International Journal of Economics and Finance; Vol. 15, No. 8; 2023
ISSN 1916-971X E-ISSN 1916-9728
Published by Canadian Center of Science and Education

Variance Risk Premium Components in Japan for Predictability: Evidence from the COVID-19 Pandemic

Masato Ubukata[1]

[1] Department of Economics, Meiji Gakuin University, Tokyo, Japan

Correspondence: Masato Ubukata, Department of Economics, Meiji Gakuin University, Shirokanedai, Minato-ku, Tokyo, 108-0071 Japan. E-mail: ubukata@eco.meijigakuin.ac.jp

Received: May 27, 2023 Accepted: June 20, 2023 Online Published: June 30, 2023

doi:10.5539/ijef.v15n8p27 URL: https://doi.org/10.5539/ijef.v15n8p27

Abstract

The literature on asset predictability suggests the usefulness of the variance risk premium (VRP) and its diffusive and jump risk components as predictors that can yield an improved forecast power. This study investigates whether there is a robust and statistically significant relation between the VRP components and the future Japanese composite index of coincident indicators (CI) and credit spreads (CS), including the outbreak of the COVID-19 pandemic which has caused economic conditions and financial markets to become unstable. The main empirical results are as follows: (i) our rolling window predictive regressions indicate the stability of the significantly negative relation between the diffusive risk component of the VRP and the future CI; (ii) the significantly positive relation of the jump risk component of the VRP and the future lower-rated CS is hampered by the inclusion of the COVID-19 period when the Bank of Japan purchased large-scale corporate bonds under the continuing Japanese expansionary monetary policy; and (iii) the diffusive risk component is partly affected by the impact of the COVID-19 pandemic, but remains significantly positive relation with the future higher- and lower-rated CS.

Keywords: predictability, COVID-19 pandemic, variance risk premium, option-implied jump variation, composite index of coincident indicators, credit spreads

1. Introduction

Over the past decade, a large body of studies has investigated asset predictability using the forward-looking premium associated with exposure to equity return variation, which mirrors the well-known empirical time-varying changes of volatility or variance of an underlying asset. The premium required for investors to accept the risk is called the variance risk premium (VRP) and is calculated as the gap between the option-based risk-neutral and the statistically expected future return variation. As such, it can gauge investor risk aversion and is derived from a consumption-based asset pricing model incorporating time-varying economic uncertainty (see Bollerslev et al., 2009; Drechsler & Yaron, 2011).

The VRP can be decomposed into a component attributable to diffusive or normal-sized price fluctuations and a component representing the compensation of jump risk. There is a large body of literature on different jump risk measures: option-implied, stock-return based, option-return based, and macroeconomic ones (for details, see Dierkes et al., 2021). Specifically, Bollerslev et al. (2015) propose the option-based estimator of left jump variation, LJV, representing exposure to abrupt downside price movements. This measure can be approximately equal to the time-varying jump tail component of VRP, leading to a straightforward calculation of the diffusive risk component as the difference between the VRP and LJV. Andersen et al. (2021) suggest that the LJV is applicable to option data for the Japanese aggregate stock market.

Since the VRP has the advantage from a statistical viewpoint that it is substantially less persistent, it generates fewer econometric problems on standard predictability regressions compared with the extremely persistent traditional predictors used in long-horizon predictability studies. Therefore, the empirical investigation of the statistical significance of the predictive ability of the VRP or its diffusive and jump risk components has been widely studied for forecasting market excess returns in the equity market (Bollerslev et al., 2009, 2014; Londono, 2011), credit and default spreads in the corporate bond market (Zhou, 2010; Wang et al., 2013; Ubukata & Watanabe, 2014; Ubukata, 2019), and real economic variables (Oya, 2011; Ubukata & Watanabe, 2014; Dierkes et al., 2021). Specifically, Andersen et al. (2015, 2020, 2021), Bollerslev et al. (2015), and Ubukata (2019)

indicate that considering the two different components of VRP separately as predictors yields significantly improved forecasting power. This finding verifies for international markets, implying that the degrees of significance vary depending on the equity index and sample period explored.

In line with the literature reviewed above, our study provides new empirical evidence of asset predictability in Japan based on VRP components using a recent sample including the COVID-19 pandemic. COVID-19 was first diagnosed in Wuhan City, China at the beginning of December 2019. As it is highly transmittable, after the first infected person was confirmed on January 15, 2020 in Japan, the total infected number exceeded 100 on February 21, 2020 and the Novel Coronavirus Special Measures Law was enacted during March 2020. The COVID-19 had multifaceted effects on economies worldwide. For example, Maliszewska et al. (2020) investigate the impact of COVID-19 on GDP and trade. Padhan and Prabheesh (2021) explore the effects of the COVID-19 pandemic and propose potential policy directions to mitigate them through a survey of previous studies.

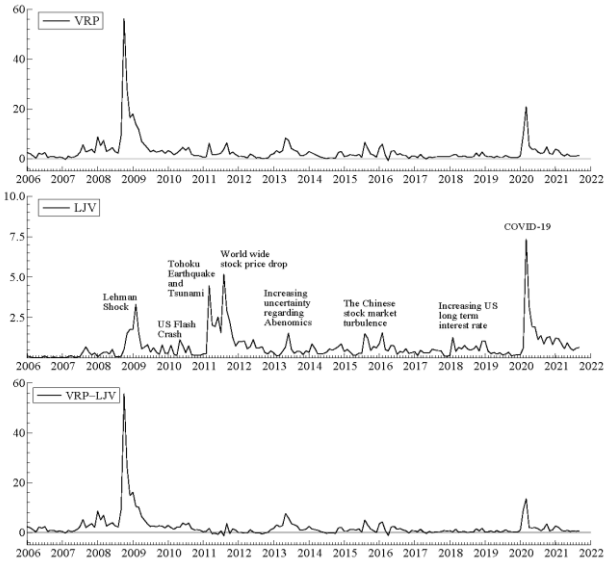

Figure 1. Monthly time series of VRP, LJV, and VRP-LJV

Our contribution is to investigate whether there is a robust and statistically significant relation between the VRP components and the future economic and financial variables, including the outbreak of the COVID-19 pandemic which has caused economic conditions and financial markets to become unstable. Surprisingly, to the best of our knowledge, no study has hitherto assessed the pandemic's impact on the asset predictability with the VRP components even for major markets such as the U.S., Europe, China, and Japan. The predicted variables employed in this paper are the Japanese composite index of coincident indicators (CI) and credit and default spreads (CS) (Note 1). Our analysis shows that the outbreak of the COVID-19 pandemic has increased national financial risks. Figure 1 displays the monthly time-series of the VRP (top panel), the jump risk component, LJV (middle panel), and the diffusive risk component, VRP-LJV (bottom panel), for the Nikkei 225 stock index in Japan from January 2006 to September 2021. The LJV is calculated as the option-implied left jump variation proposed by Bollerslev et al. (2015) and Andersen et al. (2021). The three measures are reported as the annualized percentage in variance. Interestingly, we can observe the highest distinct peak of LJV and the second highest one of VRP-LJV during March 2020 due to the Novel Coronavirus Special Measures Law being enacted, the Government announcing a state of emergency for the first time, and the International Olympic Committee (IOC) and the Tokyo 2020 Organizing Committee announcing the postponement of the Tokyo 2020 Games. The finding that there is rapid increase in stock market uncertainty, together with negative left jump in stock index return, implies the importance of an extended analysis of VRP components in the application to asset predictability for a sample including the COVID-19 period.

This paper mainly employs standard multiple predictability regressions from 1-month to 1-year ahead horizons, which are consistent with the methodologies used in many previous studies (for example, see Bollerslev et al. 2015). However, a direct analysis of monthly predictability regressions using only for the COVID-19 period (starting in January 2020 for Japan) is difficult due to the limited sample period. In this study, we explore whether the inclusion of the COVID-19 period has a material impact on the relation between the VRP

components and the future CI and CS by sequentially estimating the predictability regression models. The idea is very close to rolling window predictive regressions. For example, in the sequential 1-month ahead predictability regression, we start the sample in February 2006 and end it in December 2019 for predicted variables (in January 2006 and end it in November 2019 for predictors), corresponding to before the beginning of the COVID-19 pandemic for Japan. Next, we expand the sample period by 1 month, adding January 2020 for predicted variables (December 2019 for predictors), and re-estimate the predictive relation. We continue this procedure until the end of October 2021 for predicted variables (September 2021 for predictors) and explicitly demonstrate how the statistical significance, sign of coefficient estimates, and adjusted R^2 are sequentially affected by involving the COVID-19 period.

As described in the above, in this paper, we are more focused on documenting whether there is a robust and statistically significant relation between the VRP components and the future CI and CS including the COVID-19 period, and less concerned with the generation of actual return forecast. This is partly because we cannot have a size of the rolling estimation window for forecasting in models and a long out-of-sample period needed to assess the forecast performance. Even under the sample restriction, it would be helpful to provide at least a statistical result in the out-of-sample forecasting environment. This paper also conducts a small out-of-sample analysis based on the Campbell and Thompson's (2008) out-of-sample R^2 statistic and an adjusted version of the Diebold and Mariano's (1995) test proposed by Clark and West (2007).

