quad = \quad IV_{t,t+1} - \widetilde{RV}_{t,t+1}, \tag{9}$$

where $\widetilde{RV}_{t,t+1}$ is the one-period-ahead forecast of realized variance from the HAR model.

The HAR model is well-known as a simple approximate long-memory model of daily realized variance. Let $\ln(RV_{\tau-1,\tau})$ denote the logarithmic realized variance at day τ over the $[\tau-1,\tau]$ time period. Then, the HAR model consists of three realized variance components defined over different time periods as follows:

$$\begin{aligned} \ln(RV_{\tau-1,\tau}) = \alpha_0 + \alpha_1 \ln(RV_{\tau-2,\tau-1}) + \alpha_2 \ln(RV^w_{\tau-2,\tau-1}) + \alpha_3 \ln(RV^m_{\tau-2,\tau-1}) + v_\tau, \\ v_\tau \sim \text{NID}(0,\sigma_v^2), \end{aligned} \tag{10}$$

where $RV_{\tau-2,\tau-1}$ is one-day lagged realized variance and $RV^w_{\tau-2,\tau-1} = \frac{1}{5}\sum_{i=1}^{5} RV_{\tau-i-1,\tau-i}$ and $RV^m_{\tau-2,\tau-1} = \frac{1}{22}\sum_{i=1}^{22} RV_{\tau-i-1,\tau-i}$ are the average of the past realized volatilities corresponding to time horizons of five trading days (one week) and 22 trading days (one month), respectively. We can estimate parameters α_0, α_1, α_2, α_3, and σ_v^2 by applying simple linear regression. To obtain a time series of monthly $VRP_t^{(3)}$, we estimate the HAR model using the past 350 daily realized variances up to a time t. Given the estimated parameters, $\widetilde{RV}_{t,t+1}$ is computed as the sum of one day to 22 days ahead forecasts. We repeat this procedure for each month.

An alternative way to estimate a time-varying VRP is proposed by Bollerslev et al. (2011) which is based on the moment restrictions of $\mathcal{V}_{t,t+1}$. This VRP is more suitable for estimating a proxy of the representative investor's relative risk aversion because the VRP is allowed to be related to a set of macroeconomic variables. The risk neutral expression of (1) under the assumption of no arbitrage and the linearity of VRP is as follows:

$$\begin{aligned} dp_t &= r_t^* dt + \sqrt{V_t} dW_{1t}^*, \\ dV_t &= \kappa^*(\theta^* - V_t)dt + \sigma_t(\cdot)dW_{2t}^*, \end{aligned} \tag{11}$$

where $\mathrm{corr}(dW_{1t}^*, dW_{2t}^*) = \rho$ and r_t^* is a risk-free rate. The risk neutral parameters are related to the parameters in (1), $\kappa^* = \kappa + \lambda$ and $\theta^* = \kappa\theta/(\kappa + \lambda)$ where λ is a constant VRP parameter. To estimate a time-varying VRP, Bollerslev et al. (2011) modify the risk neutral distribution for the variance in (11) as follows:

$$dV_t = \kappa_t^*(\theta_t^* - V_t)dt + \sigma_t(\cdot)dW_{2t}^*, \tag{12}$$

where $\kappa_t^* = \kappa + \lambda_t$ and $\theta_t^* = \kappa\theta/(\kappa + \lambda_t)$. λ_t is the time-varying VRP parameter of interest which is defined as $VRP_t^{(4)} = -\lambda_t$. Moreover, λ_t is allowed to depend on some macroeconomic variables using the following augmented AR(1) model, i.e.:

$$\lambda_t = a + b\lambda_{t-1} + \sum_{j=1}^{J} c_j \mathrm{macro}_{t-1,j}, \tag{13}$$

where $\mathrm{macro}_{t-1,j}$ is the j-th macroeconomic variable. Bollerslev and Zhou (2002, 2006) derive the expression for the conditional moments among the physical and risk-neutral expectations of $\mathcal{V}_{t,t+\Delta}$ over the $[t, t+\Delta]$ time interval as follows:

$$\begin{aligned} \mathrm{E}_t^P[\mathcal{V}_{t+\Delta,t+2\Delta}] &= \alpha_\Delta \mathrm{E}_t^P[\mathcal{V}_{t,t+\Delta}] + \beta_\Delta, &(14) \\ \mathrm{E}_t^P[\mathcal{V}_{t,t+\Delta}] &= \mathcal{A}_{t,\Delta} \mathrm{E}_t^Q[\mathcal{V}_{t,t+\Delta}] + \mathcal{B}_{t,\Delta}, &(15) \end{aligned}$$

where

$$\alpha_\Delta = e^{-\kappa\Delta}, \quad \beta_\Delta = \theta(1 - \alpha_\Delta), \quad \mathcal{A}_{t,\Delta} = \frac{(1-\alpha_\Delta)/\kappa}{(1 - e^{-\kappa_t^*\Delta})/\kappa_t^*},$$
$$\mathcal{B}_{t,\Delta} = \theta[\Delta - (1-\alpha_\Delta)/\kappa] - \mathcal{A}_{t,\Delta}\theta_t^*[\Delta - (1 - e^{-\kappa_t^*\Delta})/\kappa_t^*].$$

For estimating $VRP_t^{(4)} = -\lambda_t$, we employ a GMM estimator using the sample analogues of the following moment conditions:

$$\mathrm{E}[f_t] = 0, \quad f_t = \begin{bmatrix} \mathcal{V}_{t+\Delta,t+2\Delta} - \alpha_\Delta \mathcal{V}_{t,t+\Delta} + \beta_\Delta \\ (\mathcal{V}_{t+\Delta,t+2\Delta} - \alpha_\Delta \mathcal{V}_{t,t+\Delta} + \beta_\Delta)\mathcal{V}_{t-\Delta,t} \\ \mathcal{V}_{t,t+\Delta} - \mathcal{A}_{t,\Delta} IV_{t,t+\Delta} + \mathcal{B}_{t,\Delta} \\ (\mathcal{V}_{t,t+\Delta} - \mathcal{A}_{t,\Delta} IV_{t,t+\Delta} + \mathcal{B}_{t,\Delta})\mathcal{V}_{t-\Delta,t} \\ (\mathcal{V}_{t,t+\Delta} - \mathcal{A}_{t,\Delta} IV_{t,t+\Delta} + \mathcal{B}_{t,\Delta})\mathcal{V}_{t-\Delta,t}^2 \\ (\mathcal{V}_{t,t+\Delta} - \mathcal{A}_{t,\Delta} IV_{t,t+\Delta} + \mathcal{B}_{t,\Delta}) IV_{t-\Delta,t} \\ \vdots \\ (\mathcal{V}_{t,t+\Delta} - \mathcal{A}_{t,\Delta} IV_{t,t+\Delta} + \mathcal{B}_{t,\Delta})\mathrm{macro}_{t-\Delta,j} \\ \vdots \end{bmatrix} \tag{16}$$

where the lagged realized variance, which is estimates of $\mathcal{V}_{t-\Delta,t}$, is used as an instrument for the moment in (14) and (15), and the lagged squared realized variance, lagged implied variance, and other macroeconomic variables are added as additional instruments for the cross-moment in (15).

3. Empirical analysis

3.1. Data and descriptive statistics

We analyze monthly market-level VRPs on the Nikkei 225 stock index which is the average of the prices of 225 representative stocks traded on the Tokyo Stock Exchange (TSE). The sample period is from February 1998 to July 2009 (138 months). To estimate actual market variation, we calculate realized variance using the Nikkei NEEDS-TICK data. This dataset includes the Nikkei 225 stock index for every minute from 9:01 to 11:00 in the morning session and from 12:31 to 15:00 in the afternoon session, when the TSE is open, while it is impossible to obtain high-frequency returns for 15:00-9:00 (overnight) and 11:00-12:30 (lunch-time). For estimating market realized variation over a month, our realized variance is computed as the sum of daily kernel-based realized variance within a month adding the sum of the squares of the overnight and lunch-time returns. For estimating implied variance based on the Nikkei 225 options, we rely on the squared VXJ at the end of the month while the volatility index usually refers to its square root in annualized percentage points provided by CSFI on its Website.[1]

Table 1 summarizes the descriptive statistics of the monthly implied and realized variances in percentage points (non-annualized). The mean of realized variance is much lower than that of implied variance. The values of skewness and kurtosis indicate that the distributions of implied and realized variances are nonnormal. LB(10) is the Ljung-Box statistic adjusted for heteroskedasticity following Diebold (1988) to test the null hypothesis of no autocorrelations up to 10 lags. According to this statistic, the null hypothesis is rejected at the 1% significance level. The first-order autocorrelation coefficient $\rho(1)$ of realized variance equals 0.58 which is the same as that of implied variance, 0.57. Figure 1 plots the monthly realized and implied variances. We find that the realized variance is generally lower than the implied variance over the whole period and there are sudden surges of these variance measures associated with economic and financial shocks such as the US housing and credit crisis in 2008.

Table 2 summarizes the descriptive statistics of monthly $VRP_t^{(1)}$, $VRP_t^{(2)}$, $VRP_t^{(3)}$ and $VRP_t^{(4)}$, defined in Section 2.2. The means of the VRPs are positive which is consistent with the lower mean of realized variance relative to implied variance. The positive VRP indicates that the risk neutral expectation is larger than the physical one. In such a case, we interpret that the volatility or option sellers, which are exposed to an unlimited loss potential, require a premium to the buyer. $VRP_t^{(2)}$, which is the ex-post VRP, has the largest standard deviation. From the values of skewness and kurtosis, the distributions of $VRP_t^{(1)}$, $VRP_t^{(2)}$ and $VRP_t^{(3)}$ are

[1] http://www-csfi.sigmath.es.osaka-u.ac.jp/structure/activity/vxj.php

nonnormal while that of $VRP_t^{(4)}$ is closer to normal. LB(10) for $VRP_t^{(1)}$, $VRP_t^{(3)}$ and $VRP_t^{(4)}$ indicates that the null hypothesis of no autocorrelation is rejected at the 1% significance level. In particular, $VRP_t^{(4)}$ has the highest first-order autocorrelation coefficient 0.87 of all and its autocorrelation coefficient decays more slowly than the others. On the other hand, LB(10) for $VRP_t^{(2)}$ is so low that the null hypothesis is not rejected even at the 10% significance level, where the first-order autocorrelation coefficient 0.25 is the lowest of all. Figure 2 also plots the monthly VRPs. We can see that $VRP_t^{(2)}$ takes negative values more frequently relative to the others and $VRP_t^{(4)}$ has a high degree of its persistence. These results imply that the statistical property of VRP varies substantially according to its specification.

3.2. Variance risk premium as a measure for relative risk aversion

The VRP is associated with the covariance between the pricing kernel and the quadratic variation as shown by Bakshi and Kapadia (2003) and Carr and Wu (2006, 2009). Bollerslev et al. (2011) also describe a direct link to VRP and relative risk aversion under the square-root stochastic volatility model corresponding to $\sigma_t(\cdot) = \sigma\sqrt{V_t}$ in (1) and power utility function as follows:

$$-\lambda_t V_t = \mathrm{Cov}_t\Big(\frac{dm_t}{m_t}, dV_t\Big) = -\gamma_t \rho\sigma V_t, \quad \gamma_t = \lambda_t/(\rho\sigma), \tag{17}$$

where γ_t and m_t represent a relative risk aversion and pricing kernel which is an investor's marginal utility of wealth. The expression indicates that VRP is interpreted as an indicator of the representative investor's risk aversion as well as the volatility uncertainty risk. Following the result that the relative risk aversion is proportional to $VRP_t^{(4)}$ because the leverage effect ρ is usually negative, we adopt it to capture dynamics of relative risk aversion.

