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Oil volatility risk and stock market volatility predictability: Evidence from G7 countries☆

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ABSTRACT

Academic research relies extensively on stock market information to forecast oil volatility, with relatively little attention paid to the reverse evidence. Our paper fills this gap by investigating the predictive ability of oil volatility risk to forecast stock market volatility. Using oil volatility risk premium (oil VRP) as the predictor, we find that oil VRP does exhibit statistically and economically significant in-sample and out-of-sample forecasting power for G7 countries, even controlling for some popular macroeconomic variables. These findings are robust when using alternative proxies for volatilities of stock and oil. Furthermore, the strength of the predictive evidence is substantial during relatively high and low level of stock market, while is substantially higher for recessions vis-á-vis expansions. Oil VRP can also contains additional information for predicting a series of macroeconomic variables, which serves as an available explanation for its forecasting ability.

1. Introduction

A long strand of literature suggests the great importance of commodities' predictive power to stock market, in which few, if any, other commodities have received more attention for their perceived economic significance than oil. Theoretically and empirically, the critical role of oil market for understanding macroeconomic fluctuations has been well documented (see, for example, Hamilton, 1983, 2005; Backus and Crucini, 2000; Kilian and Park, 2009; Bodenstein etal., 2011; Alquist etal., forthcoming). Among various oil market variables, oil shock is a noteworthy one as there are voluminous studies, for instance, on the short and long-runco-movements and causation relationships between oil shocks and stock volatility (see, e.g.,Arouri etal., 2011, 2012; Creti etal., 2013; Conrad etal., 2014; Du and He, 2015; Kang etal., 2015; Ewing and Malik, 2016). It is, therefore, of interest to deeply investigate the effect of oil market volatility on stock markets.

However, not much has been done on the subject of predictive ability of oil to stock volatility from an out-of-sample perspective. Existing researches are largely, almost all, based merely on in-sample empirical work. Admittedly, it is more of reason to employ an out-of-sampleapproach in the sense of prediction although in-sample results appear for reference and comparison (see, e.g.,Campbell and Thompson, 2005; Rapach etal., 2010). Therefore, in this paper, we investigate whether the oil volatility risk is useful in explaining the future volatility of international stock market returns. In particular, our forecasting exercise using a recursive out-of-sample test, confirms that oil volatility risk does exhibit statistically and economically significant and robust in-sample and out-of-sample forecasting power, clearly exceeding some of well-known macroeconomic variables. Investigating such volatility patterns in this way is critical to many fundamental issues in asset pricing, investment, corporate finance, and risk management (Bali etal., 2005).

In this paper, oil volatility risk is captured with variance risk premium (oil VRP) of West Texas Intermediate crude oil (WTI). The variance risk premium measures the price of a hedge against variance fluctuations, and it is equal to the difference between the expected variance, under the physical and the risk-neutral measures, which are thought to capture a market-wide measure of uncertainty (Bali and Zhou, 2016). We choose this proxy since it well measures the volatility risk generated within oil market and its time-varying characteristic better covers information of

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the market over time. Therefore, oil VRP better captures macroeconomic dynamics and tend to perform more accurate in predicting stock volatilities forecast.

While there is strong evidence relating oil prices to the business cycle, attempts by economists to forecast equity returns using lagged oil prices, have largely failed to find consistent evidence; i.e.,the nature of the relationship is nonlinear, time varying. Consistent with its perceived economic significance, some empirical results generally imply that oil should be an important determinant of asset prices (Ferson and Harvey, 1993; Backus and Crucini, 2000). Confounding this, Chen etal. (1986) who use deduced oil risk premium Fama-MacBeth type regressions to predict the cross-section of asset prices yield insignificant results. Huang etal. (1996) find virtually no relation between futures returns and U.S. stock market returns. Moreover, even when they have come up significantly, oil-price-based return predictability is not explained by a time-varying risk premium (Driesprong etal., 2008; Narayan and Sharma, 2011; Scholtens and Yurtsever, 2012). These negative findings may due to geopolitical events, wars, changes in economic structures, technologies, and other reasons. Until recently, Chiang etal. (2015) introduce a novel structural approach to extracting the factors, link oil factors to the macroeconomy, and establish their significance in pricing the broader cross-section of equities. Their results provide evidence that oil risk adequately filtered from noisy price data, is one of a handful of fundamental factors that affect the pricing effect, whereas information adequately filtered from derivatives prices does carry significant risk premium with rational economic interpretations. They suggest that stochastic oil volatility is as important, if not more so, for the macro economy than oil price itself. Alternatively, factors extracted from derivative prices may provide less noisy information for future economic fundamentals because they may be seen as a vehicle for aggregating both differences in interpretation of news and changes in heterogeneous expectations about the future state of the economy, shocks to hedging and liquidity demands as well as market sentiment. Along this of reasoning, oil VRP better captures macroeconomic dynamics and provides more accurate stock volatilities forecasts. To provide new insights, we show that the oil VRP provide more accurate forecasts of stock volatilities than lagged oil prices.

In this paper, oil VRP is computed merely with oil market returns of WTI oil derivatives (Cushing, OK Crude Oil Future Contract 1, which is downloaded from the EIA website). Theoretically, we think it is reasonable to proxy global oil market volatility using VRP estimated in this way since previous studies have used different evidence to illustrate the world oil market is globalized and integrated. Early, the world oil market is defined as 'one great pool', that is to say, the changes of a particular oil market can rapidly spread to other oil markets (Adelman, 1984). Later, Gülen (1997, 1999) shows the significant empirical evidence that the world oil market is integrated as a unity. In the process of globalization, this integration tends to be enhanced and the degree of globalization for the world crude oil market is being further investigated. Recently, Ji and Fan (2016) document that crude oil markets of adjacent countries or regions tend to link together. Particularly, the crude oil markets in the U.S., Angola and Saudi Arabia take up the dominant position of the international oil economy. Based on these studies, it is reasonable to measure the volatility derived from the world oil market with oil VRP from US.