The main empirical results are as follows. First, for the CI predictability, the jump risk component of the VRP has no reasonably significant relation. By contrast, the diffusive risk component of the VRP has a significantly negative relation with the future CI even when the COVID-19 pandemic sample is included. Additionally, the COVID-19 pandemic accelerates the predictive power of the diffusive risk component in terms of t-values. Therefore, we conclude that the diffusive risk component of the VRP could be a robust predictor for the future change in the Japanese CI. Second, for the predictability of higher-rated CS, the diffusive risk component is positively significant, the sign of coefficient being reasonable. The significant relation is essentially unaltered over the COVID-19 period. The jump risk component is insignificant or negatively significant, but the negative sign of the coefficient is not consistent with the viewpoint that investors facing the rare jump risks require higher CS. Third, for the predictability of lower-rated CS and default spreads, we find that the jump risk component is significantly positive in some cases without the COVID-19 sample, but then becomes insignificant, implying the negative impact of the COVID-19 pandemic. The loss of significant relation may come from the small increase in CS by the Bank of Japan's large-scale corporate bond purchases under the highly unconventional monetary easing policy in Japan, while the highest peak of LJV was recorded during the crash in March 2020 triggered by the COVID-19 pandemic. We also find that the t-value of the diffusive risk component and adjusted R^2 are affected by the negative effect of the COVID-19 pandemic, but the component remains significant. The results show a robust positive relation between the diffusive risk component and the future CS over the entire sample, including the COVID-19 pandemic. Finally, the result of 1-month ahead out-of-sample forecast performance largely supports the evidence from the multiple predictability regressions that the diffusive risk component of VRP has significantly robust relations with the future CI and CS including the COVID-19 pandemic.

The remainder of the paper is organized as follows. In Section 2, we present the VRP and its calculation method. We also briefly explain the option-implied jump risk measure for the decomposition of the VRP into the diffusive and jump risk components. In Section 3, we present the empirical results for the predictability of the Japanese CI and CS including the COVID-19 pandemic. Section 4 concludes the paper.

2. Variance Risk Premium and Its Components

2.1 Definition and Calculation of Variance Risk Premium

We introduce the VRP and explain its calculation method based on option-implied model-free implied volatility and estimates of expected future return variation. It is assumed that on a filtered probability space $(\Omega, \mathcal{F}, \mathbb{P})$, asset price S_t follows a stochastic exponential of a general jump-diffusion:

$$dS_t/S_{t-} = a_t\, \mathrm{dt} + \sigma_t\, dW_t + \int_{\mathbb{R}} (e^x - 1)\, \tilde{\mu}^{\mathbb{P}}(dx, dt), \tag{1}$$

where a_t, σ_t, W_t and x are drift and diffusive processes, a standard Brownian motion, and the jump size of the log-price, respectively. Under the actual probability measure $\mathbb{P}$, $\tilde{\mu}^{\mathbb{P}}(dx, dt) \equiv \mu(dx, dt) - \nu_t^{\mathbb{P}}(dx)dt$ is a martingale measure where $\mu(dx, dt)$ counts the jumps in S, and $\nu_t^{\mathbb{P}}(dx)$ indicates the jump compensator, for example, the (predictable) jump intensity process. Then, the quadratic variation measuring the return variation of the log-price process over t to $t + \tau$ is expressed as the sum of the integral of σ_s^2 and the jump variation:

$$QV_{t,t+\tau} = \int_t^{t+\tau} \sigma_s^2\, ds + \int_t^{t+\tau} \int_{\mathbb{R}} x^2\, \mu(dx, ds). \tag{2}$$

The no-arbitrage under standard regularity conditions as in Duffie (2001) guarantees the existence of a risk-neutral probability measure, $\mathbb{Q}$. The VRP denotes the compensation for the time-varying return variation, which is measured by the difference between the conditional expectations of $QV_{t,t+\tau}$ under $\mathbb{Q}$ and $\mathbb{P}$ in the literature on asset predictability:

$$VRP_{t,\tau} \equiv \frac{1}{\tau}\left(\mathbb{E}_t^{\mathbb{Q}}\left[QV_{t,t+\tau}\right] - \mathbb{E}_t^{\mathbb{P}}\left[QV_{t,t+\tau}\right]\right), \tag{3}$$

where it can be observed that $\mathbb{E}_t^{\mathbb{Q}}\left[QV_{t,t+\tau}\right]$ is averagely larger than $\mathbb{E}_t^{\mathbb{P}}\left[QV_{t,t+\tau}\right]$.

In the VRP calculation, we can use the option-based squared model-free volatility index as an excellent proxy for $\mathbb{E}_t^{\mathbb{Q}}\left[QV_{t,t+\tau}\right]$, where the Center for Mathematical Modeling and Data Science at Osaka University has published the volatility index for Japan (VXJ) over a fixed maturity of 30 calendar days for the Nikkei 225 stock index (for details, see Fukasawa et al., 2011). Furthermore, to obtain a proxy for $\mathbb{E}_t^{\mathbb{P}}\left[QV_{t,t+\tau}\right]$, a 1-month ahead realized variance is forecasted by a time-series model. We employ an asymmetric heterogeneous autoregressive model with continuous and jump components of the realized variance and the squared model-free implied volatility (AHAR-CJ-MFIV model):

$$\begin{aligned}\ln RV_t = \alpha &+ \beta_d \ln C_{t-1} + \beta_w \ln C_{t-5,t-1} + \beta_m \ln C_{t-22,t-1} + \gamma_d \ln(1+J_{t-1}) + \gamma_w \ln\left(1+J_{t-5,t-1}\right) \\ &+\gamma_m \ln\left(1+J_{t-22,t-1}\right) + \theta_d \ln V_{t-1}^{non} + \theta_w \ln V_{t-5,t-1}^{non} + \theta_m \ln V_{t-22,t-1}^{non} + \phi_d \ln VXJ_{t-1}^2 \\ &+\phi_w \ln VXJ_{t-5,t-1}^2 + \phi_m \ln VXJ_{t-22,t-1}^2 + \delta R_{t-1}^- + \nu_t, \qquad \nu_t \sim N(0,\sigma_\nu^2),\end{aligned} \tag{4}$$

where $\ln RV_t$ is the sum of the logarithm of realized variance during trading hours on day t and the squared overnight and lunchtime returns, denoted as V_t^{non}. The realized variance during the trading hours on day $t-1$ is decomposed into the continuous (diffusive) and jump components, denoted C_{t-1} and J_{t-1}, respectively, where $\ln C_{t-5,t-1} = \ln\left(\sum_{i=1}^{5} CV_{t-i}/5\right)$, $\ln C_{t-22,t-1} = \ln(\sum_{i=1}^{22} CV_{t-i}/22)$, $\ln J_{t-5,t-1} = \ln\left(\sum_{i=1}^{5} J_{t-i}/5\right)$, $\ln J_{t-22,t-1} = \ln(\sum_{i=1}^{22} J_{t-i}/22)$. VXJ_{t-1}^2 indicates the squared model-free implied volatility index on day $t-1$, where $\ln VXJ_{t-5,t-1}^2 = \ln\left(\sum_{i=1}^{5} VXJ_{t-i}^2/5\right)$ and $\ln VXJ_{t-22,t-1}^2 = \ln(\sum_{i=1}^{22} VXJ_{t-i}^2/22)$ are the logarithm of the average 1-week and 1-month lagged VXJ^2. $R_{t-1}^- = \mathrm{Min}[R_{t-1}, 0]$ is included for capturing the asymmetry in volatility.

First popularized by Corsi (2009), the HAR model can approximately capture the long-memory property of the daily realized variance, whose autocorrelation function decays more slowly than that of the short-memory process. The AHAR-CJ-MFIV model is an extended HAR model based on previous empirical evidence. For example, Andersen et al. (2007) suggest that the HAR model with realized volatility separately from significant jumps improves the forecast performance of future realized volatility. We decompose the realized variance into C_{t-1} and J_{t-1} by testing the null hypothesis of no jump and using the realized variance and the bipower variation as in Huang and Tauchen (2005) and Barndorff-Nielsen and Shephard (2006). Bekaert and Hoerova (2014) show that the model-free implied volatility index, such as the VIX, has a significant predictive power for the future U.S. realized variance. Ubukata (2022) suggests that the AHAR-CJ-MFIV model provide the best in-sample and out-of-sample forecasts among the HAR-type models using Japanese data.