On the result of the GMM estimation for $VRP_t^{(4)} = -\lambda_t$, we examine the 30 kinds of Japanese macroeconomic variables listed in Table 3 to specify the augmented AR(1) model in (13). If the non-stationarity hypothesis for the time-series of the macroeconomic data is not rejected, we convert the non-stationary time series into stationary series. Following Bollerslev et al. (2011), all of the macroeconomic variables are standardized to mean zero and variance one. Furthermore, we employ the Newey and West (1987) heteroskedasticity and autocorrelation consistent robust covariance matrix with Bartlett kernel and a lag length of 25.

Table 4 reports the estimation results. The estimate of the long-term mean level of the variance $\theta = 0.31\%$ is almost the same as the sample mean of the realized variance, 0.34%, reported in Table 1. The average VRP is $-a/(1-b) = 1.27$ and VRP has a degree of own persistence $b = 0.63$. The realized variance has the biggest contribution $c_1 = -0.21$ which has a positive impact on $-\lambda_t$. This means that a higher realized variance leads to a higher VRP or relative risk aversion. The price-earnings (P/E) ratio, retail sale value and price-to-book value ratio are significant at the 5% or 10% level. The test of overidentifying restrictions does not reject the null hypothesis that the model is correctly specified at the 1% significance level.

In Figure 3, the solid and dashed lines represent $VRP_t^{(4)}$ or relative risk aversion when we use macroeconomic variables and only lagged realized variance, respectively. They tended to rise during the three macroeconomic recessions in the shaded areas. They rose sharply in the periods of the Asian currency crisis, dot-com bubble burst, September 11 attacks, subprime mortgage crisis and Lehman shock. In March 1998 in Japan, retail sales have decreased substantially by 15% over a one-year period, the highest ever recorded, because the consumption tax rate increased from 3% to 5% in the previous 12 months. The first sharp increase in the solid line also captures this temporal macroeconomic shock. This result suggests that VRP or relative risk aversion involving macroeconomic variables contains plausible business cycle dynamics of the Japanese economy.

3.3. Stock return predictability

The VRP as a forward-looking variable could possibly provide information about future asset returns. In this subsection we provide empirical results for the predictive ability of the $VRP^{(1)}$, $VRP^{(2)}$ and $VRP^{(3)}$ on the Nikkei 225 returns. We do not examine the predictive ability of $VRP^{(4)}$ because the two-period-ahead realized variance is required to implement the GMM procedure and therefore the $VRP_t^{(4)}$ may not be suitable to be used as the predictor variable for the purpose of forecasting asset returns.

In previous studies that examine the predictive ability of some standard predictor variables in the Japanese stock market, Aono and Iwaisako (2010, 2011) find that (i) an interest rate loses its predictive ability in recent samples from 1991 to 2009 because of its limited variability related to the Bank of Japan's zero interest policy, (ii) one-month-ahead performances of the P/E ratio and dividend yield (DY) are very weak, (iii) however the importance of lagged returns increases in recent samples. Taking into consideration that, we employ the following multivariate forecasting regressions for overlapping multiperiod returns.

$$\frac{1}{h}ER_{t+h} = \beta_0(h) + \beta_1(h)VRP_t^{(i)} + \beta_2(h)R_t + \beta_3(h)(P/E)_t + \beta_4(h)DY_t + u_{t+h}, \tag{18}$$

where $i = 1, 2, 3$ and $\beta_1(h)$ is the parameter of interest. $\frac{1}{h}ER_{t+h}$ represents excess market returns, which is the difference between the Nikkei 225 returns and unsecured overnight call rates, scaled by the horizon $h = 1, 2, \cdots, 12$ months. R_t represents the lagged Nikkei 225 returns. $(P/E)_t$ and DY_t are the P/E ratio and weighted average yield for TSE 1st section-listed stocks obtained from the TSE's website.[2]

In the existing literature investigating the finite sample properties of regressions of stock returns on lagged financial variables, Boudoukh, Richardson and Whitelaw (2008) show that the coefficient of determination R^2, including highly persistent predictor variables and overlapping multi-period returns, increases proportionally to the return horizon even in no predictability. Thus, we should give attention to this issue regarding R^2. Furthermore, some previous studies indicate that standard statistical inference in the overlapping multiperiod return regression on highly-persistent predictor variables is inappropriate. However, we can reasonably use the Newey and West (1987) and Hodrick (1992) type t-statistics in such cases. This is because Bollerslev et al.

[2] http://www.tse.or.jp/english/market/topix/data/index.html

(2011) investigate their finite sample properties and show that they are reasonably well behaved while there are some size distortions. Second, the monthly expected and ex-post VRPs have low persistence as shown in Table 2 and so we can partly avoid this problem in our empirical analysis. The Bollerslev et al. (2011) simulation result also shows that the Newey-West based t-statistic is marginally more powerful than the Hodrick (1992) type t-statistic. Thus, this article employs the Newey and West (1987) t-statistic for the overlapping multiperiod return regression.

Table 5 summarizes the estimation results in (18). The t-statistics reported in parentheses are based on heteroskedasticity and serial correlation consistent standard errors proposed by Newey and West (1987).[3] Figure 4 also plots predictability patterns in the coefficient parameters $\beta_1(h)$ for $VRP_t^{(i)}$, $i = 1, 2, 3$ and adjusted R^2 in percentage points where the x-axis represents the h month-horizon and the dashed and dotted lines represent the 90% and 95 % confidence intervals of coefficient parameters $\beta_1(h)$ using the Newey-West standard errors. The $VRP_t^{(1)}$ and $VRP_t^{(3)}$, which are the expected VRPs, have no statistical significance over the whole period. On the other hand, the $VRP_t^{(2)}$, which is the ex-post VRP, can significantly forecast the Nikkei 225 returns over two-, seven-, and eight-month horizons. The positive slope coefficient for $VRP_t^{(2)}$ indicates that higher values of the VRP lead to higher future returns. This result may reflect that when the market anticipates high fluctuations in the return variance, there is a premium incorporated into prices, resulting in high future returns. The adjusted R^2 for $VRP_t^{(2)}$ peaks around 6.2% at two months and gradually decreases toward zero as the horizon is extended. R_t has a significant positive slope coefficient, which implies momentum in stock returns. $(P/E)_t$ has a significant positive slope coefficient while DY_t has no statistical significance over the whole period. These empirical results provide new evidence that the ex-post VRP in Japan is useful in predicting the Nikkei 225 returns while the expected VRPs lose their predictive ability.

3.4. Credit spreads predictability

The VRP could be one of influential determinants of credit spreads as shown by Zhou (2010) and Wang et al. (2011). In this subsection, we provide empirical results for the predictive ability of the market-level VRP in Japan on credit spreads. Credit spreads employed in our analysis are constructed from the difference between the average corporate bond yield of firms with investment grade rating, which is obtained from Japan Credit Rating Agency on its Website,[4] and the Japanese government bond yield. The sample period is from August 2002 to July 2009 (84 months) corresponding to the average corporate bond yield data available. For investigating the relationship between VRP and credit spreads, we estimate the following overlapping multiperiod forecasting regressions.

$$\frac{1}{h}\Delta CS_{j,m,t+h} = \beta_0(h) + \beta_1(h)VRP_t^{(i)} + \beta_2(h)\Delta r_{f,m,t} + \beta_3(h)R_t + u_{t+h}, \tag{19}$$

[3]We use a covariance matrix with a Bartlett kernel and a lag length determined by $h + 4((T-h)/100)^{2/9}$ where T is the sample size in the regression.

[4]http://www.jcr.co.jp/english/

where $i = 1, 2, 3$ and $\Delta CS_{j,m,t+h}$ is difference in the credit spread with investment grade rating j and maturity m over $h = 1, 2, \cdots, 12$ months. We add $\Delta r_{f,m,t}$ and R_t, which represent differences in the Japanese government bond yield in the corresponding maturity m and the lagged Nikkei 225 returns, as standard predictor variables.

Tables 6 and 7 summarize the estimation results for the credit spread of firms with an investment grade AAA rating and $m = 1, 3$ year maturities. The AAA long-term rating is defined as firms having the highest level of capacity of the obligor to honor its financial commitment on the obligation. Figures 5 plots the corresponding predictability patterns in coefficient parameters $\beta_1(h)$ for $VRP_t^{(i)}$, $i = 1, 2, 3$ and adjusted R^2 in percentage points. In the cases of AAA long-term rating firms with one- and three-year maturities, all VRPs have no statistical significance until around the quarterly return horizon, but they can significantly forecast the credit spreads with longer horizons. The negative slope coefficient indicates that a higher VRP lowers the future credit spread of the AAA long-term rating firms having extremely strong capacity. The adjusted R^2 gradually increases at longer monthly horizons. $\Delta r_{f,m,t}$ and R_t have significant positive and negative slope coefficients and their t-values with one-year maturity are larger than those with three-year maturity.

Tables 8 and 9 represent the results for the A long-term rating firms, which have a high level of capacity but are more susceptible to the negative effects of changes in economic conditions than higher-rated categories. Figure 6 also plots the predictability patterns and adjusted R^2. In contrast to the result for AAA long-term rating firms, the significance of the VRPs extends to around the six-month horizon and the slope coefficient of the VRP becomes insignificant at longer monthly horizons. The positive slope coefficients show that rising VRP leads to larger future credit spreads for A rating firms having less capacity than AAA long-term rating firms. Adjusted R^2 peaks at two months and gradually decreases toward zero after the six-month horizon. The estimated coefficients of $\Delta r_{f,m,t}$ and R_t are significantly positive and negative, respectively, however they have smaller t-values than those for the VRP.

The predictability patterns for the AAA and A long-term rating firms are considerably different. For the predictability of the credit spreads of AAA long-term rated firms, all VRPs have no statistical significance until around the quarterly return horizon and have a negative slope coefficient. This may reflect that the AAA long-term rated firms are less susceptible to the effect of fluctuations in the VRP than the A long-term rated firms, and even when the VRP becomes high, market participants are likely to invest in AAA corporate bonds with their lower yields because AAA firms are more secure. In the case of the A long-term rated firms, the VRP in Japan provides a positive impact which is consistent with the intuitive idea that an increase in the uncertainty risk in the stock market leads to higher corporate bond yields. These results provide evidence that the market VRPs provide significant predictability of credit spreads and the direction of their effect depends on firms' investment grades.

3.5. Predictability of composite index of coincident indicators

Some previous studies examine the predictive abilities of market excess returns and their volatility on future output growth. As the VRP can be regarded as a forward-looking variable, it is important to investigate whether the VRP provides information about future output growth. However, GDP data are available mainly on only a quarterly or annually basis. Instead of GDP, we examine the predictability of the composite index of coincident indicators which is a measure of current economic conditions. A recent study by Oya (2011a) investigates the relationship between the VRP and the composite index of coincident indicators, but they examine the ex-post VRP only and do not use the realized variance constructed from high-frequency return data. We estimate the following overlapping multi-period return regressions.

$$\frac{1}{h}CI_{t+h} = \beta_0(h) + \beta_1(h)VRP_t^{(i)} + \beta_2(h)SPRD_t + u_{t+h}, \tag{20}$$

where $i = 1, 2, 3$, $\frac{1}{h}CI_{t+h} = \frac{1}{h}\frac{CI_{t+h}-CI_t}{CI_t} \times 100$ is the future change rate in the coincident composite index over the next $h = 1, 2, \cdots, 12$ months scaled by the horizons and $SPRD_t$ is the interest rate spread which is the difference between newly issued 10-year government bond yields and the three-month Tokyo Interbank Offered Rate.