We contribute to the existing literature on the predictability of stock return volatility in several ways. Because a model's in-sample predictive performance tends to correlate poorly with its ability to deliver good out-of-sample forecasts, we conduct out-of-sample forecasting exercise using a recursive window, which suggests that the in-sample forecasting relationship holds out-of-sample. Using daily data, we provide a fresh perspective that oil VRP can forecast stock volatility. We utilize the standard predictive regression framework to examine the stock return predictability of the oil VRP indicator for the next-day over the sample from January 4, 2000 through June 30, 2016, in which the period from January 4, 2000 to December 30, 2007 is set to perform in-sample estimates and the remaining part is for out-of-sample forecast evaluation. Time-variationout-of-sample R^2 statistic is here employed as the major evaluation metric to assess the performance of oil volatility risk premium in forecasting stock volatility. Moreover, we compare the predictive power of oil VRP over different cyclical periods and volatility levels since literature (Neely et al., 2014) suggests stock market predictability is affected by different economic times, for example, economic expansions and recessions. Our forecasting exercise is also conducted for longer horizons. We find the significant predictability for the horizons of up-to-ten periods. We also find that the predictive power of oil VRP is robust after controlling for domestic stock market volatility risk measured as the lagged or daily change of realized volatility. Further, to check whether oil VRP has been covered by macro variables considered in the literature, we include 11 fundamental variables reflecting stock market activity in the benchmark of autoregressive model. Our empirical results indicate that the oil information is not overlapped with traditional macro information, which is still helpful in predicting.

These findings provide insights to one new channel that could drive time variation in stock market volatility. Existing channels include time-varying volatility in shocks to fundamentals (Bansal and Yaron, 2004), nonlinear relations between time-varying expected returns and the business cycle (Mele, 2007; Choudhry etal., 2016), learning effects related to investors' uncertainty about fundamentals (Veronesi, 1999; Adam etal., 2016), information demand and supply (Vlastakis and Markellos, 2012) and amplification of shocks to asset markets via financial intermediation (Brunnermeier and Pedersen, 2009). Through this aforementioned channel, predictability of stock volatility revealed by oil VRP exhibits solid theoretical basis.

The second contribution arise from the international evidence to the role of oil VRP in stocks volatilities. Unlike existing researches which mainly concentrate on the US market, our study investigates effects of oil VRP in G7 developed markets. An analysis of this sort seems interesting for several reasons. First, as Bodnaruk and Ostberg (2009) proposed, the relationship between uncertainty and stocks returns relies on the shadow cost of incomplete information, which turns out to depend on relative market size, institutional development, propensity of herd-like behavior and overreaction and other country-specific characteristics. Taking an international perspective allows us to test this hypothesis. Second, using international stock volatilities provides a natural out-of-sample test for earlier the US findings and pooling data across countries increases the power of tests which yields more reliable estimates (Ang and Bekaert, 2007).

Finally, we explore the economic driving forces of our findings. The success of oil VRP in forecasting stock volatilities is no *dues ex machina*. It follows from the fact that the oil VRP appears to have an economically and statistically significant predictive ability for international macroeconomic variables, such as industrial production growth, ted Spread, CPI inflation (Producer Price Index/Consumer Price Index) and policy-related economic uncertainty. In the spirit of the component model (Engle etal., 2013) and the no-arbitrage model (Corradi etal., 2013), these indicators should predict stock volatilities.

Our paper is closely related to Chiang etal. (2015), who extract oil factors from derivative markets and show that oil factors carry significant risk premium and identify them as most important to the macroeconomy and cross-section of expected returns. Recent works that explicitly models the role of oil in the pricing of securities also include Baker and Routledge (2011) and Ready (2012), Ready etal. (2013). Our findings are best viewed as a complement and thorough attempt to study the role of oil risks in pricing securities from the perspective of volatility.

Our work is also related to the literature on the predictability of stock return volatility using macroeconomic variables. Though a flood of literature evidence stock return volatility reacts to changes in economic fundamentals (see, e.g.,Bansal and Yaron, 2004; Mele, 2007; Engle and Rangel, 2008; Engle etal., 2013; Corradi etal., 2013), the out-of-sample predictive ability over the benchmark of autoregressive model is discouraging (Paye, 2012; Christiansen et al., 2012). In this paper, we improve upon existing studies by revealing both in-sample and out-of-sample predictability of stock volatility using oil VRP indicator, which is helpful to understand the economic source of changes in stock volatility.

Our main findings also survive a series of robustness checks. These include using an alternative evaluation criterion of predictability, using an alternative proxy of volatility and using a rolling window estimation scheme.

The remainder of this paper is organized as follows. Section2 provides the data description about dependent and explanatory variables. This section also describes the data we employ and present the evidence on the connection between oil VRP and macro variables as well as the fundamentals used as control variables. Section3 shows the econometric methodology for volatility forecasting. Sections 4 present the in-sample estimation and out-of-sample results and analysis. The relationship between oil VRP and real economy is described in Section5. Section6 retest the predictive power of oil VRP as robustness check. The last section concludes.

2. Data

2.1. Measuring stock volatility

As a widely accepted conditional volatility measurement in literature (Wu etal., 2015), realized volatility has advantages over the squared monthly or quarterly returns in capturing the ex-post variance. We, following Paye (2012), proxy stock realized volatility as the square-rooted monthly summation of the square stock daily return, which is given by:

$$SRV_{t-\tau,t} = \sqrt{\frac{22\sum_{i=0}^{\tau} sr_{t-i}^2}{\tau}}, \tag{1}$$

where $SRV_{t-\tau,t}$ denotes the stock realized volatility at time t with the average maturity τ and sr_t denotes the log return of the stock price, τ is the number of business days in each month. This measure of stock market volatility, i.e. SRV_t, well captures the relationship between market volatility and intra-period market returns. It emphasizes the connection between the estimation method (1) and the realized volatility literature that employs Intra-period returns to measure return variation as proposed in Paye (2012). Andersen etal. (2003) and Barndorff-Nielsen and Shephard (2002) have shown that with the increase of intra-period sample frequency, this computation converges in probability to the quadratic variation of a frictionless, arbitrage free asset price process. We choose typical stock index from G7 countries to calculate stock return realized volatility including S&P 500 composite index ofthe U.S., FTSE 100 index of the U.K., NIKKEI 225 stock average index of Japan, CAC 40 index of France, DAX 30 performance index of Germany, FTSE MIB index of Italy and S&P/TSX composite index of Canada. All the daily stock returns are downloaded from Thompson Reuters database. Apart from the realized volatility, the implied volatility also serves an efficient measure of stock volatility (Kim and Lee, 2013; Wu etal., 2015). We obtain the stock implied volatility data of the G7 countries directly from the Thomson Reuters Database.