We calculate the realized variance over trading hours as the sum of squared 5-minute returns. The parameters of the AHAR-CJ-MFIV model can be estimated by simple linear regression. For the realized variance forecasting, we assume the normality assumption on the error term because the distribution of $\ln RV_t$ is much closer to the normal distribution than that of RV_t (e.g., Andersen et al., 2001; Ubukata & Watanabe, 2014). Under this assumption, the forecasts of RV_t, which is log-normal distributed, can be obtained from the forecasts of $\ln RV_t$ and the estimates of σ_ν^2. Therefore, we use the direct 1-month ahead forecast for the AHAR-CJ-MFIV model as a proxy for $\mathbb{E}_t^{\mathbb{P}}\left[QV_{t,t+\tau}\right]$ in (3).

2.2 Risk-Neutral Left Jump Variation for Variance Risk Decomposition

We describe the risk-neutral left jump variation proposed by Bollerslev et al. (2015), who show that this measure can be used as a proxy of the compensation part associated with the jump tail risks in the VRP and can predict the future equity risk premium for the S&P 500 index. The left jump variation measure is essentially non-parametric, only imposing a general structure on the jump intensity, and is computed from different deep-out-of-the-money put options. Andersen et al. (2021) show that the left jump risk measure can be applicable to the aggregate Japanese equity market.

The left risk-neutral (large) predictable jump variation is defined as:

$$LJV_{t,\tau}^{\mathbb{Q}} = \int_t^{t+\tau} \int_{x<-k_t} x^2 \nu_s^{\mathbb{Q}}(dx)ds, \tag{5}$$

where $k_t > 0$ and $\nu_s^{\mathbb{Q}}(dx)$ indicate the time-varying cutoff for the log-jump size and the jump compensator, for example, the (predictable) jump intensity process under $\mathbb{Q}$. The jump intensity process of Bollerslev and

Todorov (2014, 2015) is expressed as:

$$\nu_t^{\mathbb{Q}}(dx) = \left(\phi_t^+ \times e^{-\alpha_t^+ x} 1_{\{x>0\}} + \phi_t^- \times e^{-\alpha_t^- |x|} 1_{\{x<0\}}\right) dx, \tag{6}$$

where $\alpha_t^{\pm}$ and $\phi_t^{\pm}$ denote the time-varying parameters for the shape and level shift of the jump tails. The time-varying shape parameter for the left jump tail, α_t^-, has a negative relation with the left jump variation. The smaller value of α_t^- indicates the slower rate of decay for the log option put prices, leading to the fatter left tail in the risk-neutral density. The time-varying level shift parameter of the left jump tail, ϕ_t^-, has a positive relation with the left jump variation because a larger value of ϕ_t^- indicates a fatter left tail.

The estimates of α_t^- and ϕ_t^- are obtained by solving the following optimization problems:

$$\hat{\alpha}_t^- = \arg\min_{\alpha^-} \frac{1}{N_t^-} \sum_{i=2}^{N_t^-} \left| \log\left(\frac{O_{t,\tau}(k_{t,i})}{O_{t,\tau}(k_{t,i-1})}\right) \left(k_{t,i} - k_{t,i-1}\right)^{-1} - \left(1 - (-\alpha^-)\right) \right|, \tag{7}$$

$$\hat{\phi}_t^- = \arg\min_{\phi^-} \frac{1}{N_t^-} \sum_{i=2}^{N_t^-} \left| \log\left(\frac{e^{r_t \tau} O_{t,\tau}(k_{t,i})}{\tau F_{t,\tau}}\right) - (1 + \hat{\alpha}_t^-) k_{t,i} + \log(\hat{\alpha}_t^- + 1) + \log(\hat{\alpha}_t^-) - \log(\phi^-) \right|, \tag{8}$$

where $O_{t,\tau}(k_{t,i})$ is the mid-quote of the out-of-the-money (OTM) put option for the i-th log-moneyness $k_{t,i}$, N_t^- is the number of puts used in the estimation with $0 < -k_{t,1} < \cdots < -k_{t,N_t^-}$, and $F_{t,\tau}$ is the forward price with maturity date $t + \tau$. α^- is estimated from (7) using information about the tail decay for the observed OTM put options, and ϕ^- is estimated from (8) using an estimate for α^- and the mid-quote level of the observed OTM put options. Based on the estimates of α_t^- and ϕ_t^-, we have the left jump tail variation under $\mathbb{Q}$ as:

$$LJV_{t,\tau}^{\mathbb{Q}} = \tau \phi_t^- e^{-\alpha_t^- |k_t|} (\alpha_t^- k_t (\alpha_t^- k_t + 2) + 2) / (\alpha_t^-)^3 = \mathbb{E}_t^{\mathbb{Q}}\left[LJV_{t,\tau}^{\mathbb{Q}}\right]. \tag{9}$$

In the calculation of LJV for the Japanese aggregate stock market, we follow the measurement procedure proposed by Andersen et al. (2021). We use regular options with maturities from 8 to 42 calendar days in consideration of a possible reduction in the effects of the diffusive price component and the market microstructure (Note 2).

Following Andersen et al. (2021), the time-varying α_t^- is assumed to change at a weekly frequency, and the weekly α_t^- is estimated by keeping the OTM put options for a week, with log-moneyness below -2.0 (-2.5) times the normalized ATM Black-Scholes implied volatility before (after) December 2008. The time-varying ϕ_t^- is allowed to change each trading day and is estimated using $\hat{\alpha}_t^-$. Finally, we compute the monthly LJV as the average of the weekly measures within the month (Note 3).

Once we obtain the LJV as a proxy of jump risk component in the VRP, the diffusive risk component is calculated by subtracting the LJV from the VRP. The previous studies suggest that the inclusion of the diffusive and jump risk components as separate predictors significantly increases a forecasting power for future financial variables (e.g., Bollerslev et al., 2015; Ubukata, 2019, 2022; Andersen et al., 2021). However, no study has assessed the asset predictability with the two components around the outbreak of the COVID-19 pandemic which has caused economic conditions and financial markets to become unstable. In this paper, we explore whether the inclusion of the COVID-19 period has a substantial impact on the relation between the VRP components and future economic and financial variables in Japan.

3. Empirical Analysis

3.1 Data

In the empirical analysis, we use Japanese financial and economic data from various sources to investigate whether there is a robust and statistically significant relation between the VRP components and future economic and financial variables in Japan including the COVID-19 pandemic period when the economic conditions and financial markets become unstable. First, the data on the volatility index Japan, VXJ, is obtained from the webpage at Center for Mathematical Modeling and Data Science at Osaka University. The VXJ is used for the calculation of VRP as a proxy for $\mathbb{E}_t^{\mathbb{Q}}\left[QV_{t,t+\tau}\right]$, as explained in Section 2.1. The Nikkei NEEDS-TICK data include 5-minute Nikkei 225 index returns, which are used to calculate realized variance and bipower variation for forecasting $\mathbb{E}_t^{\mathbb{P}}\left[QV_{t,t+\tau}\right]$ from the AHAR-CJ-MFIV model in (4). Second, we obtain data on Nikkei 225 put options traded on the Osaka Securities Exchange from Nikkei NEEDS Financial Quest 2.0 and the Certificate of Deposit rate as a risk-free interest rate from the Bank of Japan. These data are used for estimating α_t^- and ϕ_t^- in (7) and (8) and the calculation of LJV in (9). Third, we use the Japanese composite index of coincident indicators, CI, as a measure of the current economic condition, obtained from Economic and Social Research Institute, Cabinet Office. The interest rate spread, SPRD, calculated as the difference between newly issued

10-year government bond yields and the 3-month Tokyo Interbank Offered Rate, is obtained from the Japanese Bankers Association TIBOR Administrations. These variables are employed to analyze a relation between the VRP components and the future change of CI including the COVID-19 period. Finally, we calculate credit spreads, CS, using data obtained from the Japan Credit Rating Agency, Ltd. to analyze a relation between the VRP components and the future CS including the COVID-19 pandemic period. We define the difference between the average corporate bond yield of firms with investment grade rating i at m-year maturity and the corresponding Japanese government bond (JGB) yield as $CS_{i,m}$. We consider two different investment grades, i = AA and A. The AA-rated firms have very high level of the obligor's capacity to honor their financial commitment to their obligations. The A-rated firms also have a high level of capacity but are more susceptible to the negative effects of changes in economic conditions than the AA-rated firms. The maturities of $m = 2, 4, 10$ described here indicate below 2 years, ranging from 3 to 4 years, and from 9 to 10 years, respectively. We also use the 1-year JGB yield as a short rate, SR, the difference between JGB yields at 10- and 1-year maturities as a term spread, TS, and a monthly log-return for the Nikkei 225 index as a market return, MR.