Table 10 summarizes the estimation results and Figure 7 plots predictability patterns in the coefficient parameters $\beta_1(h)$ for $VRP_t^{(i)}$, $i = 1, 2, 3$ and adjusted R^2 in percentage points. The significance of all VRPs extends to around the six-month horizon. The negative slope coefficient means that a rising VRP lowers the future rate of change in the coincident composite index. This may imply that when the market anticipates greater volatility in the forward return variance, the short-term interest rate may be higher, leading to lower economic activity. Adjusted R^2 peaks at around 25 % at two months and gradually decreases toward zero. $SPRD_t$ has a significant positive slope coefficient but VRP has larger t-values than that for $SPRD_t$. Thus, the result is suggestive of a significant relationship between VRP and the composite index of coincident indicators.

4. Conclusion

This article constructs different types of VRP for the Japanese stock market such as expected and ex-post VRPs, which are estimated from model-free implied and realized variances. Their predictive performance on the Nikkei 225 returns, credit spreads, and the composite index of coincident indicators are investigated based on multivariate forecasting regressions for overlapping multi-period returns. We also estimate an additional VRP involving Japanese macroeconomic variables in order to approximate the dynamics of the representative investor's relative risk aversion. The following are the main findings from our empirical analysis. First, the ex-post VRP, which is defined as the difference between implied and ex-post realized variances, is useful in predicting the Nikkei 225 returns while the expected VRPs, which are the differences between implied and current or model-based realized variances, lose their predictive ability. Second, the expected and ex-post VRPs provide significant predictability of credit spreads and the composite index of coincident indicators. Third, the VRP constructed using Japanese macroeconomic variables contains business cycle dynamics of the Japanese economy.

Several extensions are possible. We do not consider the Hansen and Lunde (2005) adjustment method or jumps in returns in calculating realized variance. Some previous empirical studies point out the importance of the Hansen and Lunde (2005) adjustment method, which scales the intraday realized variance using low-frequency stock returns to take into account nontrading hours in the stock market. In the latter case, for instance, Barndorff-Nielsen and Shephard (2004) propose a method for calculating realized volatility taking account of jumps. Andersen, Bollerslev, and Diebold (2007) also show that the performance of forecasting future volatility is improved by removing significant jumps from realized variance and adding significant jumps to the HAR model as an explanatory variable. It would be interesting to investigate whether the predictive performance of the VRP would also improve through these changes.

Appendix. Kernel-based realized variance

In this Appendix, we explain the flat-top modified Tukey-Hanning kernel estimator of quadratic variation $\mathcal{V}_{t,t+1}$ to take into account microstructure noise. Barndorff-Nielsen et al. (2008) propose the following unbiased flat-top kernel type estimator (called realized kernel):

$$RK = \gamma_0 + \sum_{h=1}^{H} k\left(x\right)\left(\gamma_h + \gamma_{-h}\right), \tag{A.1}$$

where $\gamma_h = \sum_{i=1+h}^{n} r_{t+i/n} r_{t+(i-h)/n}$, $\gamma_{-h} = \sum_{i=1}^{n-h} r_{t+i/n} r_{t+(i+h)/n}$ and the non-stochastic $k(x) \in [0,1]$ for $x = \frac{h-1}{H}$ is a weight function. The flat-top modified Tukey-Hanning kernel is equivalent to RK in the case where $k(x) = \{1 - \cos\pi(1-x)^2\}/2$. Barndorff-Nielsen et al. (2008) show the asymptotically optimal number of autocovariances H that minimizes the asymptotic variance. Meanwhile, Bandi and Russell (2011) provide an alternative way to choose the number of autocovariances in finite samples. Denote H as δn with $0 < \delta \leq 1$. The optimal value of δ is defined in Theorem 3 of Bandi and Russell (2011) as follows:

$$\delta^* = \underset{0<\delta\leq 1}{\arg\min} \left[(\text{bias}(RK))^2 + \text{Var}(RK)\right], \tag{A.2}$$

where bias$(RK) = 0$ and

$$\text{Var}(RK) = \frac{IQ}{n}\omega^{\mathrm{T}}\Omega_1\omega + 4\sigma_\eta^4 n(\omega^{\mathrm{T}}\Omega_2\omega) + 4\sigma_\eta^4(\omega^{\mathrm{T}}\Omega_3\omega) + (2\sigma_\eta^2 IV)4(\omega^{\mathrm{T}}\Omega_4\omega), \tag{A.3}$$

with $\omega = \left(1, 1, k\left(\frac{1}{\delta n}\right), \cdots, k\left(\frac{\delta n - 1}{\delta n}\right)\right)^{\mathrm{T}}$ and Ω_a $a = 1, \cdots, 4$ are ($\delta n + 1, \delta n + 1$) square matrices. IQ is an integrated quarticity of a continuous-time stochastic volatility process ($IQ = \int_t^{t+1} V_s^2 ds$). It is estimated by $\hat{IQ} = \frac{n}{3}\sum_{i=1}^{n} r_{t+i/n}^4$ (realized quarticity) with low frequency returns such as 15-minute returns. σ_η^2 represents the variance of microstructure noise which is estimated by $\hat{\sigma}_\eta^2 = \frac{1}{2n}\sum_{i=1}^{n} r_{t-1+i/n}^2$ at the highest frequencies. For $j \leq \delta n$, the matrices Ω_1 and Ω_4 are defined as:

$$\begin{aligned}
&\Omega_1[1,1] = 2, \quad \Omega_1[1+j,1+j] = 4, \\
&\Omega_4[1,1] = 1, \quad \Omega_4[2,1] = -1, \quad \Omega_4[1,2] = -1, \quad \Omega_4[2,2] = 2, \\
&\Omega_4[1+j,1+j] = 2, \quad \Omega_4[1+j,j] = -1, \quad \Omega_4[j,j+1] = -1,
\end{aligned} \tag{A.4}$$

and zeros everywhere else. For $j \leq \delta n - 1$, the matrices Ω_2 and Ω_3 are defined as:

$$\begin{aligned}
&\Omega_2[1,1] = 3, \quad \Omega_2[1,2] = -4, \quad \Omega_2[2,1] = -4, \quad \Omega_2[2,2] = 7, \\
&\Omega_2[2+j,2+j] = 6, \quad \Omega_2[2+j,1+j] = -4, \quad \Omega_2[1+j,2+j] = -4, \quad \Omega_2[2+j,j] = 1, \\
&\Omega_2[j,2+j] = 1, \quad \Omega_3[1,1] = -1, \quad \Omega_3[1,2] = 2, \quad \Omega_3[2,1] = 2, \quad \Omega_3[2,2] = -4.5, \\
&\Omega_3[j+2,j+2] = -3(j+1) - 1, \quad \Omega_3[2+j,1+j] = 2(j+1), \quad \Omega_3[1+j,2+j] = 2(j+1), \\
&\Omega_3[2+j,j] = -(j+1)/2, \quad \Omega_3[j,2+j] = -(j+1)/2,
\end{aligned} \tag{A.5}$$

and zeros everywhere else. The estimator RK with $H = \delta^* n$ for the modified Tukey-Hanning kernel is employed in our empirical analysis.

References

[1] Andersen, T. G., Bollerslev, T. and Diebold, F. X. (2007), "Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility," *Review of Economics and Statistics*, Vol.89, No.4, pp.701–720.

[2] Aono, K. and Iwaisako, T. (2010), "On the predictability of Japanese stock returns using dividend yield," *Asia-Pacific Financial Markets*, Vol.17, No.2, pp.141–149.

[3] Aono, K. and Iwaisako, T. (2011), "Forecasting Japanese stock returns with financial ratios and other variables," *Asia-Pacific Financial Markets*, forthcoming.

[4] Bakshi, G. and Kapdia, N. (2003), "Delta-hedged gains and the negative market volatility risk premium," *The Review of Financial Studies*, Vol.16, No.2, pp.527–566.

[5] Bandi, F. M. and Russell, J. R. (2008), "Microstructure noise, realized variance, and optimal sampling," *Review of Economic Studies*, Vol.75, No.2, pp.339–369.

[6] Bandi, F. M. and Russell, J. R. (2011), "Market microstructure noise, integrated variance estimators, and the accuracy of asymptotic approximations," *Journal of Econometrics*, Vol.160, No.1, pp.145–159.

[7] Barndorff-Nielsen, O. E., Hansen, P. R., Lunde, A. and Shephard, N. (2008), "Designing realized kernels to measure the ex-post variation of equity prices in the presence of noise," *Econometrica*, Vol.76, No.6, pp.1481–1536.

[8] Barndorff-Nielsen, O. E. and Shephard, N. (2004), "Power and bipower variation with stochastic volatility and jumps (with Discussions)," *Journal of Financial Econometrics*, Vol.2, No.1, pp.1–48.

[9] Bollerslev, T., Gibson, M. and Zhou, H. (2011), "Dynamic estimation of volatility risk premia and investor risk aversion from option-implied and realized volatilities," *Journal of Econometrics*, Vol.160, No.1, pp.235–245.

[10] Bollerslev, T., Marrone, J., Xu, L. and Zhou, H. (2011), "Stock return predictability and variance risk premia: statistical inference and international evidence," Working paper.

[11] Bollerslev, T., Tauchen, G. and Zhou, H. (2009), "Expected Stock Returns and Variance Risk Premia," *Review of Financial Studies*, Vol.22, No.11, pp.4463–4492.

[12] Bollerslev, T. and Zhou, H. (2002), "Estimating stochastic volatility diffusion using conditional moments of integrated volatility," *Journal of Econometrics*, Vol.109, No.1, pp.33–65 (2004, Corrigendum, *Journal of Econometrics*, Vol.119, No.1, pp.221–222).

[13] Bollerslev, T. and Zhou, H. (2006), "Volatility puzzles: a simple framework for gauging return-volatility regressions," *Journal of Econometrics*, Vol.131, No.1–2, pp.123–150.

[14] Boudoukh, J., Richardson, M. and Whitelaw, R. F. (2008), "The Myth of Long-Horizon Predictability," *Review of Financial Studies*, Vol.21, No.4, pp.1577–1605.

[15] Britten-Jones, M. and Neuberger, A. (2000), "Option prices, implied price processes, and stochastic volatility," *Journal of Finance*, Vol.55, No.2, pp.839–866.

[16] Campbell, J. Y., Lo, A. W. and MacKinlay, A. C. (1997), *The Econometrics of Financial Markets*, Princeton: Princeton University Press.

[17] Carr, P. and Wu, L. (2006), "A tale of two indices," *The Journal of Derivatives*, Vol.13, No.3, pp.13–29.

[18] Carr, P. and Wu, L. (2009), "Variance risk premiums," *The Review of Financial Studies*, Vol.22, No.3, pp.1311–1341.

[19] CBOE (2009), "The CBOE volatility index - VIX," CBOE website.

[20] Corsi, F. (2009), "A simple approximate long-memory model of realized volatility," *Journal of Financial Econometrics*, Vol.7, No.2, pp.174–196.

[21] Demeterfi, K., Derman, E., Kamal, M. and Zou, J. (1999), "A Guide to Volatility and Variance Swaps," *Journal of Derivatives*, Vol. 6, pp.9–32.

[22] Diebold, F. X. (1988), *Empirical Modeling of Exchange Rate Dynamics*, Berlin: Springer-Verlag.

[23] Fukasawa, M., Ishida, I., Maghrebi, N., Oya, K., Ubukata, M. and Yamazaki, K. (2011), "Model-Free Implied Volatility: From Surface to Index," *International Journal of Theoretical & Applied Finance*, Vol.14, No.4, pp.433–463.

[24] Hansen, P. R. and Lunde, A. (2005), "A forecast comparison of volatility models: Does anything beat a GARCH(1,1)?" *Journal of Applied Econometrics*, Vol.20, No.7, pp.873–889.

[25] Hansen, P. R. and Lunde, A. (2006), "Realized variance and market microstructure noise," *Journal of Business and Economic Statistics*, Vol.24, No.2, pp.127–161.