2.2. Measuring oil volatility

In this section, we construct oil volatility risk premium (oil VRP), which serves as the main predictor of the regressions. As in Carr and Wu (2011), we define oil volatility risk premium as the difference between the risk-neutral and the physical expectation. Simply we calculate it as the difference between oil realized volatility and oil implied volatility as in (Bollerslev etal., 2009):

$$OV_t = OR_t - OI_t, \tag{2}$$

where OV_t is the oil volatility risk premium at time t, OR_t is the oil realized volatility at time t and OI_t is the oil implied volatility at time t. This approach is widely employed in prediction tests. It makes the oil VRP can be directly observed at time t without any modeling assumptions and is consistent with the stylized fact that realized volatility is highly persistent. Therefore, we can proxy the volatility risk premium over the $[t, t+\tau]$ period as the difference between the ex post realized volatility and the ex an implied volatility as in Della Corte etal. (2016).

The oil realized volatility is given following the same approach with the stock realized volatility:

$$OR_t = \sqrt{\sum_{i=1}^{n} ro_{t-i}^2}, \tag{3}$$

where OR_t denotes the realized volatility of oil on time t, n denotes thenumber of trading times in a given day and ro_{t-i} is the log return of oil options on time $t-i$. Remarkably, here we use the price of WTI oil derivatives (Cushing, OK Crude Oil Future Contract 1, which is downloaded from the EIA website) to compute the log return instead of the spot price because the information incorporated in the derivatives are less noisy as proposed by literature. Since our empirical work are mainly based on daily data, we use intraday oil returns to compute the realized volatility index.

The implied volatility of oil, known as OVX index, is directly downloaded from the FRED Database. Concerning the limitation of oil market implied volatility, the OVX index released by CME begins in 2007. The data of the front periods before 2007 is calculated using the same algorithm to construct OVX. Fig. 1 depicts the realized volatility and implied volatility of oil for the whole sample period, in which both series are stationary. We note that the OVX constructed before 2007 is consecutive with the later part as expected, which is theoretical and reasonable. Table 1 summarizes the basic statistics for the variables used in this paper, which suggests the time-series are all stationary over time.

2.3. Other variables

To better detect the predictive power of oil volatility risk premium (oil VRP) under the traditional regression frameworks, we employ a total of 11 fundamental predictors, which can be seen as macroeconomic variables to forecast stock returns (see, e.g.,Neely etal., 2014; Dangl and Halling, 2012; Rapach etal., 2010) and stock volatility (see, e.g., Christiansen et al., 2012), as control variables, among which the first 10 are used in Welch and Goyal (2008) and available at the homepage of Amit Goyal.

To briefly present these variables, we give a short description of the predictors as follows:

- Dividend-price ratio (DP): the log of dividends on the S&P 500 index minus the log of stock prices.
- Earning-price ratio (EP): the log of earnings on the S&P 500 index minus the log of stock prices.
- Book-to-market ratio (B/M): the ratio of book value at the end of the previous year divided by the end-of-month market value for the DJIA.
- Treasury bill rate (TBL): the second market rate of the 3-monthUS Treasury bills.
- Long-term yield (LTY): the long-term government bond yields.
- Net equity expansion (NTIS): the ratio of a twelve-month moving sum of net equity issues by NYSE-listed stocks to the total end-of-yearmarket capitalization of NYSE stocks.
- Risk free rate (RF): the risk-free interest rate.
- Inflation (INFL): the Consumer Price Index (CPI) for all urban consumers. The one-month lagged CPI is because CPI is published with a delay of one month.
- Long-term return (LTR): the returns on long-term government bond.
- Stock variance (SVAR): the sum of squared daily returns on the S&P 500.
- Economic policy uncertainty (EPU): the economic policy uncertainty index obtained from the FRED Database.

When investigating whether oil volatility risk premium (oil VRP) is related to the real economy, we try to using oil volatility risk premium as the explanatory variable of a variety of macroeconomic variables by both in-sample relationship and out-of-sample prediction, which includes the economic policy uncertainty (EPU) for G7 countries, the

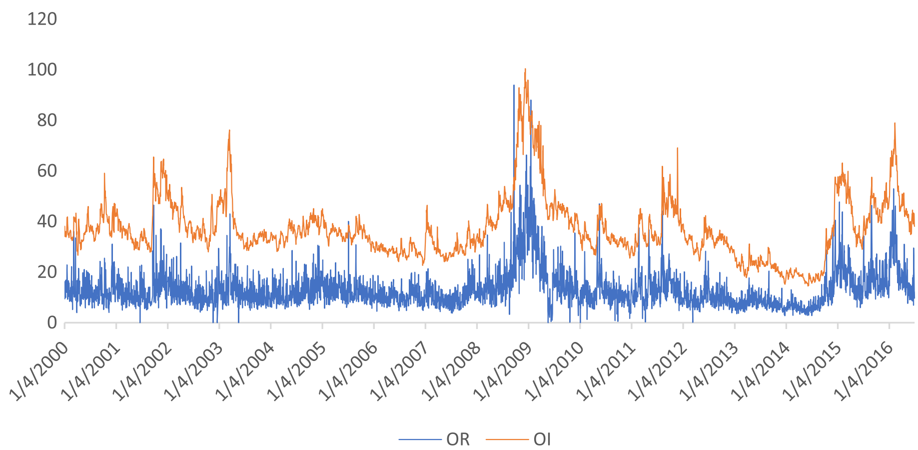

Fig.1. Oil realized volatility and implied volatility Notes: This figure illustrates the realized volatility and implied volatility of oil from January 4, 2000 to July 30, 2016. The blue line shows the change in oil realized volatility and the red line shows the change in oil implied volatility. Both series are demonstrated in the form of daily frequency.

producer price index (PPI), consumer price index (CPI), ADS indicator proposed by Aruoba etal. (2009), the macroeconomic uncertainty (MACU) and financial uncertainty (FINU) for h = 1,3, 12 months proposed by Jurado et al. (2015), unemployment rate, industrial production index and TED spread of the U.S. and Chicago Fed National Activity Index (CFNAI). As in Rapach etal. (2013), the U.S. has a predictive power for other countries in stock markets, so the predictability of the variables of the U.S. can serve as a good detection when investigating the global economic meaning of oil volatility risk premium.