Table 1. Descriptive statistics

	VRP-LJV	LJV	CI	SPRD	$CS_{AA,2}$	$CS_{AA,4}$	$CS_{AA,10}$
Mean	0.19	0.06	97.04	0.40	0.29	0.35	0.42
Std.Dev.	0.42	0.07	8.09	0.46	0.19	0.15	0.09
Skewness	7.40	4.06	-1.16	0.58	3.91	2.71	0.95
Kurtosis	72.93	25.57	4.04	2.74	21.45	12.39	5.78
Minimum	-0.11	0.00	71.50	-0.35	0.14	0.18	0.22
Maximum	4.64	0.61	107.40	1.78	1.45	1.11	0.86
ACF(1)	0.60	0.53	0.97	0.97	0.91	0.93	0.76
	$CS_{A,2}$	$CS_{A,4}$	$CS_{A,10}$	SR	TS	MR	
Mean	0.65	0.71	0.58	0.09	0.53	0.32	
Std.Dev.	0.54	0.44	0.17	0.28	0.39	5.57	
Skewness	1.90	1.76	0.55	0.89	0.39	-0.91	
Kurtosis	5.98	5.24	2.84	3.02	2.04	5.54	
Minimum	0.20	0.34	0.29	-0.33	-0.07	-27.22	
Maximum	2.64	2.24	1.06	0.83	1.59	14.01	
ACF(1)	0.97	0.97	0.92	0.98	0.96	0.12	

Note. The sample period covers from January 2006 to September 2021 (189 months) including the COVID-19 pandemic period. We report VRP-LJV, LJV, and MR in non-annualized percentage form and CS, SPRD, SR, and TS in annualized percentage form. The value of CI for reference year 2015 is 100. ACF(1) is the estimated first-order autocorrelation of the monthly variables.

The descriptive statistics are reported in Table 1. The monthly means of VRP-LJV and LJV are 0.19 and 0.06 in percentage form. The VRP-LJV and LJV are moderately persistent, with the first-order monthly auto-correlation coefficients of 0.60 and 0.53. They are substantially less persistent than other predictors, SPRD, SR, and TS, generating fewer econometric problems. The time series of VRP-LJV and LJV are already described in Figure 1 of Section 1. The monthly mean of CI is 97.04, where the value for reference year 2015 is 100. The first-order autocorrelation coefficient of CI is 0.97, so that we use the change rate of CI as a predicted variable. For Japanese credit spreads, the annualized monthly means of CS increase from 0.29 to 0.65 for $CS_{\cdot,2}$, from 0.35 to 0.71 for $CS_{\cdot,4}$, and from 0.42 to 0.58 for $CS_{\cdot,10}$ in percentage form as the credit ratings degrade from AA to A. For the CS predictability regressions, we include the lagged CS as a predictor because the CS is highly persistent, except for $CS_{AA,10}$ of 0.76. We will provide further explanations about the time-series of CI and CS later.

3.2 Sequential Predictability Regressions Including the COVID-19 Pandemic

3.2.1 Predicting the Composite Index of Coincident Indicators

Previous studies have investigated whether there is a relation between several variables and the future real economic variables such as output growth, industrial production, and CI. The VRP is a forward-looking variable, so if one faces high VRP, one has a high degree of risk aversion to the future economy, meaning firms may refrain from new investments and pause hiring new workers. Therefore, it is interesting to investigate whether the VRP components affect real economic activity (Oya, 2011; Ubukata & Watanabe, 2014; Dierkes et al., 2021). GDP data for output growth are available only quarterly or annually. The industrial production focuses on real output for all facilities in manufacturing, mining, and electric and gas industries, and so on. Instead, we examine

the predictability of CI because it is composed of various components such as industrial production, producer's shipments, sales values, operating profits, effective job offer rate, and exports volume. To the best of our knowledge, an investigation of whether there is a significant relation between the VRP components and the future CI including the COVID-19 pandemic period has not been analyzed before.

Figure 2 plots monthly time-series of CI from January 2006 to March 2022. The series starts out larger than 100 during the tranquil market period of 2006-2007, but rapidly drops to 71.5 in March 2009 in the aftermath of the Lehman Shock and the global financial crisis. CI increases over 2 years after the crisis, but there is a large spike in the series that reflect the Tohoku Earthquake and Tsunami in March 2011. The series also decreases during the slowdown in overseas economies and considerable decline in exports in 2012 and due to the double increase of the consumption tax rate from 5% to 8% and from 8% to 10% in April 2014 and October 2019, respectively. Interestingly, there is clearly discernible drop to 74.6 in May 2020 associated with the COVID-19 pandemic and the recent series remains less than 100 for reference year 2015. This evidence suggests that the CI is readily interpretable and economically meaningful.

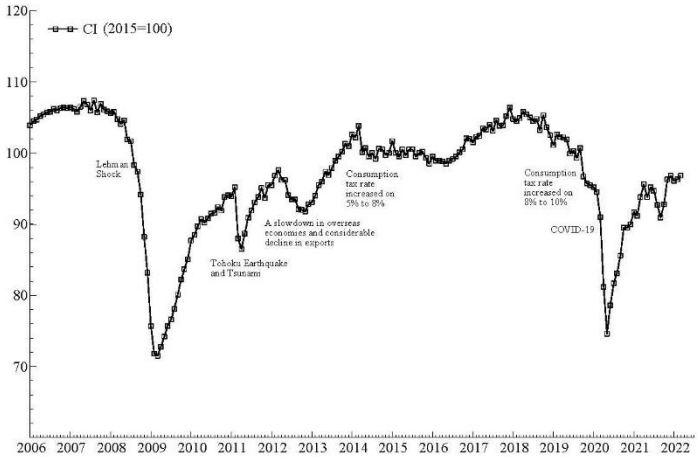

Figure 2. Monthly time series of CI

Following the literature, we consider the monthly multiple predictive regressions:

$$\frac{1}{h}\Delta CI_{t,t+\tau h} = \beta_0(h) + \beta_1(h)[VRP_t - LJV_t] + \beta_2(h)LJV_t + \beta_3(h)SPRD_t + u_{t,t+\tau h}, \quad (10)$$

where $\Delta CI_{t,t+\tau h} = (CI_{t+\tau h} - CI_t)/CI_t \times 100$ is the change rate of CI at time $t + \tau h$ for $\tau = 30$ calendar days (1 month) and $h = 1, \dots, 12$. Thus, we consider the predictability over 1 month to 1 year. $VRP_t - LJV_t$ and LJV_t represent the diffusive and jump risk components of the VRP at time t. $SPRD_t$ is the interest rate spread controlled for. For testing the significance of coefficients in the overlapping multiperiod return regression, we use the standard robust Newey-West t-statistic with a lag length of $2h$.

Due to the limited sample for the COVID-19 pandemic, starting in January 2020 for Japan, we investigate whether the inclusion of the COVID-19 period has a substantial impact on the relation between the VRP components and the future change rate of CI. Thus, the multiple predictive regression model in (10) is estimated sequentially. For example, in the sequential 1-month ahead predictability regression for $h = 1$, we start the sample in February 2006 and initially end it in December 2019 for predicted variable (in January 2006 and initially end it November 2019 for predictors), corresponding to before the beginning of the COVID-19 pandemic for Japan. Next, we expand the sample period by 1 month, adding January 2020 for predicted variable (December 2019 for predictors), and re-estimate the predictive relation. We continue this procedure all through the end of in October 2021 for predicted variable (September 2021 for predictors). In the sequential 1-year ahead predictability regression for $h = 12$, we start the sample in January 2007 and initially stop by December 2019 for predicted variable (in January 2006 and initially stop by December 2018 for predictors), corresponding to the period before the beginning of the COVID-19 pandemic for Japan. Next, we expand the sample period by 1 month, adding January 2020 for predicted variable (January 2019 for predictors), and re-estimate the predictive relation. We continue this procedure until the end of March 2022 for predicted variable (March 2021 for predictors).

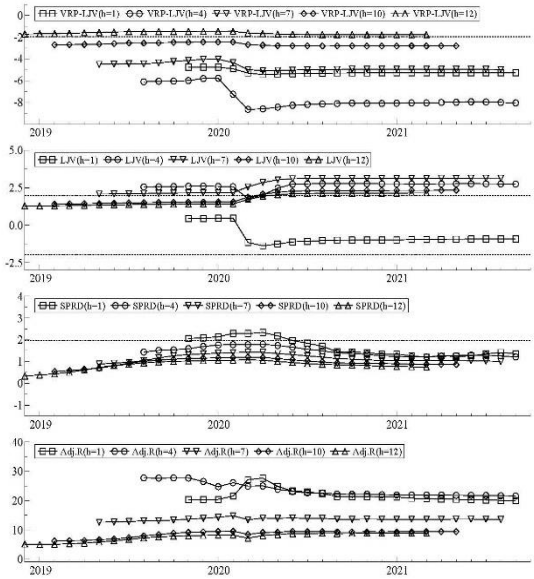

Figure 3. Sequential multiple CI predictability regressions

Figure 3 depicts the Newey-West t-statistics and the adjusted R^2 estimated sequentially from the multiple CI predictability regressions in (10) for 1-month ($h = 1$), 1-quarter ($h = 4$), 7-month ($h = 7$), 10-month ($h = 10$), and 1-year ($h = 12$) horizons. The top, second, and third panels depict the Newey-West t-statistics for the predictors, VRP-LJV, LJV, and SPRD. The bottom panel plots the adjusted R^2. Since we estimate the regressions explained above sequentially, the horizontal axis represents the end month in each sample of the predictors used for re-estimation. The end months of the predictors for the first and last sequential estimation periods are November 2019 and September 2021 for ($h = 1$), August 2019 and September 2021 for ($h = 4$), May 2019 and August 2021 for ($h = 7$), February 2019 and May 2021 for ($h = 10$), and December 2018 and March 2021 for ($h = 12$), respectively. In particular, the left point in each marked line represents the results from predictive regressions without the COVID-19 pandemic sample for both of the CI and predictors. We sequentially expand the sample period every month over the COVID-19 period as the marked point moves to the right.