[26] Hodrick, R. J. (1992), "Dividend yields and expected stock returns: Alternative procedures for inference and measurement," *Review of Financial Studies*, Vol.5, No.3, pp.357–386.

[27] Jiang, G. and Tian, Y. (2005), "The model-free implied volatility and its information content," *Review of Financial Studies* Vol.18, No.4, pp.1305–1342.

[28] Jiang, G. and Tian, Y. (2007), “Extracting model-free volatility from option prices: An examination of the VIX index,” *Journal of Derivatives* Vol.14, No.3, pp.35–60.

[29] Kunitomo, N. and Sato, S. (2008), “Separating information maximum likelihood estimation of realized volatility and covariance with micro-market noise,” Discussion Paper CIRJE-F-581, Graduate School of Economics, University of Tokyo.

[30] Londono, J.-M. (2010), ”The variance risk premium around the world”, Working paper, Tilburg University Department of Finance, The Netherlands.

[31] Newey, W. K. and West, K. D. (1987), “A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix,” *Econometrica*, Vol.55, No.3, pp.703-708.

[32] Oya, K. (2011a), “Business cycle predictability with variance risk premium,” *Great Recession in the Global Economy and Business Cycle Analyses*, pp.141–157, (in Japanese).

[33] Oya, K. (2011b), “Bias corrected realized variance under dependent microstructure noise,” *Mathematics and Computers in Simulation*, Vol.81, No.7, pp.1290–1298.

[34] Roll, R. (1984), “A simple implicit measure of the effective bid-ask spread in an efficient market,” *Journal of Finance*, Vol.39, No.4, pp.1127–1139.

[35] Sugihara, Y. (2010), “Global contagion of volatilities and volatility risk premiums,” Working paper.

[36] Ubukata, M. and Oya, K. (2009), “Estimation and Testing for Dependence in Market Microstructure Noise,” *Journal of Financial Econometrics*, Vol.7, No.2, pp.106–151.

[37] Wang, H., Zhou, H. and Zhou, Y. (2011), “Credit default swap spreads and variance risk premia,” Working paper, Federal Reserve Board.

[38] Zhang, L., Mykland, P. A. and Aït-Sahalia, Y. (2005), “A tale of two time scales: Determining integrated volatility with noisy high-frequency data,” *Journal of the American Statistical Association*, Vol.100, No.472, pp.1394–1411.

[39] Zhou, H. (2010), “Variance risk premia, asset predictability puzzles, and macroeconomic uncertainty,” Working paper, Federal Reserve Board.

Table 1: Descriptive statistics of monthly implied and realized variances

	$IV_{t,t+1}(\%)$	$RV_{t-1,t}(\%)$
Sample size	138	138
Mean	0.67	0.34
Std.dev.	0.77	0.31
Skewness	6.14	5.45
Kurtosis	52.03	43.80
Minimum	0.12	0.05
Maximum	7.68	2.99
LB(10)	59.40	49.59
$\rho(1)$	0.57	0.58

The sample period is from February 1998 to July 2009. All variables are reported in percentage points (non-annualized). LB(10) is the Ljung-Box statistic adjusted for heteroskedasticity following Diebold (1988) to test the null hypothesis of no autocorrelations up to 10 lags.

Table 2: Descriptive statistics for monthly variance risk premiums

	$VRP_t^{(1)}(\%)$	$VRP_t^{(2)}(\%)$	$VRP_t^{(3)}(\%)$	$VRP_t^{(4)}$
Sample size	138	138	138	138
Mean	0.33	0.33	0.42	1.27
Std.dev.	0.49	0.63	0.55	0.48
Skewness	5.86	5.64	5.20	1.38
Kurtosis	48.01	48.62	38.49	4.87
Minimum	-0.07	-1.46	0.04	0.41
Maximum	4.69	5.99	5.01	3.05
LB(10)	48.09	14.56	56.89	185.75
$\rho(1)$	0.53	0.25	0.63	0.87
$\rho(2)$	0.30	0.10	0.38	0.73
$\rho(3)$	0.31	0.18	0.32	0.63
$\rho(4)$	0.27	0.14	0.27	0.57
$\rho(5)$	0.24	0.13	0.24	0.52
$\rho(6)$	0.11	0.05	0.14	0.45
$\rho(7)$	0.11	0.08	0.14	0.36
$\rho(8)$	0.12	0.04	0.13	0.29
$\rho(9)$	0.08	0.10	0.13	0.22
$\rho(10)$	0.05	0.01	0.09	0.15

The sample period is from February 1998 to July 2009. LB(10) is the Ljung-Box statistic adjusted for heteroskedasticity following Diebold (1988) to test the null hypothesis of no autocorrelations up to 10 lags.

Table 3: List of Japanese macroeconomic variables

	Macroeconomic variables
1	Nikkei225 index realized variance
2	Nikkei225 implied variance
3	Trading volume for TSE 1st section-listed stocks
4	Market capitalization for TSE 1st section-listed stocks
5	Weighted average of yield for TSE 1st section-listed stocks
6	Price-to-book value ratio for TSE 1st section-listed stocks
7	Price-earnings (P/E) ratio for TSE 1st section-listed stocks
8	Unemployment rate
9	Effective job offer rate (Excluding new school graduates)
10	Index of non-scheduled worked hours (Manufacturing)
11	Index of regular workers employment
12	Consumer price index
13	Domestic corporate goods price index
14	Index of industrial production (Mining and manufacturing)
15	Index of capacity utilization ratio (Manufacturing)
16	Index of Producer's Inventory Ratio
17	Index of producer's shipment of durable consumer goods
18	Building floor area
19	Housing start number
20	Total floor area of new housing construction started
21	Machinery order
22	Business expenditures for new plant and equipment at constant prices (All industries)
23	Large industrial power consumption
24	Retail sales value
25	Wholesale sales value
26	Operating profits (All industries)
27	Index of sales in small and medium sized enterprises (Manufacturing)
28	Consumer confidence index
29	Interest rate spread
30	Money stock (M2)

Table 4: GMM estimation result for estimating $VRP_t^{(4)}$

	Estimates	Std. error	t-value
κ	0.64	0.10	6.51
$\theta(\%)$	0.31	0.05	6.45
a	-0.50	0.12	-4.21
b	0.61	0.09	6.97
c_1 Realized variance	-0.21	0.02	-12.30
c_2 P/E ratio	-0.10	0.04	-2.16
c_3 Retail sales value	0.13	0.07	2.00
c_4 Price-to-book value ratio	-0.07	0.04	-1.75
Test of overidentifying restrictions (p-values)	0.70	(0.94)	

All of the macroeconomic variables are standardized to mean zero and variance one. For ensuring stationarity of macroeconomic variables, we use the level of P/E ratio, the logarithmic difference for the past twelve months of retail sales value, and the difference for the past month of price-to-book value ratio, respectively. The Newey-West weighting matrix with a Bartlett kernel lag length set to 25 is employed in the estimation.

Table 5: Nikkei 225 index excess returns on $VRP_t^{(i)}$, lagged Nikkei 225 returns, P/E ratio, and dividend yield

Monthly horizon	1	2	3	4	5	6	7	8	9	10	11	12
const	-1.23	-0.99	-1.17	-1.21	-1.32	-1.19	-1.10	-1.09	-1.09	-1.07	-1.02	-0.97
	(-0.71)	(-0.59)	(-0.83)	(-1.02)	(-1.21)	(-1.13)	(-1.09)	(-1.13)	(-1.15)	(-1.15)	(-1.11)	(-1.06)
$VRP_t^{(1)}(\%)$	0.22	0.99	0.23	0.19	0.22	0.51	0.74	0.70	0.64	0.59	0.48	0.43
	(0.12)	(0.72)	(0.22)	(0.21)	(0.22)	(0.53)	(0.77)	(0.78)	(0.72)	(0.69)	(0.57)	(0.52)
R_t	0.18	0.15	0.12	0.11	0.08	0.06	0.06	0.06	0.06	0.05	0.05	0.04
	(1.29)	(1.91)	(1.86)	(1.77)	(1.68)	(1.67)	(1.60)	(1.54)	(1.57)	(1.39)	(1.22)	(1.12)
$(P/E)_t/100$	0.31	0.25	0.16	0.12	0.15	0.09	0.11	0.10	0.09	0.10	0.08	0.05
	(2.13)	(2.37)	(1.94)	(1.74)	(2.36)	(1.71)	(2.15)	(2.11)	(1.66)	(1.63)	(1.36)	(0.81)
DY_t	0.50	0.13	0.58	0.65	0.74	0.56	0.42	0.45	0.49	0.48	0.48	0.47
	(0.23)	(0.07)	(0.36)	(0.49)	(0.61)	(0.48)	(0.38)	(0.44)	(0.49)	(0.51)	(0.53)	(0.54)
adj $R^2(\%)$	2.08	2.63	1.85	2.07	2.08	0.77	1.77	2.08	2.35	2.57	1.93	1.21
Monthly horizon	1	2	3	4	5	6	7	8	9	10	11	12
const	-0.35	-0.66	-0.99	-1.06	-1.14	-1.06	-1.03	-1.04	-1.07	-1.06	-1.00	-0.95
	(-0.19)	(-0.39)	(-0.71)	(-0.88)	(-1.03)	(-1.01)	(-1.04)	(-1.10)	(-1.14)	(-1.15)	(-1.10)	(-1.04)
$VRP_t^{(2)}(\%)$	2.80	1.75	0.71	0.61	0.72	0.79	0.78	0.67	0.55	0.47	0.43	0.39
	(2.50)	(2.02)	(1.06)	(1.01)	(1.19)	(1.53)	(1.83)	(1.68)	(1.32)	(1.15)	(1.13)	(1.05)
R_t	0.26	0.17	0.13	0.12	0.10	0.07	0.06	0.05	0.05	0.05	0.04	0.04
	(1.86)	(2.49)	(2.34)	(2.13)	(2.21)	(2.34)	(2.32)	(2.16)	(2.12)	(1.77)	(1.64)	(1.51)
$(P/E)_t/100$	0.27	0.23	0.16	0.12	0.14	0.09	0.10	0.10	0.09	0.10	0.08	0.05
	(1.78)	(2.24)	(1.84)	(1.64)	(2.22)	(1.58)	(2.06)	(2.01)	(1.61)	(1.59)	(1.32)	(0.77)
DY_t	-1.02	-0.37	0.29	0.40	0.44	0.37	0.35	0.42	0.50	0.51	0.47	0.46
	(-0.49)	(-0.20)	(0.19)	(0.32)	(0.38)	(0.35)	(0.38)	(0.49)	(0.60)	(0.65)	(0.64)	(0.64)
adj $R^2(\%)$	8.29	6.19	2.77	2.89	3.45	2.38	3.12	3.07	2.90	2.86	2.38	1.66
Monthly horizon	1	2	3	4	5	6	7	8	9	10	11	12
const	-1.24	-1.10	-1.28	-1.30	-1.39	-1.25	-1.16	-1.14	-1.16	-1.15	-1.10	-1.05
	(-0.70)	(-0.65)	(-0.90)	(-1.09)	(-1.27)	(-1.18)	(-1.15)	(-1.19)	(-1.23)	(-1.25)	(-1.22)	(-1.16)
$VRP_t^{(3)}(\%)$	0.17	0.51	-0.15	-0.15	-0.06	0.25	0.46	0.43	0.32	0.22	0.15	0.13
	(0.10)	(0.39)	(-0.15)	(-0.16)	(-0.06)	(0.25)	(0.50)	(0.49)	(0.38)	(0.27)	(0.19)	(0.17)
R_t	0.18	0.14	0.10	0.10	0.07	0.06	0.06	0.05	0.05	0.04	0.04	0.04
	(1.28)	(1.83)	(1.70)	(1.59)	(1.47)	(1.46)	(1.45)	(1.39)	(1.38)	(1.15)	(1.02)	(0.95)
$(P/E)_t/100$	0.31	0.25	0.17	0.13	0.15	0.09	0.11	0.10	0.09	0.10	0.09	0.05
	(2.13)	(2.43)	(2.02)	(1.84)	(2.48)	(1.76)	(2.19)	(2.15)	(1.72)	(1.70)	(1.43)	(0.85)
DY_t	0.50	0.33	0.80	0.84	0.89	0.67	0.52	0.54	0.62	0.64	0.63	0.60
	(0.22)	(0.16)	(0.47)	(0.60)	(0.68)	(0.54)	(0.45)	(0.51)	(0.60)	(0.66)	(0.69)	(0.69)
adj $R^2(\%)$	2.08	2.21	1.83	2.05	2.03	0.49	1.26	1.55	1.72	1.84	1.37	0.73

The results are based on the multivariate forecasting regressions in (18). The Newey-West based t-statistics are reported in parentheses. The sample period is from February 1998 to July 2009 (138 months).