Due to the limited availability of data, the variables described in this subsection (Section2.3) are all at monthly frequency. In accordance, market volatility indexes used in these models are also adjusted to be at monthly frequency.

3. Econometric methodology

In this section, we present the predictive regression framework. Both in-sample analysis and out-of-sample tests are employed as to better detect the significance and robustness of the predictive power of oil VRP.

3.1. In-sample predictive regressions

A standard benchmark to forecast stock volatility at horizon of one month is the following autoregressive model (AR):

$$SRV_t = \alpha + \sum_{i=1}^{p} \omega_i SRV_{t-i} + \varepsilon_t, \tag{4}$$

where the error term ε_t is assumed to follow an independent and identically normal distribution. In this paper, to catch a practical meaning, the lag order p is set to be 5 and 10 to proxy for one and two trading weeks, respectively. Moreover, we set the lag order to be 28, which is the maximum lag order produced by AIC and SC criteria, to optimally eliminate the impact caused by the autocorrelation in stock volatility.

To investigate the predictive content of oil volatility, the benchmark model, the conventional econometric predictive framework is employed as the benchmark model given as:

$$SRV_t = \alpha + \sum_{i=1}^{p} \omega_i SRV_{t-i} + \beta OV_{t-1} + \varepsilon_t, \tag{5}$$

where SRV_t denotes the stock realized volatility at time t and OV_{t-1}-denotes the oil volatility risk premium at time $t-1$. Traditionally, the null hypothesis of no predictive power, i.e. $\beta = 0$, can be tested using a standard t-statistic. Apart from that, a one-sided alternative hypothesis provided by Inoue and Kilian (2004), which can improve the power ofin-sample tests, is also adopted, that is to say, we also test the nullof $\beta = 0$ against the alternative of $\beta > 0$ by calculating a heteroskedasticity-consistentt-statistic.

Empirical literature (Neely et al., 2014) suggests that the strength of the predictability of stock market is related with different economic times, such as economy cycles. Here we use NBER-datedbusiness-cycle expansions and recessions to label economy periods and calculating R^2 statistics for cyclical expansions and recessions, respectively. Since R^2-statistic describes the degree of the predictive power and has no definite

Table1
Summary statistics for regression variables.

	OR	OI	OV	DAX	CAC	MIB	S&P	FTSE	NIKKEI	S&P/TSX
Mean	13.0557	37.0919	−24.0362	0.2261	0.2208	0.2272	0.1792	0.1778	0.2273	0.1613
S.E.	0.1152	0.1874	0.1334	0.0013	0.0012	0.0013	0.0013	0.0011	0.0011	0.0012
Median	11.3941	34.8726	−23.0535	0.2090	0.2174	0.2187	0.1704	0.1737	0.2138	0.1384
Kurt.	14.0268	3.8959	3.1497	0.0988	0.2024	−0.2946	2.9252	1.2277	4.2090	3.7011
Skew.	2.6849	1.5009	−0.9517	0.9646	0.8406	0.3344	1.6354	1.1551	1.8708	1.9500
Max.	0.0000	14.5000	−75.1578	0.1156	0.1054	0.0921	0.0915	0.0792	0.1217	0.0726
Min.	93.9516	100.4200	36.4816	0.4600	0.4244	0.4391	0.4535	0.3891	0.4642	0.4314
Obs.	4121	4121	4121	4121	4121	4121	4121	4121	4121	4121

Notes: This table reports the basis statistics of the major regression variables, which is shown in the first row of the table. OR, OI and OV denotes the realized volatility, implied volatility and volatility risk premium, respectively. DAX, CAC, MIB, S&P, FTSE, NIKKEI and S&P/TSX denotes the realized volatility for the corresponding stock index. The mean value, standard deviation, median, coefficients of kurtosis and skewness, range and the number of observations are shown by row in this table.

decomposition for full sample regression, we redefine the R^2 statistic following Neely et al. (2014):

$$R_b^2 = 1 - \frac{\sum_{t=1}^{T} I_t^b \left(SRV_t - \widehat{SRV}_t\right)^2}{\sum_{t=1}^{T} I_t^b \left(SRV_t - \overline{SRV}_t\right)^2}, (b = EXP, REC), \tag{6}$$

where I_t^{EXP} (I_t^{REC})is a dummy variable that equals to 1at the NBER-dated expansion (recession) periods and zero otherwise; $\widehat{SRV}_t$ is the forecast value and $\overline{SRV}_t$ is the mean of the stock realized volatility. Different from the full-sample R^2 statistics, the R_b^2 statistics can be negative in value as the forecast error produced by predictive model may be greater than that for historical average method.

3.2. Out-of-sample forecasts

3.2.1. Forecast approach

Theoretically, out-of-sample tests have advantages in the sense prediction comparing to in-sample regressions (Rapach etal., 2010). As a widely-accepted method of out of sample tests, firstly we separate the full data spanning into two subsamples: the initial m periods of samples are for in sample parameter evaluation and the remaining r periods are for out of sample forecast. Parsimoniously identical predictive framework with the in-sample analysis is adopted to test and compare the predictability. Here the recursive estimation window raised by Welch and Goyal (2008) is employed and the first out-of-sample forecast of stock return realized volatility based on oil volatility risk premium is given by,

$$\widehat{SRV}_{m+1} = \hat{\alpha}_m + \sum_{i=0}^{p-1} \hat{\omega}_{i,m} SRV_{m-i} + \hat{\beta}_m OV_m, \tag{7}$$

where $\hat{\alpha}_m$ and $\hat{\beta}_m$ are the ordinary least squares (OLS) regression results from regressing $\{SRV\}_{t=2}^{m}$ on a constant vector and $\{OV\}_{t=1}^{m-1}$. Following this approach the second out-of-sample forecast of stock return realized volatility should be:

$$\widehat{SRV}_{m+2} = \hat{\alpha}_{m+1} + \sum_{i=0}^{p-1} \hat{\omega}_{i,m+1} SRV_{m-i+1} + \hat{\beta}_{m+1} OV_{m+1}, \tag{8}$$

where $\hat{\alpha}_{m+1}$ and $\hat{\beta}_{m+1}$ are, similarly, the ordinary least squares (OLS) regression results from regressing $\{SRV\}_{t=3}^{m+1}$ on a constant vector and $\{OV\}_{t=2}^{m}$. In this manner, a series of $\widehat{SRV}$ from period $m+1$ to $m+r$ is generated. For the daily-frequency tests, the initial 1987 periods and 2364 periods are used for the in-sample parameter estimation, respectively, since both the time points are NBER business cycle turning points.

3.2.2. Forecast evaluation

The accuracy of prediction using out-of-sample forecast is emphasized in this part. We firstly calculated out-of-sample R^2 (OOS_R^2), a widely-used evaluation, to investigate whether the out-of-sample forecast outperforms the historical average benchmark. The out-of-sample R^2 is calculated by:

$$OOS\_R^2 = 1 - \frac{\sum_{k=m+1}^{m+r} \left(SRV_{m+k} - \widehat{SRV}_{m+k}\right)^2}{\sum_{k=m+1}^{m+r} \left(SRV_{m+k} - \overline{SRV}_{m+k}\right)^2}, \tag{9}$$

where SRV_{m+k} denotes the true value of stock return realized volatility, $\widehat{SRV}_{m+k}$ denotes the forecast value and $\overline{SRV}_{m+k}$ denotes the average of the true value.The out-of-sample R^2 statistic measures the improvement of forecast power for using out-of-sample prediction comparing to the historical average method in the sense of mean squared forecast error (MSFE), which is given by:

$$MSFE = \frac{\sum_{t=m+1}^{m+r} \left(SRV_t - \widehat{SRV}_t\right)^2}{r}. \tag{10}$$

Taking Eqs.(9)and (10) into consideration jointly, a positive value of OOS_R^2 means a reduction in MSFE when using out-of-sample forecast instead of the historical average benchmark, indicating the better performance of out-of-sample prediction comparing with the historical average.

Furthermore, the MSFE-adjusted statistic is also used as an evaluation criteria. Clark and West (2007) provide a one-sided (upper-tail) test method which is performed to test the null hypothesis that the benchmark forecast MSFE is less than or equal to competing forecast MSFE against the alternative hypothesis that the benchmark forecast MSFE is greater than the competing forecast MSFE. As an amendment of Diebold and Mariano (2002) statistic, this MSFE-adjusted statistic has efficient evaluation power for nested models, which is calculated as:

$$MSFE_{ADJ} = MSFE_1 - MSFE_2 + \frac{\sum_{t=m+1}^{m+r} \left(\widehat{SRV}_{t,1} - \widehat{SRV}_{t,2}\right)^2}{r}, \tag{11}$$

where $MSFE_i (i = 1,2)$ denotes the MSFE statistic calculated using model1 and model 2, $\widehat{SRV}_{t,i}$ $(i = 1,2)$ denotes the forecast of stock return realized volatility using model 1 and model 2, respectively and r denotes the length of out-of-sample forecast periods.

Finally, we also adopt an evaluation statistic (GW) proposed by Giacomini and White (2006) to test the superior predictive ability. Different from the Clark and West (2007) statistic, GW statistic provides a two-sided test method whose null hypothesis emphasizes expectations of the estimated MSFE instead of the population MSFE of two different predictive models, which is given by

$$E(MSFE_1 - MSFE_2 | \mathcal{F}_t) = 0, \tag{12}$$

where E is the expectation operator and $\mathcal{F}_t$ is the information set as time t. According to the framework developed by Giacomini and White (2006), the GW statistic is:

$$GW = \frac{MSFE_1 - MSFE_2}{\hat{\sigma}/\sqrt{r}}, \tag{13}$$

where $\hat{\sigma}$ is a heteroskedasticity and autocorrelation consistent estimator of asymptotic variance $\sigma^2[\sqrt{r}(MSFE_1 - MSFE_2)]$.

4. Empirical results

4.1. In-sample results and analysis

Firstly, the predictive power of oil VRP is test using the bivariate model. Table2 reports the full sample regression results which is based on the econometric model (5). Panel A demonstrates the results generated by the basic framework, in which the lag order of stock realized volatility in model (5) is set to be 1. The coefficients of oil volatility risk premium to forecast international stock realized volatility are shown in the first line of panel A, of which the corresponding t-statistics are shown in the first row of panel B. For all the G7 countries, the slope coefficients are all around 0.004, which are all followed with a standard error of one basis point. What's more, all the coefficients are labeled with three asterisks, indicating that all the G7 countries' stock realized volatility can be significantly forecast by oil volatility risk premium, due to the standard t-statistic absolutes are all >25. Theoretically, the Stambaugh (1999) bias will inflate the magnitude of the t-statistics potentially. To eliminate this bias the one-sided (upper-tail) test

Table2
In-sample results for the basic predictive model.