The diffusive risk component of the VRP, VRP-LJV, has the negative relation with the future change in CI at the 5% significant level, except for $h = 12$. The coefficients remain significant, even when we include the COVID-19 pandemic sample. Specifically, the t-values for $h = 1$ become negatively larger after the end month of predictors is February 2020. Therefore, the COVID-19 pandemic accelerated the significant relation between the VRP-LJV and CI. By contrast, the jump risk component of the VRP, LJV, is insignificant or positively significant for all h. The positive relation between the LJV and the future change in CI might be inconsistent with a reasonable interpretation because, if the high left jump tail risk has an impact on CI, it affects the delay of real economic activity such as new firms' investments, producers' shipments, and employment of labor. The interest rate spread, SPRD, as a traditional predictor, has insignificant relation with the future change in CI expect for $h = 1$. The adjusted R^2 is essentially unaltered for each sample period. In particular, although we observe that the adjusted R^2 increases during part of the COVID-19 pandemic period from March 2020 to April 2020 for $h = 1$, there might be an overall minor difference between the adjusted R^2s without and with the COVID-19 pandemic period. Comparing the different forecasting horizons, the adjusted R^2 for short horizons such as $h = 1$ and 4 is larger than that for long horizons such as $h = 7, 10,$ and 12. We conclude that the VRP-LJV has a robust and negative relation with the future Japanese CI, which is accelerated by the COVID-19 pandemic in terms of t-values.

3.2.2 Predicting Credit and Default Spreads

Previous studies have argued that VRP or its diffusive and jump risk components could provide information about future CS in the U.S. and Japanese corporate bond markets (see, e.g., Zhou, 2010; Wang et al., 2013; Ubukata & Watanabe, 2014; Ubukata, 2019). However, it has note been investigated whether there is a significant relation between the VRP components and the future CS including the COVID-19 pandemic period.

We employ the monthly multiple predictive regressions:

$$CS_{i,m,t+\tau h} = \beta_0(h) + \beta_1(h)[VRP_t - LJV_t] + \beta_2(h)LJV_t + \beta_3(h)SR_t + \beta_4(h)TS_t + \beta_5(h)MR_t + \beta_6(h)LagCS_t + u_{i,m,t+\tau h}, \quad (11)$$

where $CS_{i,m,t+\tau h}$ denotes credit spreads at time $t + \tau h$ and m-year maturity for investment grade rating $i =$ AA and A, $\tau = 30$ calendar days (1 month), and $h = 1, \ldots, 12$. We also consider default spreads calculated by the difference between A- and AA-rated CS as additional predicted variables.

Because several variables have been previously documented for predicting future credit and default spreads (see, e.g., Merton, 1974; Longstaff & Schwartz, 1995; Collin-Dufresne et al., 2001, 2003), we use four traditional explanatory variables: the short rate (SR), the term spread (TS), the market return (MR), and the lagged credit spread (LagCS), respectively. Regarding the significance of SR, TS, and MR, the sign of each coefficient might be consistent with the implication from classical structural models that a higher risk-free rate and an increase in the firm's value lowers CS, while a high term spread increases CS. Moreover, the LagCS are considered to have strong predictive power, as Collin-Dufresne et al. (2001) note that the CS change rates are much harder to forecast than the levels. To explore whether there is a significant relation between the VRP components and the future CS including the COVID-19 pandemic period, we estimate the multiple predictive regression model in (11) sequentially, which is the same as in Section 3.2.1 for the CI predictability.

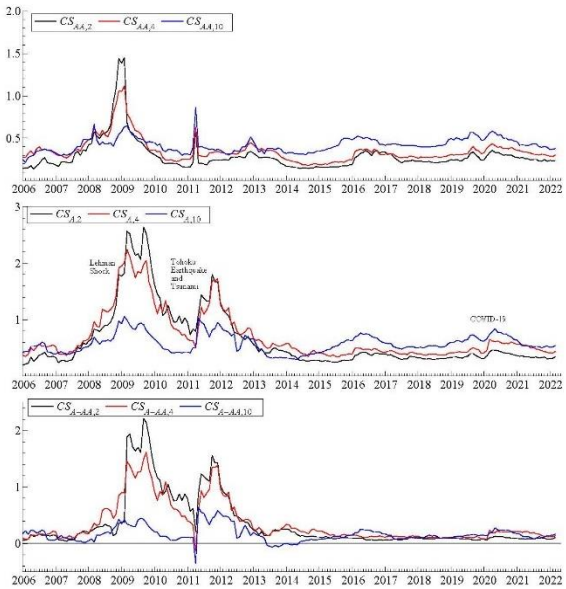

Figure 4. Monthly time series of credit and default spreads

Figure 4 plots the monthly time-series of credit and default spreads from January 2006 to March 2022, which are AA-rated credit spreads, $CS_{AA,2}$, $CS_{AA,4}$, and $CS_{AA,10}$, in the top panel, A-rated credit spreads, $CS_{A,2}$, $CS_{A,4}$, and $CS_{A,10}$, in the middle panel, and default spreads, $CS_{A-AA,2}$, $CS_{A-AA,4}$, and $CS_{A-AA,10}$, in the bottom panel. Before the COVID-19 pandemic, the A-rated CS tended to increase more than the higher AA-rated CS in the aftermath of the Lehman Shock and the global financial crisis, as well as the Tohoku Earthquake and Tsunami. The default spreads also tended to increase over this period. Comparing different maturities ($m = 2, 4,$ and 10), we observe inverted corporate bond yields for the AA- and A-rated CS in the aftermath of the Lehman Shock and for the A-rated CS in the aftermath of Tohoku Earthquake and Tsunami.

An interesting observation emerges during the COVID-19 pandemic. Although there is the discernible large drop in CI described in Section 3.2.1, the AA- and A-rated credit and default spreads show only a slight increase at the beginning of the COVID-19 pandemic. The corresponding corporate bond yield curve remains normal, which is opposite in sign to that in the aftermath of the Lehman Shock and Tohoku Earthquake and Tsunami. There is a possible reason that the Japanese credit and default spreads are little susceptible to the effects of changes in economic conditions caused by the COVID-19 pandemic. The Bank of Japan has conducted large-scale purchases of corporate bonds and commercial paper under the quantitative monetary easing policy to curb the market turmoil caused by the COVID-19 pandemic. The large-scale corporate bond purchases by BOJ's open market operations put strong downward pressure on the Japanese corporate bond yields, although credit spreads

in the global corporate bond market have not decreased to the levels before the COVID-19 pandemic. Additionally, high-risk subordinated and low-rated corporate bonds have been issued during the non-traditional monetary easing policy. Under these circumstances and given the return to the low interest rate before COVID-19, it is difficult for investors to assess the firms' creditworthiness, leading to a possible decline in market function, such as the price discovery in the Japanese corporate bond market.

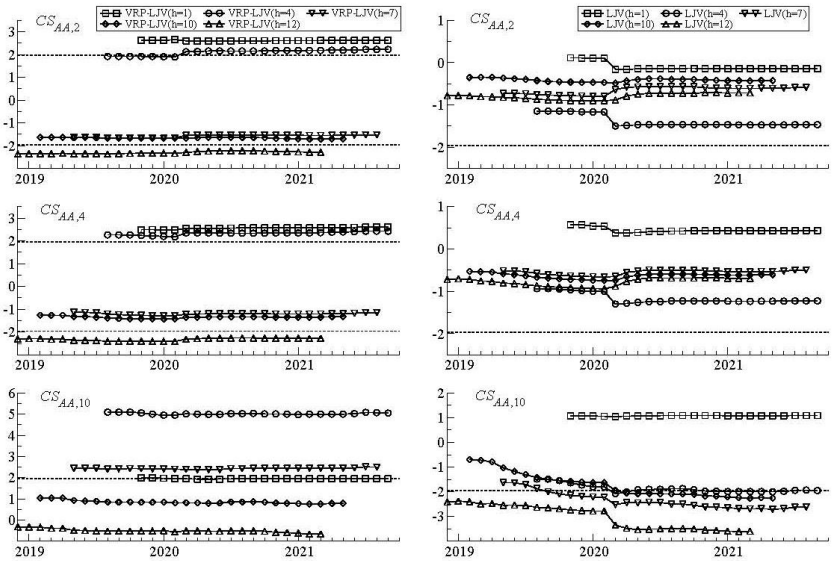

Figure 5. Newey-West t-statistics from the sequential predictability regressions of $CS_{AA,2}$, $CS_{AA,4}$, and $CS_{AA,10}$