Table 6: Credit spreads with AAA rating and one-year maturity on $VRP_t^{(i)}$, corporate bond yield, and lagged Nikkei 225 returns

Monthly horizon	1	2	3	4	5	6	7	8	9	10	11	12
const	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.66)	(0.90)	(1.20)	(1.33)	(1.57)	(1.77)	(1.69)	(1.81)	(1.72)	(1.61)	(1.52)	(1.56)
$VRP_t^{(1)}$	−0.12	−0.20	−0.34	−0.48	−0.62	−0.76	−0.73	−0.77	−0.74	−0.68	−0.66	−0.69
	(−0.16)	(−0.43)	(−0.70)	(−1.20)	(−1.71)	(−2.52)	(−2.67)	(−3.00)	(−3.21)	(−3.12)	(−3.23)	(−3.64)
$\Delta r_{f,m,t}$	0.04	0.03	0.01	0.02	0.01	0.04	0.03	0.03	0.02	0.03	0.03	0.02
	(0.80)	(1.41)	(0.45)	(0.81)	(0.95)	(3.15)	(3.18)	(2.04)	(2.59)	(4.38)	(4.74)	(2.24)
R_t	−0.09	−0.11	−0.08	−0.08	−0.08	−0.07	−0.06	−0.05	−0.05	−0.04	−0.04	−0.04
	(−1.16)	(−2.57)	(−1.92)	(−2.01)	(−2.27)	(−2.47)	(−2.30)	(−2.23)	(−2.00)	(−1.98)	(−1.79)	(−1.87)
adj $R^2(\%)$	1.09	11.47	5.65	7.91	11.39	21.70	20.91	24.56	24.56	27.33	28.41	26.99
Monthly horizon	1	2	3	4	5	6	7	8	9	10	11	12
const	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.91)	(0.92)	(1.22)	(1.22)	(1.33)	(1.48)	(1.23)	(1.28)	(1.10)	(1.00)	(0.92)	(0.94)
$VRP_t^{(2)}$	−0.22	−0.21	−0.34	−0.40	−0.44	−0.53	−0.43	−0.46	−0.39	−0.36	−0.34	−0.37
	(−0.59)	(−0.82)	(−1.36)	(−1.85)	(−2.24)	(−3.31)	(−2.62)	(−2.81)	(−2.58)	(−2.51)	(−2.54)	(−2.89)
$\Delta r_{f,m,t}$	0.03	0.03	0.00	0.01	0.01	0.04	0.03	0.03	0.03	0.03	0.03	0.02
	(0.69)	(1.26)	(0.19)	(0.66)	(0.87)	(3.81)	(3.70)	(2.31)	(3.07)	(4.81)	(4.54)	(2.07)
R_t	−0.10	−0.11	−0.08	−0.07	−0.07	−0.06	−0.04	−0.04	−0.03	−0.02	−0.02	−0.03
	(−1.45)	(−3.05)	(−2.39)	(−2.38)	(−2.75)	(−3.06)	(−2.62)	(−2.33)	(−1.73)	(−1.65)	(−1.44)	(−1.60)
adj $R^2(\%)$	1.39	11.85	7.15	9.40	11.27	21.12	16.18	19.35	16.51	19.51	19.68	17.06
Monthly horizon	1	2	3	4	5	6	7	8	9	10	11	12
const	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.39)	(0.69)	(1.06)	(1.23)	(1.54)	(1.67)	(1.61)	(1.72)	(1.63)	(1.53)	(1.44)	(1.50)
$VRP_t^{(3)}$	0.07	−0.08	−0.23	−0.37	−0.53	−0.62	−0.61	−0.64	−0.59	−0.54	−0.51	−0.56
	(0.11)	(−0.20)	(−0.56)	(−1.06)	(−1.71)	(−2.37)	(−2.45)	(−2.72)	(−2.73)	(−2.66)	(−2.71)	(−3.12)
$\Delta r_{f,m,t}$	0.04	0.04	0.01	0.02	0.01	0.04	0.03	0.03	0.02	0.03	0.03	0.02
	(0.91)	(1.53)	(0.59)	(0.86)	(0.94)	(3.42)	(3.03)	(2.07)	(2.67)	(4.04)	(4.34)	(2.07)
R_t	−0.08	−0.11	−0.07	−0.07	−0.08	−0.07	−0.06	−0.05	−0.04	−0.04	−0.03	−0.04
	(−1.07)	(−2.52)	(−1.93)	(−2.02)	(−2.28)	(−2.45)	(−2.21)	(−2.12)	(−1.82)	(−1.79)	(−1.58)	(−1.69)
adj $R^2(\%)$	1.07	11.19	4.97	6.92	10.88	19.89	19.23	22.26	21.38	24.02	24.57	23.13

The results are based on the multivariate forecasting regressions in (19). The Newey-West based t-statistics are reported in parentheses. The sample period is from August 2002 to July 2009 (84 months).

Table 7: Credit spreads with AAA rating and three-year maturity on $VRP_t^{(i)}$, corporate bond yield, and lagged Nikkei 225 returns

Monthly horizon	1	2	3	4	5	6	7	8	9	10	11	12
const	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.87)	(1.00)	(1.69)	(1.80)	(2.16)	(2.59)	(2.87)	(3.04)	(2.71)	(2.80)	(2.92)	(2.96)
$VRP_t^{(1)}$	−0.10	−0.16	−0.37	−0.44	−0.59	−0.75	−0.75	−0.74	−0.62	−0.59	−0.63	−0.64
	(−0.18)	(−0.31)	(−0.84)	(−1.21)	(−1.99)	(−2.80)	(−3.34)	(−3.67)	(−3.44)	(−3.32)	(−4.13)	(−4.45)
$\Delta r_{f,m,t}$	0.04	0.02	0.01	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.01	0.00
	(1.52)	(2.01)	(0.66)	(0.53)	(0.40)	(0.83)	(0.99)	(0.43)	(1.51)	(1.71)	(1.62)	(0.33)
R_t	−0.10	−0.10	−0.07	−0.06	−0.07	−0.07	−0.04	−0.03	−0.03	−0.03	−0.03	−0.03
	(−1.46)	(−1.97)	(−1.66)	(−1.61)	(−2.11)	(−1.94)	(−1.57)	(−1.59)	(−1.39)	(−1.21)	(−1.34)	(−1.27)
adj $R^2(\%)$	2.95	7.53	3.18	3.38	10.18	17.89	20.25	23.98	20.74	20.70	26.26	25.33
Monthly horizon	1	2	3	4	5	6	7	8	9	10	11	12
const	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(1.01)	(1.07)	(1.57)	(1.55)	(1.76)	(2.22)	(2.29)	(2.11)	(1.67)	(1.69)	(1.69)	(1.58)
$VRP_t^{(2)}$	−0.12	−0.18	−0.33	−0.34	−0.42	−0.53	−0.50	−0.44	−0.33	−0.34	−0.36	−0.35
	(−0.35)	(−0.60)	(−1.42)	(−1.67)	(−2.35)	(−3.45)	(−3.62)	(−3.11)	(−2.55)	(−2.77)	(−3.33)	(−3.28)
$\Delta r_{f,m,t}$	0.04	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.00
	(1.47)	(1.88)	(0.46)	(0.32)	(0.18)	(0.52)	(0.59)	(0.20)	(1.29)	(1.53)	(1.55)	(0.13)
R_t	−0.11	−0.10	−0.07	−0.05	−0.06	−0.05	−0.03	−0.02	−0.01	−0.01	−0.02	−0.01
	(−1.73)	(−2.42)	(−1.95)	(−1.83)	(−2.40)	(−2.30)	(−1.63)	(−1.17)	(−0.94)	(−0.89)	(−1.00)	(−0.83)
adj $R^2(\%)$	3.04	7.93	4.51	4.15	10.01	18.01	17.67	15.91	11.14	13.35	16.92	14.51
Monthly horiozn	1	2	3	4	5	6	7	8	9	10	11	12
const	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.56)	(0.89)	(1.51)	(1.73)	(2.18)	(2.62)	(2.91)	(3.14)	(2.90)	(3.06)	(3.17)	(3.21)
$VRP_t^{(3)}$	0.04	−0.12	−0.26	−0.36	−0.53	−0.68	−0.68	−0.65	−0.55	−0.53	−0.55	−0.55
	(0.09)	(−0.27)	(−0.71)	(−1.16)	(−2.05)	(−2.88)	(−3.45)	(−3.69)	(−3.42)	(−3.41)	(−4.12)	(−4.53)
$\Delta r_{f,m,t}$	0.04	0.02	0.01	0.00	0.00	0.01	0.01	0.00	0.01	0.01	0.01	0.00
	(1.54)	(2.02)	(0.66)	(0.51)	(0.34)	(0.76)	(0.89)	(0.34)	(1.49)	(1.72)	(1.65)	(0.25)
R_t	−0.10	−0.10	−0.07	−0.06	−0.07	−0.07	−0.04	−0.03	−0.03	−0.03	−0.03	−0.03
	(−1.36)	(−1.99)	(−1.65)	(−1.63)	(−2.16)	(−2.01)	(−1.64)	(−1.64)	(−1.40)	(−1.24)	(−1.34)	(−1.27)
adj $R^2(\%)$	2.91	7.47	2.51	2.86	10.40	18.79	21.45	24.03	20.73	21.50	25.76	24.93

The results are based on the multivariate forecasting regressions in (19). The Newey-West based t-statistics are reported in parentheses. The sample period is from August 2002 to July 2009 (84 months).