	DAX_t	CAC_t	MIB_t	$S\&P_t$	$FTSE_t$	$NIKKEI_t$	$S\&P/TSX_t$
Panel A:lags = 1							
OV_{t-1}	−0.0047***	−0.0044***	−0.0036***	−0.0048***	−0.0044***	−0.0035***	−0.0043***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
	[−34.4201]	[−35.4775]	[−25.8430]	[−37.6818]	[−39.3293]	[−30.8380]	[−34.6299]
	[−34.1582]	[−33.0076]	[−28.5598]	[−29.3073]	[−31.9791]	[−22.0295]	[−25.4991]
R^2	0.2234	0.2341	0.1395	0.2564	0.2731	0.1876	0.2255
Panel B:lags = 5							
OV_{t-1}	−1.7827E-05***	−1.7443E-05***	−1.6085E-05***	−1.1461E-05***	−1.1770E-05***	−8.4900E-06***	−8.7884E-06***
	(3.0396E-06)	(3.0742E-06)	(3.0981E-06)	(2.6965E-06)	(2.5214E-06)	(3.2236E-06)	(2.4124E-06)
	[−5.8647]	[−5.6739]	[−5.1920]	[−4.2504]	[−4.6681]	[−2.6337]	[−3.6430]
	[−4.0888]	[−4.4545]	[−3.9143]	[−3.2057]	[−3.9575]	[−2.6258]	[−3.0808]
R^2	0.9997	0.9997	0.9996	0.9998	0.9997	0.9995	0.9998
Panel C:lags = 10							
OV_{t-1}	−1.3045E-05***	−1.2674E-05***	−1.1616E-05***	−6.2339E-06**	−8.8273E-06***	−6.5126E-06**	−3.5464E-06
	(3.0395E-06)	(3.0709E-06)	(3.1077E-06)	(2.6544E-06)	(2.5172E-06)	(3.2045E-06)	(2.3477E-06)
	[−4.2917]	[−4.1272]	[−3.7379]	[−2.3485]	[−3.5067]	[−2.0323]	[−1.5106]
	[−3.1481]	[−3.4610]	[−2.9816]	[−1.9460]	[−3.1484]	[−2.0471]	[−1.3365]
R^2	0.9997	0.9997	0.9997	0.9998	0.9997	0.9995	0.9998
Panel D:lags = 28							
OV_{t-1}	−9.8680E-06***	−9.4379E-06***	−7.6196E-06**	−3.4637E-06	−6.4683E-06***	−5.3866E-06*	−1.2752E-06
	(3.0711E-06)	(3.1044E-06)	(3.1902E-06)	(2.6555E-06)	(2.5387E-06)	(3.2081E-06)	(2.3354E-06)
	[−3.2131]	[−3.0401]	[−2.3884]	[−1.3043]	[−2.5479]	[−1.6790]	[−0.5460]
	[−2.4982]	[−2.6953]	[−2.0095]	[−1.1662]	[−2.4428]	[−1.6846]	[−0.5168]
R^2	0.9997	0.9997	0.9997	0.9998	0.9997	0.9995	0.9998

Notes: This table shows the results for the full-sample in sample regression. The first row shows the stock realized volatility for G7 countries, in which DAX_t denotes the realized volatility of DAX 30 performance index of Germany, CAC_t denotes the realized volatility of CAC 40 index of France, MIB_t denotes the realized volatility of FTSE MIB index of Italy, $S\&P_t$ denotes the realized volatility of S&P 500 composite index of the U.S., $FTSE_t$ denotes the realized volatility of FTSE 100 index of the U.K., $NIKKEI_t$ denotes the realized volatility of NIKKEI 225 stock average index of Japan and $S\&P/TSX_t$ denotes the realized volatility of S&P/TSX composite index of Canada. Panel A shows the slope coefficients of oil volatility risk premium which are estimated from the ordinary least square (OLS) regression using model (5). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Numbers in brackets are standard error of mean corresponding to each coefficient. Panel B reports the regression t-statistics, where the standard t-values calculated from the two-sided hypothesis test are shown in the sixth row and the t-values calculated from the one-sided (upper-tail) hypothesis test are shown in the seventh row. R^2 statistics are shown in the bottom row of the table.

proposed by Inoue and Kilian (2004), which tests the null hypothesis of $\beta=0$ against $\beta>0$, is also performed and the one-sidedt-statistics are shown in the second row of panel B. We can see that the one-sidedt-value absolutes are all >20, great enough to make sure the predictive power is significant. The bottom row demonstrates the R^2 statistic for each regression, which shows that the explanatory power of the oil volatility risk premium is considerable. At first glance, it seems that the R^2 statistics appear too small. However, a monthly R^2statistic near 0.5% is big enough to represent an economically significant predictive power as proposed by Campbell and Thompson (2008). For daily data, a smaller magnitude of R^2 statistic can stand for a strong effect. In the bottom line, 7 R^2 statistics are all above 18%, indicating the explanatory power of this model is big enough.

Moreover, looking at panel B,C and D, which represent the results produced by model (5) with 5, 10 and 28 lags of stock realized volatility, respectively. Generally, we find that for most countries, oil VRP still has a significant predictive power although the strong correlation of stock volatility is eliminated. Overall, our oil volatility risk premium does have a significant in-sample predictive ability to forecast stock market volatility.

4.2. Out-of-sample results and analysis: basic model

Although the in-sample analysis provides efficient parameter estimates and thus more precise pricing differentials forecast, Welch and Goyal (2008), among others, argue that out-of-sample tests seem more relevant for assessing genuine predictability in real time and avoid the in-sampleover-fitting issue. In addition, out-of-sample tests are much less affected by the small-sample size distortions such as the Stambaugh bias and the look-ahead bias concern. Hence, it is of interest

Table3
Out-of-sample results for the basic predictive model.

	DAX_t	CAC_t	MIB_t	$S\&P_t$	$FTSE_t$	$NIKKEI_t$	$S\&P/TSX_t$
$MSFE_{HA}$	0.0056	0.0061	0.0085	0.0097	0.0063	0.0074	0.0091
$MSFE_{OV}$	0.0038	0.0043	0.0076	0.0070	0.0042	0.0060	0.0067
$MSFE_{ADJ}$	22.5972	18.1208	11.3840	18.6390	19.7152	13.3847	19.7931
OOS_R^2	32.6320	30.3952	10.4163	27.7594	33.9902	18.7552	26.2931
ENC_{NEW}	1119.8124	978.2649	367.9785	747.8204	1015.1088	523.0436	618.0859
$\overline{(\hat{e})}^2{}_{HA}$	0.0001	0.0002	0.0033	0.0001	0.0000	0.0003	0.0000
$Var(\hat{e})_{HA}$	0.0055	0.0060	0.0052	0.0096	0.0063	0.0071	0.0091
$\overline{(\hat{e})}^2{}_{OV}$	0.0000	0.0003	0.0036	0.0002	0.0001	0.0005	0.0001
$Var(\hat{e})_{OV}$	0.0037	0.0040	0.0041	0.0068	0.0041	0.0055	0.0066
GW	0.2899	0.2938	0.2024	0.3522	0.3147	0.2536	0.3331

Notes: This table reports the out-of-sample forecast evaluation results based on the recursive predicting window suggested by Welch and Goyal (2008). Ten rows are given in this table to describe the forecast statistics, where $MSFE_{HA}$ denotes the mean squared forecast error (MSFE) for historical average, $MSFE_{OV}$ denotes the mean squared forecast error (MSFE) for predictive model, OOS_R^2 denotes the out-of-sample R^2 statistics, ENC_{NEW} denotes the encompassing test ENC statistics, GW denotes the statistics proposed by Giacomini and White (2006) and the remaining four denote the decomposition of MSFEs.

to investigate the out-of-sample predictive performance of oil VRP. Following Goyal and Welch (2008), we run the out-of-sample analysis by estimating the predictive regression model recursively based on individual oil VRP indicator.