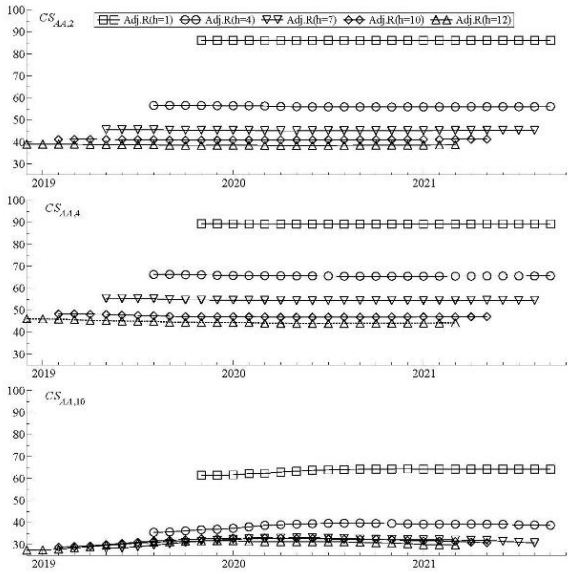

Figure 6. Adjusted R^2 from the sequential predictability regressions of $CS_{AA,2}$, $CS_{AA,4}$, and $CS_{AA,10}$

Figures 5 and 6 plot the Newey-West t-statistics and adjusted R^2 from the sequential multiple regressions in (11) for predicting AA-rated credit spreads, $CS_{AA,2}$ (top panel), $CS_{AA,4}$ (middle panel), and $CS_{AA,10}$ (bottom panel). In particular, the left and right panels of Figure 5 depict the Newey-West t-statistics of the diffusive risk component, VRP-LJV, and the jump risk component, LJV, in the VRP. The horizontal axis represents the end point of the predictors when we estimate the regression in (11) sequentially for $h = 1$ (solid square line), $h = 4$ (solid circle line), $h = 7$ (solid lower triangle line), $h = 10$ (solid rhombus line), and $h = 12$ (solid triangle line), respectively. The VRP-LJV is positively significant in predicting 1-month and 1-quarter ahead $CS_{AA,2}$ and $CS_{AA,4}$ and in predicting 1-quarter and 7-month ahead $CS_{AA,10}$ at the 5% level. For the impact of the COVID-19 pandemic on the positive relation between the VRP-LJV and the future AA-rated CS, the t-values are essentially unaltered on the horizontal axis. Comparing the t-values at the extreme left point and the other points, there is

only a minor difference for VRP-LJV. By contrast, the LJV is insignificant or negatively significant where the negative sign on the coefficient is not consistent with the viewpoint that the CS contract of firms facing high uncertainty associated rare jump risks requires large CS. We omit the detailed results for the control variables in (11) to save space. They are available upon request. Overall, there are significantly positive coefficients on LagCS until $h = 7$, but most cases of SR, TS, and MR are not significant. The degree of the adjusted R^2 tends to be larger for shorter-month ahead predictability regressions and there is only a minor difference with and without the COVID-19 pandemic sample.

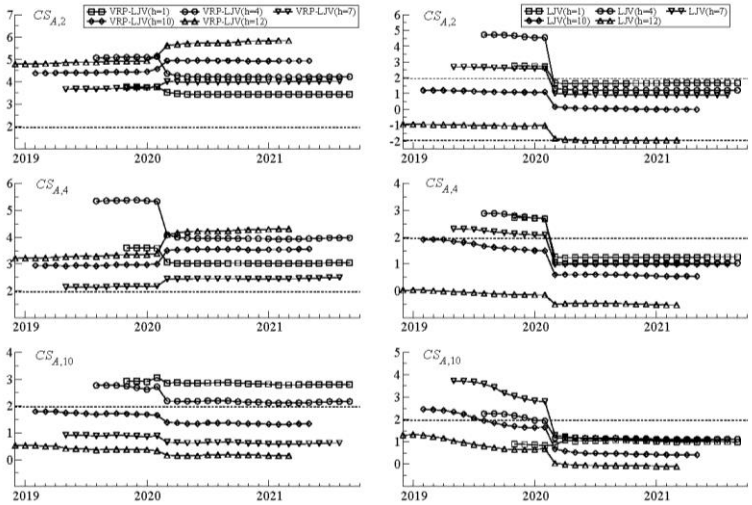

Figure 7. Newey-West t-statistics from the sequential predictability regressions of $CS_{A,2}$, $CS_{A,4}$, and $CS_{A,10}$

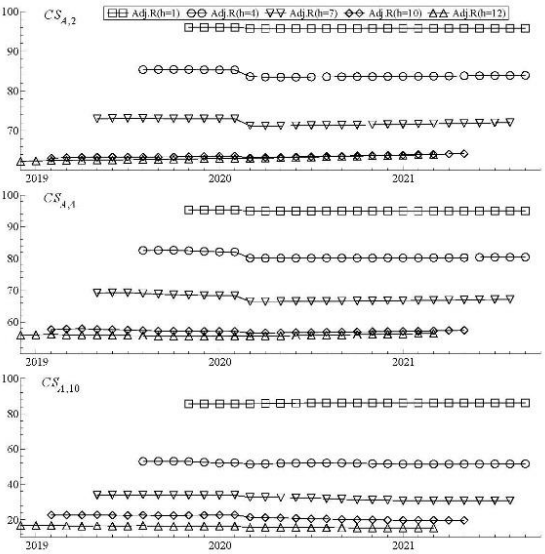

Figure 8. Adjusted R^2 from the sequential predictability regressions of $CS_{A,2}$, $CS_{A,4}$, and $CS_{A,10}$

For the predictability of A-rated credit spreads $CS_{A,2}$, $CS_{A,4}$, and $CS_{A,10}$, we report the Newey-West t-statistics and adjusted R^2 in Figures 7 and 8 using the same format as in Figures 5 and 6. Using the sample before the COVID-19 pandemic, Ubukata (2019) shows that the LJV could predict the future Japanese lower-rated CS, even when several predictors and LagCS are controlled for. We obtain similar results from the t-values at the extreme left point in right panels of Figure 7 without the COVID-19 pandemic sample, that is, the LJV is significantly positive in predicting $CS_{A,2}$ and $CS_{A,4}$ for $h = 1, 4$, and 7 months and $CS_{A,10}$ for $h = 4, 7$, and 10 months at the 5% level. However, when the end of sample of predictors is expanded to March 2020, the LJV becomes insignificant for all A-rated CS, implying a negative impact of the COVID-19 pandemic. The result might stem from that the credit spreads are little susceptible to the effect of the COVID-19 pandemic by Bank of Japan's large-scale corporate bond purchases, as opposed to the fact that the highest distinct peak of LJV

is recorded in March 2020. The left panels in Figure 7 show that there is a significant relation between the VRP-LJV and the future $CS_{A,2}$ and $CS_{A,4}$ for all h and $CS_{A,10}$ for $h = 1$ and 4 at the 5% level even when the COVID-19 period is included. The t-values show a discernible change in March 2020 when the second highest peak of VRP-LJV is recorded. The direction of the change is not singular, that is, there is a negative (positive) impact of the COVID-19 pandemic on A-rated CS for $h = 1$ and 4 ($h = 7, 10$, and 12). Figure 8 shows that the adjusted R^2 is negatively affected, especially for the predictability of A-rated CS for $h = 4$ and 7 after including the sample of predictors in March 2020.

Figures 9 and 10 plot the Newey-West t-statistics and adjusted R^2 from the sequential multiple regressions in (11) for predicting default spreads $CS_{A-AA,2}$ (top panel), $CS_{A-AA,4}$ (middle panel), and $CS_{A-AA,10}$ (bottom panel). The results are similar to those for the predictability of A-rated CS in Figures 7 and 8. Without ending the sample of predictors in March 2020, the LJV is significant for $CS_{A-AA,2}$ with $h = 4$ and 7 months, $CS_{A-AA,4}$ for $h = 4, 7,$ and 10 months, and $CS_{A-AA,10}$ for $h = 4, 7, 10,$ and 12 months at the 5% level. However, it failed to be significant for all default spreads since March 2020, implying the negative impact of the COVID-19 pandemic. All cases of VRP-LJV are significantly positive for $CS_{A-AA,2}$ except for $h = 1$ month and $CS_{A-AA,4}$ for all h at the 5% level. The negative effect of the COVID-19 pandemic on the predictability with the VRP-LJV is observed in $CS_{A-AA,2}$ for $h = 4$ and 7 and $CS_{A-AA,4}$ for $h = 1, 4,$ and $CS_{A-AA,10}$ for all h. Figure 10 shows that the adjusted R^2 is negatively affected by the COVID-19 after the sample from March 2020 is included, especially for the default spreads for $h = 4, 7,$ and 10 months. In summary, we can conclude that the jump risk component of the VRP representing the significance before the COVID-19 period loses the significant relation with the future credit spreads, implying a negative impact of the COVID-19 pandemic, but the diffusive risk component retains a significant relation even after the inclusion of the COVID-19 period.