Table 8: Credit spreads with A rating and one-year maturity on $VRP_t^{(i)}$, corporate bond yield, and lagged Nikkei 225 returns

Monthly horizon	1	2	3	4	5	6	7	8	9	10	11	12
const	−0.02	−0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01
	(−1.49)	(−0.80)	(0.27)	(0.28)	(0.09)	(0.33)	(0.56)	(0.69)	(0.84)	(0.85)	(0.84)	(1.04)
$VRP_t^{(1)}$	9.58	8.36	5.40	5.24	5.60	4.23	2.80	2.01	1.11	1.00	1.09	0.04
	(3.75)	(6.69)	(4.72)	(4.39)	(5.36)	(5.48)	(3.13)	(1.98)	(0.94)	(0.82)	(0.86)	(0.04)
$\Delta r_{f,m,t}$	0.48	0.27	0.05	0.03	0.01	0.06	0.07	0.08	0.02	0.08	0.09	0.08
	(1.76)	(2.22)	(0.52)	(0.61)	(0.29)	(1.54)	(1.50)	(1.19)	(0.39)	(1.14)	(1.12)	(0.86)
R_t	−0.11	−0.36	−0.25	−0.11	−0.15	−0.24	−0.24	−0.26	−0.29	−0.26	−0.27	−0.34
	(−0.37)	(−1.47)	(−1.44)	(−0.91)	(−1.21)	(−1.53)	(−1.44)	(−1.37)	(−1.46)	(−1.38)	(−1.45)	(−1.70)
adj $R^2(\%)$	23.01	43.22	28.58	24.44	37.01	31.99	18.56	13.98	11.46	8.63	10.75	12.14
Monthly horizon	1	2	3	4	5	6	7	8	9	10	11	12
const	0.00	0.00	0.02	0.01	0.01	0.01	0.02	0.02	0.02	0.01	0.01	0.02
	(−0.27)	(0.36)	(1.08)	(0.95)	(0.75)	(0.94)	(1.03)	(1.05)	(1.10)	(1.05)	(0.99)	(1.20)
$VRP_t^{(2)}$	5.72	4.82	1.75	2.26	2.96	1.38	0.52	0.39	0.09	0.21	0.50	−0.43
	(2.83)	(5.17)	(1.57)	(1.94)	(3.48)	(1.49)	(0.64)	(0.59)	(0.14)	(0.32)	(0.76)	(−0.68)
$\Delta r_{f,m,t}$	0.47	0.25	−0.01	0.00	−0.01	0.01	0.02	0.05	0.00	0.06	0.08	0.06
	(1.72)	(2.12)	(−0.11)	(−0.05)	(−0.23)	(0.23)	(0.44)	(0.71)	(0.03)	(0.88)	(0.97)	(0.67)
R_t	−0.31	−0.54	−0.44	−0.27	−0.29	−0.38	−0.36	−0.34	−0.34	−0.30	−0.30	−0.36
	(−1.25)	(−2.10)	(−1.95)	(−1.69)	(−1.67)	(−1.79)	(−1.84)	(−1.81)	(−1.85)	(−1.79)	(−1.83)	(−2.07)
adj $R^2(\%)$	18.24	36.30	18.53	15.11	28.21	21.97	13.28	11.19	10.53	7.90	10.17	12.47
Monthly horizon	1	2	3	4	5	6	7	8	9	10	11	12
const	−0.02	−0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01
	(−2.25)	(−1.30)	(−0.18)	(−0.24)	(−0.32)	(0.06)	(0.35)	(0.50)	(0.65)	(0.62)	(0.63)	(0.87)
$VRP_t^{(3)}$	9.55	7.77	5.56	5.59	5.54	4.21	2.94	2.25	1.56	1.60	1.59	0.62
	(4.40)	(7.37)	(5.07)	(5.00)	(5.95)	(5.68)	(3.48)	(2.38)	(1.44)	(1.45)	(1.36)	(0.53)
$\Delta r_{f,m,t}$	0.53	0.29	0.08	0.07	0.03	0.07	0.08	0.10	0.04	0.10	0.10	0.09
	(1.80)	(2.31)	(0.98)	(1.35)	(1.03)	(1.99)	(1.73)	(1.33)	(0.67)	(1.36)	(1.27)	(0.97)
R_t	−0.06	−0.35	−0.21	−0.07	−0.12	−0.22	−0.22	−0.23	−0.26	−0.22	−0.23	−0.31
	(−0.21)	(−1.37)	(−1.21)	(−0.55)	(−0.99)	(−1.38)	(−1.31)	(−1.25)	(−1.33)	(−1.23)	(−1.31)	(−1.60)
adj $R^2(\%)$	27.38	45.35	33.13	31.24	42.05	35.45	20.94	15.81	12.94	10.45	12.48	12.57

The results are based on the multivariate forecasting regressions in (19). The Newey-West based t-statistics are reported in parentheses. The sample period is from August 2002 to July 2009 (84 months).

Table 9: Credit spreads with A rating and three-year maturity on $VRP_t^{(i)}$, corporate bond yield, and lagged Nikkei 225 returns

Monthly horizon	1	2	3	4	5	6	7	8	9	10	11	12
const	−0.01	−0.01	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(−1.12)	(−0.97)	(−0.05)	(0.11)	(0.27)	(0.50)	(0.63)	(0.76)	(0.77)	(0.85)	(0.90)	(1.01)
$VRP_t^{(1)}$	6.58	6.34	3.85	3.12	2.28	0.96	0.11	−0.41	−0.45	−0.64	−0.86	−1.34
	(2.74)	(3.22)	(2.47)	(2.48)	(2.01)	(1.05)	(0.13)	(−0.41)	(−0.43)	(−0.59)	(−0.80)	(−1.34)
$\Delta r_{f,m,t}$	0.18	0.17	0.08	0.05	0.03	0.05	0.06	0.08	0.07	0.06	0.07	0.05
	(2.01)	(2.29)	(1.11)	(1.12)	(0.88)	(1.40)	(1.60)	(1.70)	(1.85)	(1.56)	(1.38)	(1.07)
R_t	−0.06	−0.24	−0.23	−0.15	−0.21	−0.28	−0.27	−0.27	−0.26	−0.23	−0.26	−0.29
	(−0.21)	(−1.10)	(−1.29)	(−1.04)	(−1.35)	(−1.64)	(−1.59)	(−1.60)	(−1.53)	(−1.47)	(−1.65)	(−1.75)
adj $R^2(\%)$	14.41	33.73	20.63	13.26	13.21	10.69	6.23	5.77	5.18	3.44	5.47	6.97
Monthly horizon	1	2	3	4	5	6	7	8	9	10	11	12
const	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(−0.35)	(−0.18)	(0.62)	(0.62)	(0.63)	(0.78)	(0.82)	(0.85)	(0.80)	(0.86)	(0.87)	(0.96)
$VRP_t^{(2)}$	4.19	3.91	1.45	1.17	0.87	−0.15	−0.56	−0.63	−0.43	−0.52	−0.55	−0.95
	(2.53)	(3.95)	(1.63)	(1.41)	(1.28)	(−0.25)	(−1.10)	(−1.18)	(−0.76)	(−0.90)	(−0.93)	(−1.74)
$\Delta r_{f,m,t}$	0.19	0.19	0.08	0.05	0.03	0.05	0.05	0.08	0.07	0.06	0.06	0.05
	(1.96)	(2.21)	(1.02)	(1.04)	(0.83)	(1.30)	(1.46)	(1.61)	(1.78)	(1.50)	(1.35)	(1.02)
R_t	−0.20	−0.38	−0.36	−0.26	−0.28	−0.33	−0.30	−0.28	−0.26	−0.23	−0.25	−0.26
	(−0.87)	(−1.90)	(−1.67)	(−1.44)	(−1.64)	(−1.91)	(−1.94)	(−1.95)	(−1.82)	(−1.73)	(−1.92)	(−2.01)
adj $R^2(\%)$	12.02	29.18	13.78	7.96	9.93	9.80	6.88	6.50	5.38	3.61	5.30	6.97
Monthly horizon	1	2	3	4	5	6	7	8	9	10	11	12
const	−0.02	−0.01	−0.01	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01
	(−1.74)	(−1.45)	(−0.48)	(−0.24)	(0.02)	(0.34)	(0.49)	(0.63)	(0.65)	(0.71)	(0.78)	(0.91)
$VRP_t^{(3)}$	6.92	6.19	4.17	3.44	2.55	1.29	0.53	0.09	0.06	−0.05	−0.28	−0.78
	(3.19)	(3.62)	(2.95)	(2.97)	(2.42)	(1.44)	(0.61)	(0.10)	(0.06)	(−0.05)	(−0.28)	(−0.84)
$\Delta r_{f,m,t}$	0.19	0.18	0.09	0.06	0.04	0.06	0.06	0.09	0.07	0.07	0.07	0.05
	(2.03)	(2.54)	(1.30)	(1.35)	(1.05)	(1.50)	(1.68)	(1.76)	(1.93)	(1.64)	(1.44)	(1.12)
R_t	−0.01	−0.22	−0.19	−0.12	−0.18	−0.25	−0.24	−0.25	−0.23	−0.20	−0.24	−0.26
	(−0.04)	(−0.97)	(−1.07)	(−0.82)	(−1.17)	(−1.49)	(−1.46)	(−1.48)	(−1.41)	(−1.33)	(−1.54)	(−1.66)
adj $R^2(\%)$	19.66	38.08	25.54	17.50	16.04	11.91	6.59	5.59	4.95	2.92	4.62	5.54

The results are based on the multivariate forecasting regressions in (19). The Newey-West based t-statistics are reported in parentheses. The sample period is from August 2002 to July 2009 (84 months).

Table 10: Composite index of coincident indicators on $VRP_t^{(i)}$ and interest rate spread

Monthly horizon	1	2	3	4	5	6	7	8	9	10	11	12
const	−0.76	−0.63	−0.54	−0.48	−0.47	−0.53	−0.52	−0.50	−0.46	−0.43	−0.38	−0.35
	(−1.94)	(−1.53)	(−1.24)	(−1.03)	(−0.94)	(−0.97)	(−0.93)	(−0.88)	(−0.80)	(−0.73)	(−0.65)	(−0.59)
$VRP_t^{(1)}(\%)$	−0.63	−0.60	−0.55	−0.46	−0.33	−0.16	−0.05	0.02	0.07	0.13	0.17	0.22
	(−3.57)	(−4.89)	(−4.27)	(−3.35)	(−2.53)	(−1.25)	(−0.39)	(0.14)	(0.57)	(1.02)	(1.39)	(1.76)
$SPRD_t$	0.87	0.76	0.68	0.60	0.57	0.58	0.55	0.52	0.48	0.44	0.39	0.35
	(3.00)	(2.54)	(2.18)	(1.86)	(1.64)	(1.58)	(1.46)	(1.36)	(1.22)	(1.11)	(0.98)	(0.88)
adj R $(\%)$	20.92	25.93	22.73	18.52	13.08	8.78	6.36	5.07	3.89	3.21	2.79	2.88
Monthly horizon	1	2	3	4	5	6	7	8	9	10	11	12
const	−1.00	−0.88	−0.77	−0.70	−0.66	−0.67	−0.60	−0.55	−0.49	−0.43	−0.37	−0.31
	(−2.12)	(−1.75)	(−1.49)	(−1.31)	(−1.21)	(−1.20)	(−1.09)	(−1.00)	(−0.88)	(−0.78)	(−0.66)	(−0.56)
$VRP_t^{(2)}(\%)$	−0.35	−0.31	−0.28	−0.21	−0.11	0.00	0.04	0.08	0.10	0.13	0.15	0.17
	(−2.67)	(−2.86)	(−2.57)	(−1.91)	(−1.05)	(0.02)	(0.49)	(0.88)	(1.23)	(1.64)	(1.97)	(2.27)
$SPRD_t$	1.00	0.90	0.80	0.72	0.67	0.65	0.60	0.55	0.49	0.44	0.38	0.33
	(2.89)	(2.48)	(2.20)	(1.96)	(1.79)	(1.72)	(1.58)	(1.46)	(1.30)	(1.16)	(1.01)	(0.87)
adj R $(\%)$	17.72	20.95	18.12	14.32	10.22	7.90	6.39	5.45	4.40	3.83	3.39	3.22
Monthly horizon	1	2	3	4	5	6	7	8	9	10	11	12
const	−0.60	−0.47	−0.39	−0.36	−0.38	−0.45	−0.46	−0.45	−0.41	−0.38	−0.34	−0.31
	(−1.53)	(−1.17)	(−0.90)	(−0.76)	(−0.74)	(−0.83)	(−0.80)	(−0.77)	(−0.69)	(−0.64)	(−0.58)	(−0.52)
$VRP_t^{(3)}(\%)$	−0.65	−0.63	−0.57	−0.48	−0.35	−0.19	−0.10	−0.04	0.01	0.06	0.10	0.14
	(−4.48)	(−6.05)	(−5.61)	(−4.39)	(−3.40)	(−1.81)	(−0.92)	(−0.33)	(0.09)	(0.56)	(0.95)	(1.32)
$SPRD_t$	0.78	0.67	0.59	0.54	0.52	0.54	0.52	0.49	0.45	0.41	0.37	0.33
	(2.76)	(2.32)	(1.94)	(1.67)	(1.49)	(1.46)	(1.35)	(1.26)	(1.13)	(1.03)	(0.91)	(0.82)
adj R $(\%)$	23.16	28.91	25.69	20.62	14.45	9.44	6.69	5.11	3.69	2.69	1.98	1.73

The results are based on the multivariate forecasting regressions in (20). The Newey-West based t-statistics are reported in parentheses. The sample period is from February 1998 to July 2009 (138 months).