Table3 summarizes the out-of-sample forecast evaluation metrics for the bivariate model. This top row gives the mean squared forecast error (MSFE) computed from the historical average benchmark and the second row shows MSFE computed from the out-of-sample recursive window based on model (5). A smaller mean squared forecast error signals a better forecast effectiveness. Comparing the MSFE statistics, we note that the MSFE statistics in the second row are several basis points smaller than those in the first row, suggesting using oil volatility risk premium as a predictor to forecast stock realized volatility outperforms using the historical average method for all G7 countries. The out-of-sample R^2 statistics (OOS_R^2 hereafter) are shown in the fourth row of the table, which exactly measure the proportional reduction in mean squared forecast error (MSFE) for the predictive method of the oil volatility risk premium relative to the historical average benchmark. As has talked above, a positive value of OOS_R^2 represents a better predictive power of the predictor model comparing with the historical average while a negative value indicates the opposite. All the 7 OOS_R^2 are positive and >10%. Similar with their in-sample counterparts, the predictive power is significant enough as these OOS_R^2 statistics are all significantly great.

The MSFE-adjusted statistics provided by Clark and West (2007), also known as the CW statistics, are shown in the third row of the table, which test the null hypothesis that the historical average mean squared forecast error (MSFE) is equal to or less than the MSFE computed from the predictor model against the alternative that the historical average MSFE is greater than that of the predictor model. According to these MSFE-adjusted statistics, the MSFEs for the oil VRP are significantly less than those for the historical benchmark, echoing the results of the positive OOS_R^2 statistics. Besides, looking at the GW statistics shown at the bottom row of this table, which emphasize the information of expectation, we find that all the GW statistics are 1000 basis points or so, among which the maximum is 0.3522 and the minimum is 0.2024. These positive values again prove that the MSFE statistics for the predictive model withoil VRP is less than the MSFE statistics for the historical average benchmark.

Overall, the predictive power of the model using oil VRP as the predictor outperforms the historical average method in the sense of mean squared forecast error. All the OOS_R^2 statistics are positive and >0.5%, even exceeding 10%. Plus, the CW statistics and the GW statistics prove the reduction in MSFE is significant. Again, matching the in-sample results, the out-of-sample tests tells that the predictability of stock realized volatility based on oil VRP is economically significant.

To intuitively present the outperformance of oil VRP predictive framework over the HA benchmark, time-series plots of the difference between the cumulative square forecast error (CSFE) for the historical average benchmark prediction and the cumulative square forecast error (CSFE) for the oil VRPout-of-sample forecasting model is introduced as in Welch and Goyal (2008). Statistically, an increasing trend means the difference of the cumulative square forecasting error between the historical average and oil VRP predictive model gets larger over time, which suggests the out-of-sample framework outperforms the historical average. Particularly, we compare the height of the plot at the two points corresponding to the beginning and end of a given out-of-sample period: if the curve is higher (lower) at the end of the out-of-sample period than at the beginning, the oil VRP predictive model (historical average) has a lower MSFE over the out-of-sampleperiod. A predictive model that always outperforms the historical average for any out-of-sample period, therefore, will have a curve that is always sloping up; the closer a predictive regression model is in this sense, the greater its forecasting power to consistently beat the historical average in terms of MSFE.

Fig. 2 shows these CSFE-difference graphs. Generally, we find that all the 7 countries see generally sloping-up over time despite of some small fluctuations. From 2010, the curves are all above the horizontal line, indicating the positive difference of the error between HA and our VRP model. This quantitively suggests the outperformance of the out-of-sample predictive model over the benchmark. Meanwhile, we see that the curves see some drops during particular periods, in which the forecasting error of our predictive model may be larger that of HA. Overall, during recent times, we document an excessive forecasting power of oil VRP than the historical average benchmark.

It is of interest to get a sense of potential bias-efficiency tradeoffs in the forecasts. According to the definition of mean squared forecast error (MSFE), it is decomposed into squared forecast bias and variance components:

$$\mathrm{MSFE} = \overline{(\hat{e})}^2 + \mathrm{Var}(\hat{e}), \tag{14}$$

where $\overline{(\hat{e})}^2$ denotes the squared error of the forecasts and $\mathrm{Var}(\hat{e})$ denotes the forecast error variance. The results for decomposition of the MSFE for historical average are reported in the sixth and seventh row in Table3 and the results for decomposition of the MSFE for out-of-sample predictive model are reported in the eighth and ninth row in Table3. It is interesting to note that the squared error of the forecasts for historical average and the out-of-sample predictive window are almost equal, at several basis points or so. However, the forecast error variance sees an apparent decrease. From the table, all $\mathrm{Var}(\hat{e})$s generated from the out-of-sample predictive model are tens of basis points less than those generated from historical average, among which the reduction in $\mathrm{Var}(\hat{e})$ for S&P/TSX volatility even exceeds seven basis points. Therefore, the out-of-sample forecast based on the oil volatility risk premium are generally less variance biased and more efficient than the historical average.