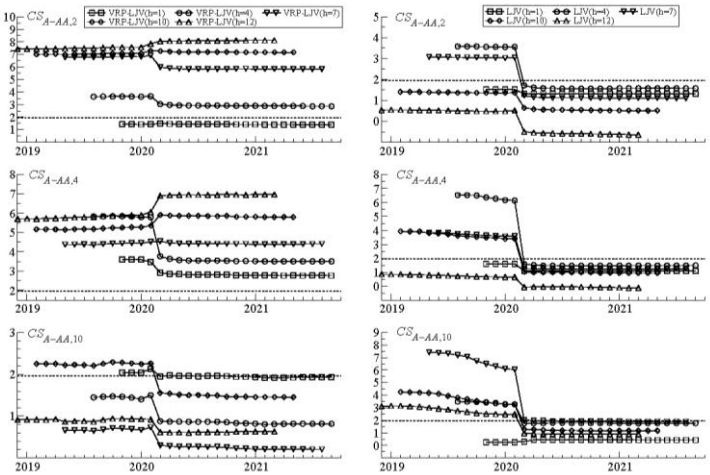

Figure 9. Newey-West t-statistics from the sequential regressions of $CS_{A-AA,2}$, $CS_{A-AA,4}$, and $CS_{A-AA,10}$

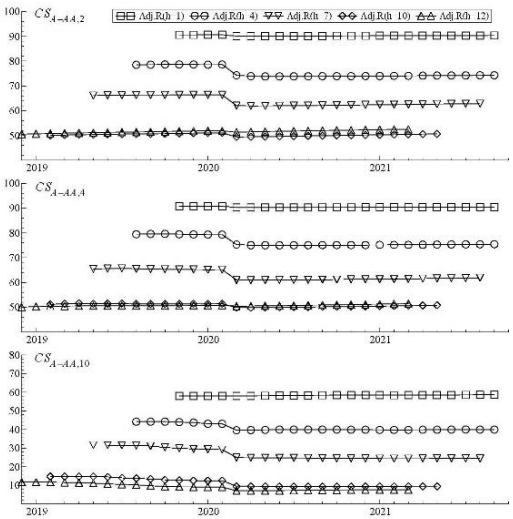

Figure 10. Adjusted R^2 from the sequential predictability regressions of $CS_{A-AA,2}$, $CS_{A-AA,4}$, and $CS_{A-AA,10}$

3.3 Out-of-Sample Forecasts During the COVID-19 Pandemic

This paper focuses on documenting whether there is a robust and significant relation between the VRP components and the future CI and CS including the COVID-19 pandemic period. A reason that we are less concerned with the generation of actual forecast is that we cannot obtain a long out-of-sample period needed to assess the forecast performance including the COVID-19 period. Although the sample of the rolling estimation window is also limited in size, we provide a simple statistical result in the 1-month ahead out-of-sample forecasting environment. To assess the out-of-sample performance relative to a benchmark, we calculate the Campbell and Thompson's (2008) out-of-sample R^2 statistic (OOS-R^2) by:

$$OOS - R^2 = 1 - \frac{\sum_{t=s_0}^{T-1}\left(R_{e,t+1} - \hat{R}_{e,t+1}\right)^2}{\sum_{t=s_0}^{T-1}\left(R_{e,t+1} - \bar{R}_{e,t+1}\right)^2}, \tag{12}$$

where $\hat{R}_{e,t+1}$, for $t = s_0, \dots, T-1$, is a sequence of $T - s_0$ 1-month ahead out-of-sample forecasts based on a rolling predictive regression for a given window of constant length s_0. We use a rolling window of $s_0 = 168$ month, where the first and last in-sample estimation periods are from January 2006 to December 2019 and from October 2007 to September 2021, respectively. The out-of-sample period is therefore from January 2020 to October 2021 (22 months). $R_{e,t+1}$ is the realized value of predicted variable and $\bar{R}_{e,t+1}$ is the rolling estimate of the historical average of predicted variable as a well-known benchmark value (see Batten et al. 2022 for equity premium prediction). The OOS-R^2 is positive (negative) if a predictive regression model performs better than the benchmark in terms of a lower (higher) mean squared error (MSE).

To test whether the relative out-of-sample performance is statistically significant when the benchmark is a historical average, we employ the Diebold-Mariano test statistic (DM) adjusted by Clark and West (2007), which is expressed as

$$DM = \hat{\mu}/\sigma_{\hat{\mu}}. \tag{13}$$

$\hat{\mu}$ and $\sigma_{\hat{\mu}}$ are the estimated intercept and the standard error of $\hat{\mu}$ in the regression, $\epsilon_{t+1} = \mu + \xi_{t+1}$, where $\epsilon_{t+1} = \left(R_{e,t+1} - \bar{R}_{e,t+1}\right)^2 - \left[\left(R_{e,t+1} - \hat{R}_{e,t+1}\right)^2 - \left(\bar{R}_{e,t+1} - \hat{R}_{e,t+1}\right)^2\right]$ for $t = s_0, \dots, T-1$. The null hypothesis is rejected if DM is larger than the p-quantile of a standard normal distribution for a given significance level p, indicating a significantly lower MSE of the predictive regression model than the historical average.

Table 2. Out-of-sample forecasts

	CI change prediction					
Predictor	OOS-R^2	DM				
VRP-LJV	13.7	1.307*				
AR(1)	13.9	1.073				
	$CS_{AA,10}$ prediction		$CS_{A,10}$ prediction		$CS_{A-AA,10}$ prediction	
Predictor	OOS-R^2	DM	OOS-R^2	DM	OOS-R^2	DM
VRP-LJV, LagCS	89.5	3.422***	93.6	4.278***	80.9	5.598***
VRP-LJV	12.4	1.081	12.4	1.277	6.3	1.862**
LagCS	87.7	3.620***	91.7	4.213***	78.8	5.257***

Note. The asterisks, ***, **, and *, represent significant out-of-sample forecasts at the 1%, 5%, and 10% level.

The out-of-sample CI and CS forecast results are reported in Table 2 where the first column shows predictors included in predictive regression models. For the CI predictability, we consider the simple predictive regression model with the VRP-LJV, which has the significantly negative relation with the future CI as showed in Section 3.2.1. We also report the out-of-sample performance of AR(1) model relative to the historical average. The results show that the VRP-LJV with significantly postive OOS-R^2 of 13.7% at the 10% level outperforms the historical average of the CI change. The time series model of AR(1) achieves positive OOS-R^2 of 13.9%, but this is insignificant even at 10% level.

For the CS predictability, we consider the simple and multiple predictive regression models with the robust predictors in Section 3.2.2, VRP-LJV and LagCS. Not surprisingly, the LagCS provides significantly high OOS-R^2 at the 1% level because CS is so highly persistent that the LagCS has a strong explanatory power as noted in Collin-Dufresne et al. (2001). The VRP-LJV achieves significantly postive OOS-R^2 of 6.3% at the 5% level for predicting $CS_{A-AA,10}$. The OOS-R^2 of the multiple predictive regression model with the VRP-LJV and LagCS can yield an improved forecast power for $CS_{AA,10}$, $CS_{A,10}$, and $CS_{A-AA,10}$. Overall, the VRP-LJV shows a consistent result in our in-sample analysis.

4. Conclusions

This paper investigated whether there is a robust and significant relation between the VRP components and the future Japanese economic and financial variables including the COVID-19 pandemic period. Our analysis provides new empirical evidence as follows. The diffusive risk component of the VRP has a robust positive relation with the future CI, with higher significance by the inclusion of the COVID-19 pandemic. But the jump risk component of the VRP does not have statistically reasonable relation with the future CI.

For the predictability of higher-rated CS, the diffusive risk component is positively significant and it is essentially unaltered over the COVID-19 period. For the lower-rated credit and default spreads, the jump risk component is significantly positive in some cases without the COVID-19 sample, but then becomes insignificant, implying the negative impact of the COVID-19 pandemic. This might be associated with the small increase in CS by the Bank of Japan's large-scale corporate bond purchases under the highly unconventional monetary easing policy in Japan. The diffusive risk component remains a significantly positive relation with the lower-rated credit and default spreads, although the t-value and adjusted R^2 are affected by the COVID-19 pandemic. Additionally, the 1-month ahead out-of-sample forecast performance largely supports the evidence that the diffusive risk component is a robust predictor over the entire sample including the COVID-19 pandemic.

Our predictability results might shed more light on the usefulness of the diffusive risk component in the VRP for analyzing the Japanese CI and CS during the COVID-19 pandemic. The application is limited to a country-specific analysis. Since the COVID-19 pandemic had multifaceted effects on all economies worldwide, future studies should explore how the COVID-19 pandemic affected the predictability with the VRP components in other major markets such as the U.S., Europe, and China. It would be also worthwhile to investigate the predictability of the other international assets during the COVID-19 pandemic period.