Figure 1: Plots of implied and realized variances

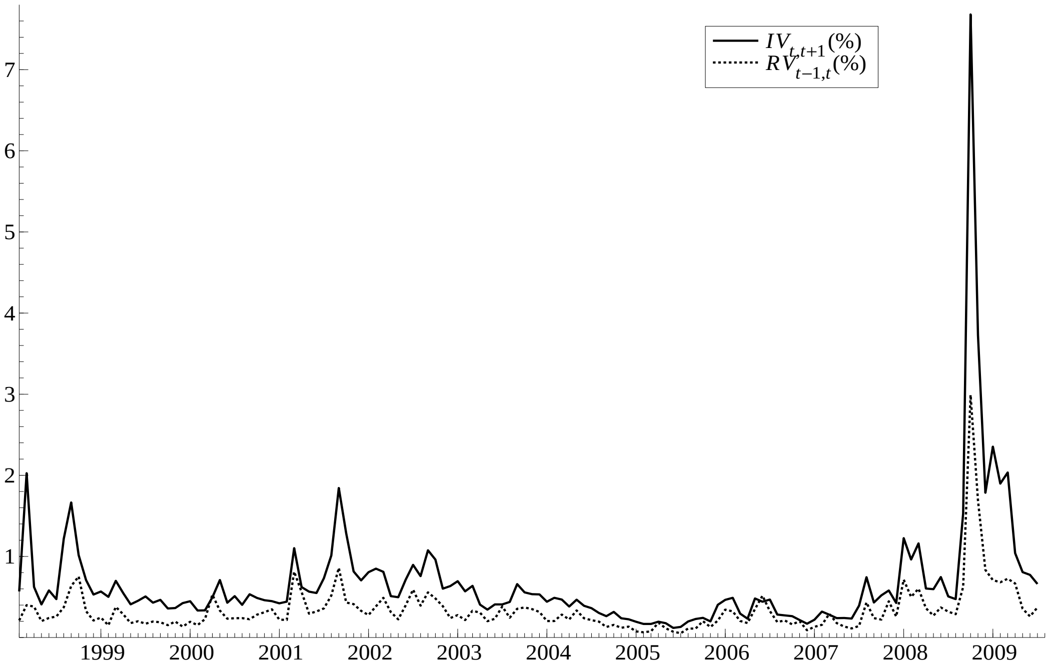


Figure 2: Plots of monthly VRPs

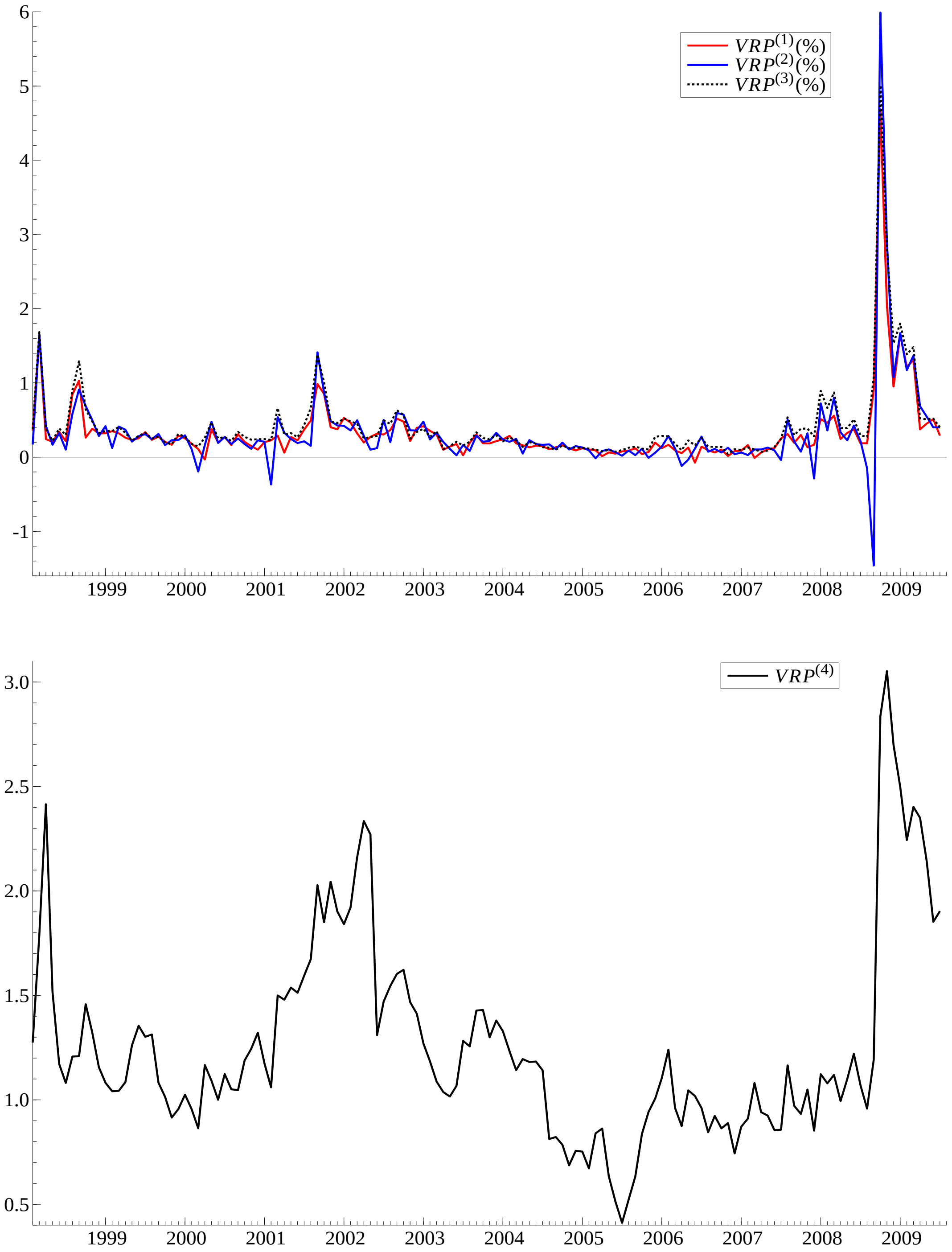
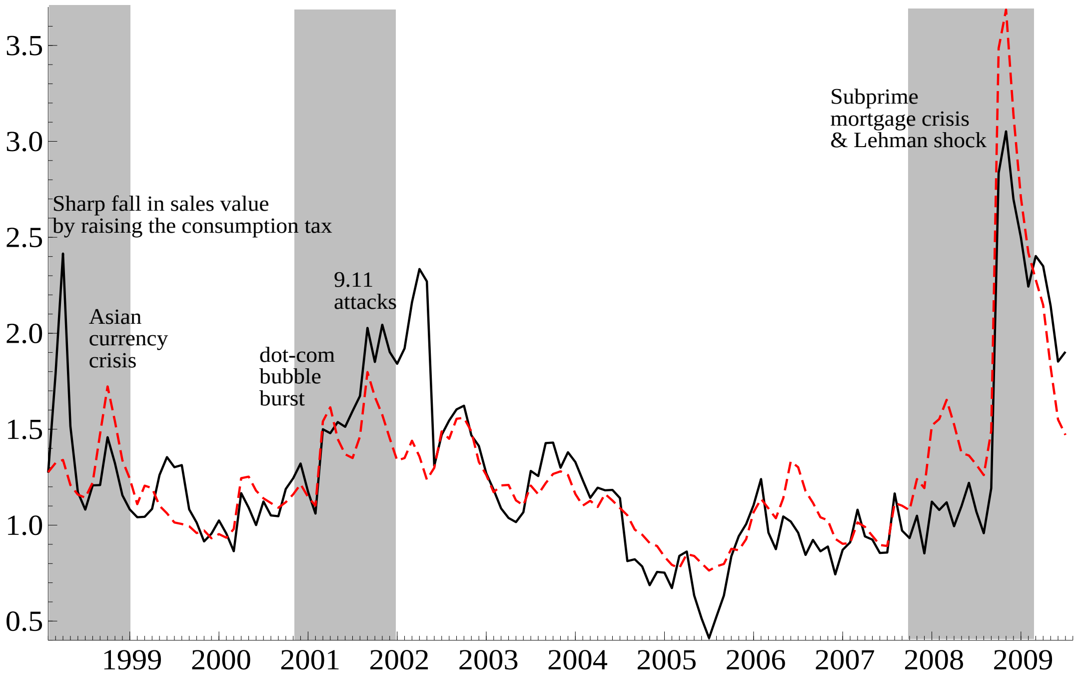
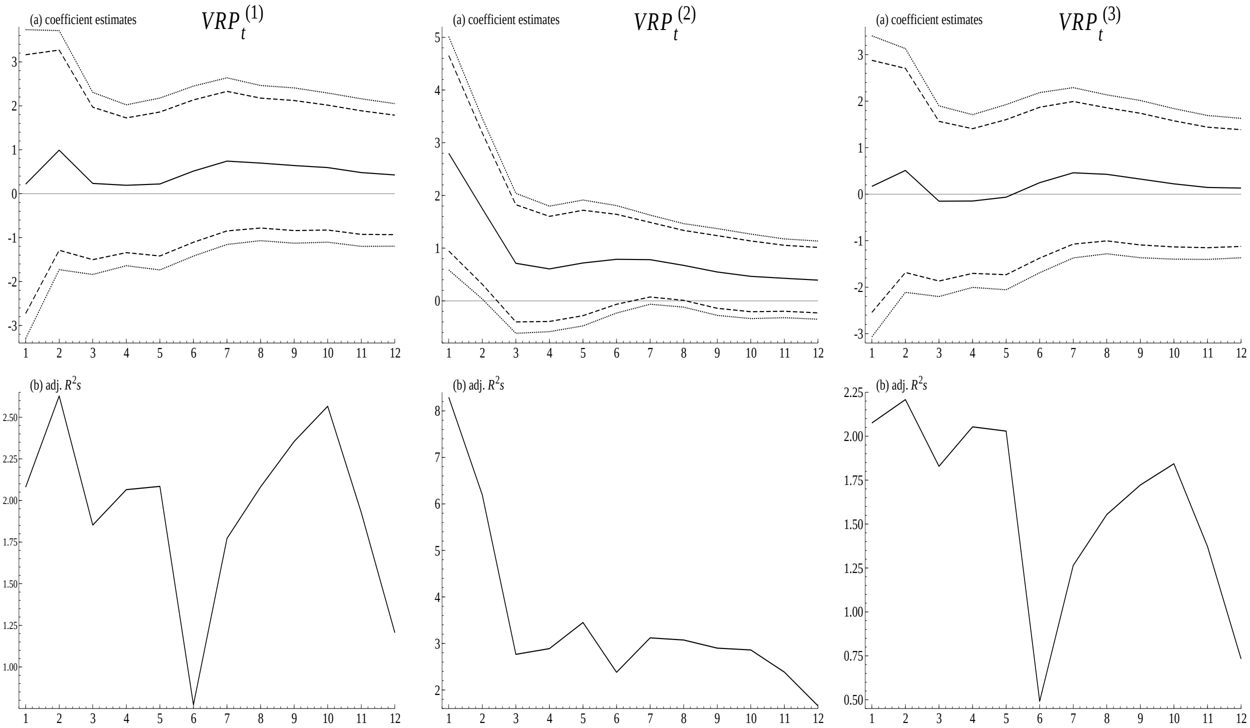


Figure 3: Plots of $VRP_t^{(4)}$ as a proxy of relative risk aversion



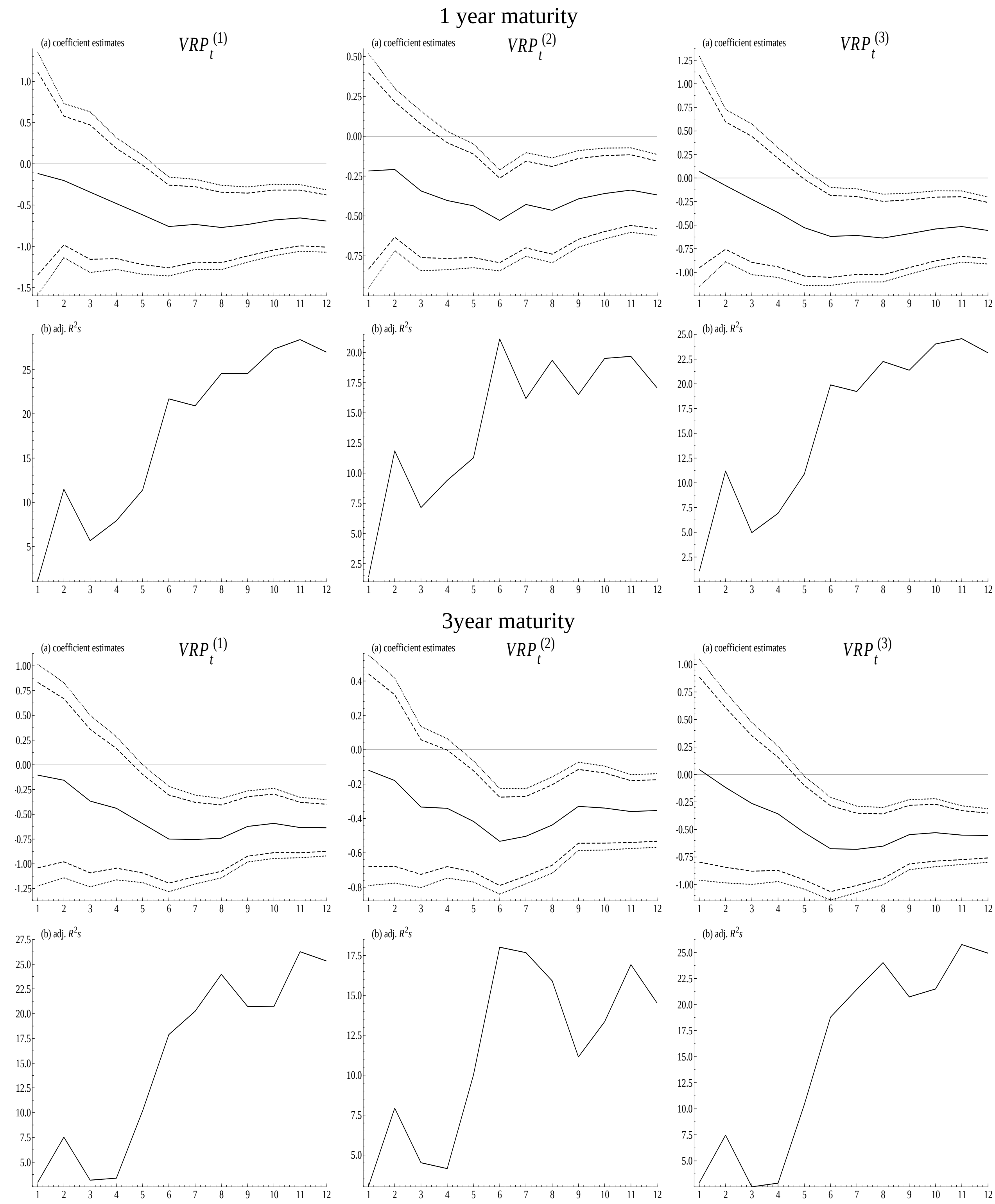
The solid and dashed lines represent $VRP_t^{(4)}$ when we use macroeconomic variables and only lagged realized variance, respectively.

Figure 4: Coefficient parameters for $VRP_t^{(i)}$ and adjusted R^2 on stock return predictability



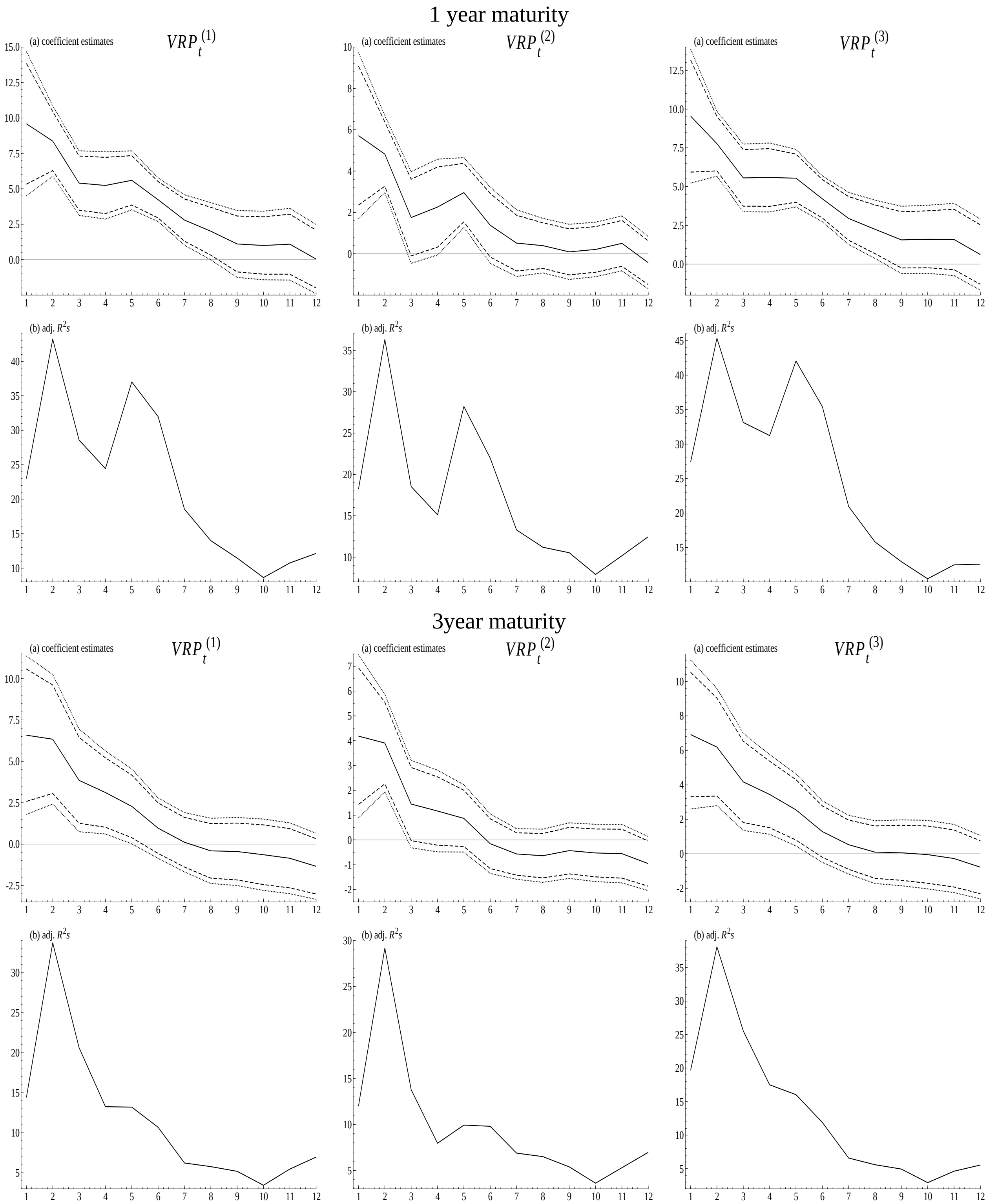
The dashed and dotted lines represent the 90 % and 95 % confidence intervals of the coefficient parameters.

Figure 5: Coefficient parameters for $VRP_t^{(i)}$ and adj. R^2 on credit spreads with AAA rating



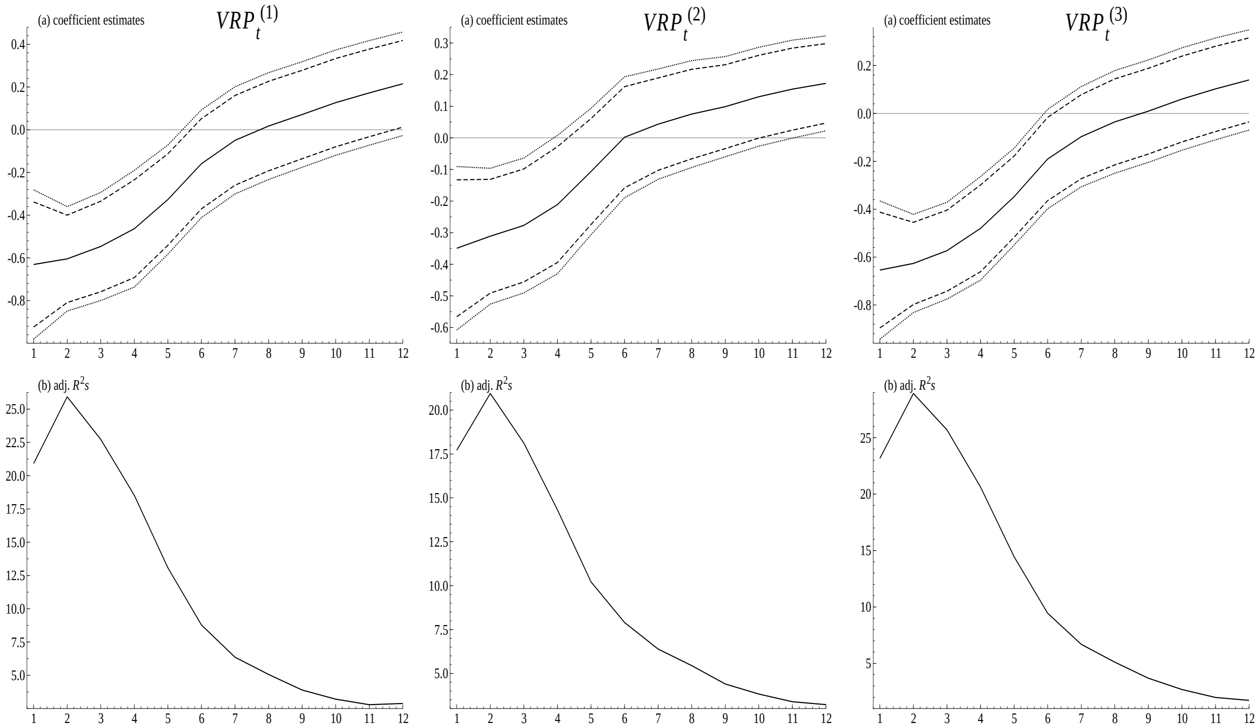
The dashed and dotted lines represent the 90% and 95% confidence intervals of the coefficient parameters.

Figure 6: Coefficient parameters for $VRP_t^{(i)}$ and adj. R^2 on credit spreads with A rating



The dashed and dotted lines represent the 90% and 95% confidence intervals of the coefficient parameters.

Figure 7: Coefficient parameters for $VRP_t^{(i)}$ and adj. R^2 on composite index of coincident indicators



The dashed and dotted lines represent the 90% and 95% confidence intervals of the coefficient parameters.