Acknowledgments

This work is supported by the Grants-in-Aid for Scientific Research (grant number 20H00073).

References

Andersen, T. G., Bollerslev, T., & Diebold, F. X. (2007), Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility, *Review of Economics and Statistics, 89*(4), 701-720. https://doi.org/10.1162/rest.89.4.701

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Ebens, H. (2001) The distribution of realized stock return volatility. *Journal of Financial Economics, 61*(1), 43-76. https://doi.org/10.1016/S0304-405X(01)00055-1

Andersen, T. G., Fusari, N., & Todorov, V. (2015). The risk premia embedded in index options. *Journal of Financial Economics, 117*(3), 558-584. https://doi.org/10.1016/j.jfineco.2015.06.005

Andersen, T. G., Fusari, N., & Todorov, V. (2020). The pricing of tail risk and the equity premium: Evidence from international option markets. *Journal of Business Economics and Statistics, 38*(3), 662-678. https://doi.org/10.1080/07350015.2018.1564318

Andersen, T. G., Todorov, V., & Ubukata, M. (2021). Tail risk and return predictability for the Japanese equity market. *Journal of Econometrics, 222*(1), 344-363.

Barndorff-Nielsen, O. E., & Shephard, N. (2006). Econometrics of testing for jumps in financial economics using bipower variation. *Journal of Financial Econometrics, 4*(1), 1-30. https://doi.org/10.1093/jjfinec/nbi022

Batten, J. A., Kinateder, H., & Wagner, N. (2022). Beating the average: Equity premium variations, uncertainty, and liquidity. *ABACUS, 58*(3), 567-588. https://doi.org/10.1111/abac.12250

Bekaert, G., & Hoerova, M. (2014). The VIX, the variance premium and stock market volatility. *Journal of Econometrics, 183*(2), 181-192. https://doi.org/10.1016/j.jeconom.2014.05.008

Bollerslev, T., & Todorov, V. (2014). Time-varying jump tails. *Journal of Econometrics, 183*(2), 168-180. https://doi.org/10.1016/j.jeconom.2014.05.007

Bollerslev, T., Marrone, J., Xu, L., & Zhou, H. (2014). Stock return predictability and variance risk premia: Statistical inference and international evidence. *Journal of Financial and Quantitative Analysis, 49*(3), 633-661. https://doi.org/10.1017/S0022109014000453

Bollerslev, T., Tauchen, G., & Zhou, H. (2009). Expected stock returns and variance risk premia. *The Review of Financial Studies, 22*(11), 4463-4492. https://doi.org/10.1093/rfs/hhp008

Bollerslev, T., Todorov, V., & Xu, L. (2015). Tail risk premia and return predictability. *Journal of Financial Economics, 118*(1), 113-134. https://doi.org/10.1016/j.jfineco.2015.02.010

Campbell, J. Y., & Thompson, S. B. (2008). Predicting excess stock returns out of sample: Can anything beat the historical average? *Review of Financial Studies, 21*(4), 1509-1531. https://doi.org/10.1093/rfs/hhm055

Clark, T. E., & West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics, 138*(1), 291-311. https://doi.org/10.1016/j.jeconom.2006.05.023

Collin-Dufresne, P., Goldstein, R. S., & Martin, S. (2001). The determinants of credit spread changes. *The Journal of Finance, 56*(6), 2177-2207. https://doi.org/10.1111/0022-1082.00402

Collin-Dufresne, P., Goldstein, R.S. and Helwege, J. (2010) Is credit event risk priced? modeling contagion via the updating of beliefs. *NBER Working Paper No.15733*. https://doi.org/10.3386/w15733

Corsi, F. (2009). A simple approximate long-memory model of realized volatility. *Journal of Financial Econometrics, 7*(2), 174-196. https://doi.org/10.1093/jjfinec/nbp001

Diebold, F. X., & Mariano, R. S. (1995). Comparing Predictive Accuracy. *Journal of Business and Economic Statistics, 13*(3), 253-263. https://doi.org/10.1198/073500102753410444

Dierkes, M., Hollstein, F., Prokopczuk, M., & Wursig, C. M. (2021). *Measuring tail risk*. Working Paper. https://doi.org/10.2139/ssrn.3789005

Drechsler, I., & Yaron, A. (2011). What's vol got to do with it? *Review of Financial Studies, 24*(1), 1-45. https://doi.org/10.1093/rfs/hhq085

Duffie, D. (2001). *Dynamic Asset Pricing Theory.* Princeton University Press.

Fukasawa, M., Ishida, I., Maghrebi, N., Oya, K., Ubukata, M., & Yamazaki, K. (2011). Model-free implied volatility: From surface to index. *International Journal of Theoretical and Applied Finance, 14*(4), 433-463. https://doi.org/10.1142/S0219024911006681

Huang, X., & Tauchen, G. (2005). The relative contribution of jumps to total price variance. *Journal of Financial Econometrics, 3*(4), 456-499. https://doi.org/10.1093/jjfinec/nbi025

Londono, J. M. (2011). The variance risk premium around the world. *International Finance Discussion Papers 1035*. Board of Governors of the Federal Reserve System. https://doi.org/10.2139/ssrn.1780203

Longstaff, F. A., & Schwartz, S. S. (1995). A simple approach to valuing risky fixed and floating rate debt. *The Journal of Finance, 50*(3), 789-820. https://doi.org/10.1111/j.1540-6261.1995.tb04037.x

Maliszewska, M., Mattoo, A., & Mensbrugghe. D. V. D. (2020). The potential impact of COVID-19 on GDP and trade: A preliminary assessment. *World Bank Research Working Paper 9211*. https://doi.org/10.1596/1813-9450-9211

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *Journal of Finance, 29*(2), 449-470. https://doi.org/10.1111/j.1540-6261.1974.tb03058.x

Oya, K. (2011). Business cycle predictability with variance risk premium. *Great Recession in the Global Economy and Business Cycle Analyses (Sekai douji fukyo to keiki junkan bunseki)* (pp.141-157). University of Tokyo Press, (in Japanese).

Padhan, R., & Prabheesh, K. P. (2021). The economics of COVID-19 pandemic: A survey. *Economic Analysis and Policy, 70*, 220-237. https://doi.org/10.1016/j.eap.2021.02.012

Ubukata, M. (2019). Jump tail risk premium and predicting US and Japanese credit spreads. *Empirical Economics, 57*(1), 79-104. https://doi.org/10.1007/s00181-018-1431-x

Ubukata, M. (2022). A time-varying jump tail risk measure using high-frequency options data. *Empirical Economics, 63*(5), 2633-2653. https://doi.org/10.1007/s00181-022-02209-5

Ubukata, M., & Watanabe, T. (2014). Market variance risk premiums in Japan for asset predictability. *Empirical Economics, 47*(1), 169-198. https://doi.org/10.1007/s00181-013-0741-2

Wang, H., Zhou, H., & Zhou, Y. (2013). Credit default swap spreads and variance risk premia. *Journal of Banking & Finance, 37*(10), 3733-3746. https://doi.org/10.1016/j.jbankfin.2013.02.021

Zhou, H. (2010). Variance risk premia, asset predictability puzzles, and macroeconomic uncertainty. *Finance and Economics Discussion series 2010-14*, Board of Governors of the Federal Reserve System (US). https://doi.org/10.2139/ssrn.1783624

Notes

Note 1. First, we do not focus on market excess return predictability in the Japanese equity market. Andersen et al. (2021) use a sample before the COVID-19 pandemic and find that: (i) the U.S. left jump variation measure has a strong predictive power for U.S. dollar-denominated Japanese excess returns and (ii) neither Japanese VRP nor its jump risk component provides significant forecasts for the Japanese yen-denominated Nikkei 225 index returns. Although we cannot examine the predictive power of U.S. VRP components during the COVID-19 period due to data availability, we find an insignificant predictive power of the Japanese VRP and its components for the future excess returns of the Nikkei 225 index during the COVID-19 pandemic, which is qualitatively identical to the results of Andersen et al. (2021) without the COVID-19 period. Second, another study using a sample before the COVID-19 pandemic is Ubukata and Watanabe (2014), who find a significant negative relation between the VRP and the future change rate in the Japanese CI, implying that greater forward return variance leads to lower economic activity. However, they do not analyze the VRP decomposition. Ubukata (2019) show that the significant positive relation between the VRP components and the future CS in the Japanese corporate bond market, where the predictive patterns over horizons ranging from 1-month to 1-year differ in terms of the diffusive and jump risk components, but the study does not investigate whether the relation is robust to the COVID-19 period.

Note 2. We refrain from the weekly options with maturities of the nearest 4 weeks because they are only available from May 25, 2015, thus making a meaningful empirical evaluation infeasible.

Note 3. Ubukata (2022) uses high-frequency options data to relax the constancy assumption to more general cases, such that α_t^- varies each trading day, and conducts a daily frequency-based analysis. In this paper, we do not use the high-frequency data because our empirical analysis focuses on monthly frequency-based predictability of economic and financial variables during the COVID-19 pandemic period.