4.3. Predictability with longer horizons

The aim of this paper is at the predictability of stock realized volatility based on the oil volatility risk premium, to deeply study this effect we investigate the predictability over longer horizons in this subsection. In this process, the bivariate model (5) is adjusted to:

$$\mathrm{SRV}_{t+i} = \alpha + \sum_{i=1}^{p} \omega_i \mathrm{SRV}_{t-i} + \beta \mathrm{OV}_t + \varepsilon_{t+i},\ i = 1, 2, \ldots, 10 \tag{15}$$

where SRV_{t+i} denotes the stock realized volatility at time $t+i$ and OV_t denotes the oil volatility risk premium at time t. Different from the benchmark bivariate model, this long-horizon forecast model focuses on the predictive power of more time periods apart, here serving as a robustness check of the predictability.

Table4 reports the in-sample and out-of-sample results of the predictive power over long horizons from overnight to ten days apart. Panel A summarizes the slope coefficients of oil volatility risk premium estimated from model (15). For all the regressions to forecast 7 stock realized volatilities, the coefficients of oil volatility risk premium see a gradual increase, from 0.004 or so for overnight to about 0.04 for ten days apart, indicating the long-time impact of oil volatility on stock market volatility may be more powerful comparing with a short time. The t-statistics produced from the one-sided tests are shown in panel B. With the increase of time horizon, the t-statistics are dropping down to a rather small degree. The significances of the slope coefficients are stably over 99%, with even for a ten-day-long time horizon the t-statistic absolutes all above 20. Then to test the out-of-sample forecast ability of oil volatility risk premium, out-of-sample tests are performed and the out-of-sample R^2 statistics are shown in the panel C of Table4. A positive out-of-sample R^2 statistic indicates a smaller mean squared forecast error (MSFE) comparing with the benchmark, which means the out-of-sample forecast method outperforms the historical average.

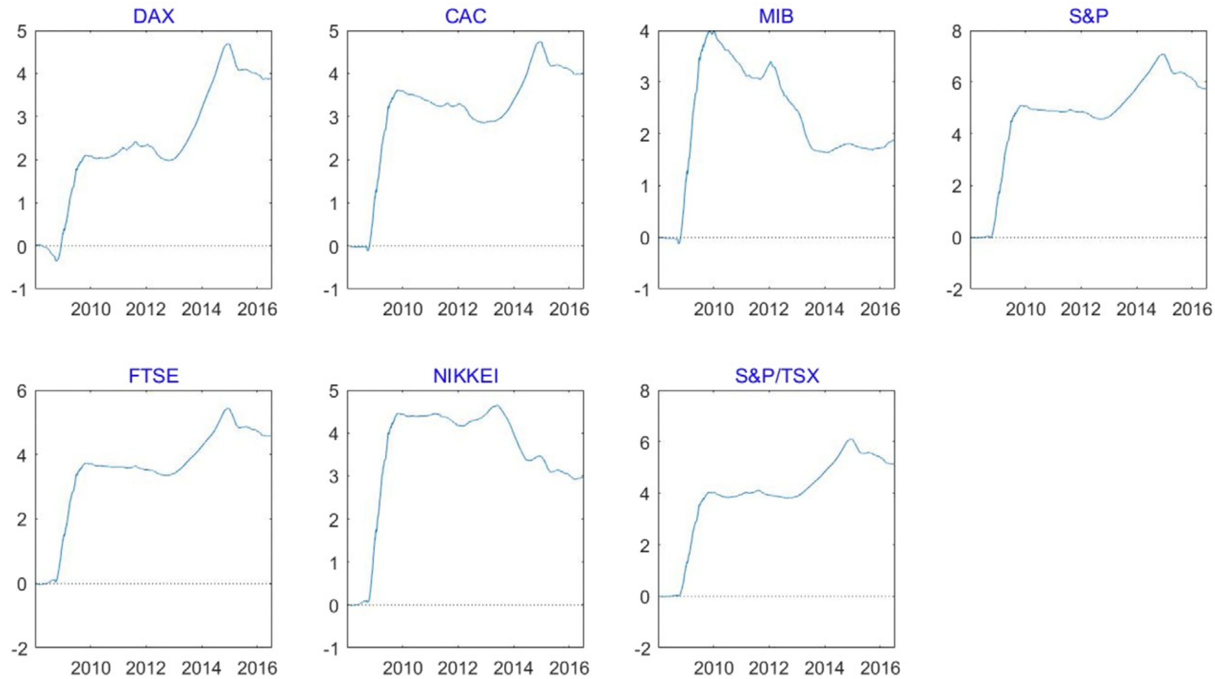

Fig.2. Cumulative square forecasting error (CSFE) graphs Notes: This figure depicts the differences of cumulative forecasting error (CSFE) over time between the historical average benchmark and oil VRP predictive model. The solid line exhibits these differences of CSFE and the dotted line shows the zero line for comparison.

Shown in the form of percentage, the out-of-sample R^2 statistics are all positive and bigger than 0.5, making sure the predictability. Since the data frequency we use is daily and all the R^2 statistics are above 10%, the predictive power of oil volatility risk premium is efficient in practice. The R^2 statistics also see a gradual increase with the increase of time horizon length, indicating the explanatory degree is decreasing over time.

Table4
In-sample and out-of-sample predictive results over long horizons.

	DAX_t	CAC_t	MIB_t	$S\&P_t$	$FTSE_t$	$NIKKEI_t$	$S\&P/TSX_t$
Panel A: slope coefficients of OV_t							
1 Day	-0.0047^{***}	-0.0044^{***}	-0.0036^{***}	-0.0048^{***}	-0.0044^{***}	-0.0035^{***}	-0.0043^{***}
2 Days	-0.0093^{***}	-0.0089^{***}	-0.0071^{***}	-0.0096^{***}	-0.0087^{***}	-0.0070^{***}	-0.0086^{***}
3 Days	-0.0140^{***}	-0.0134^{***}	-0.0108^{***}	-0.0144^{***}	-0.0131^{***}	-0.0105^{***}	-0.0128^{***}
4 Days	-0.0188^{***}	-0.0179^{***}	-0.0144^{***}	-0.0193^{***}	-0.0175^{***}	-0.0140^{***}	-0.0172^{***}
5 Days	-0.0235^{***}	-0.0224^{***}	-0.0180^{***}	-0.0241^{***}	-0.0219^{***}	-0.0176^{***}	-0.0215^{***}
6 Days	-0.0283^{***}	-0.0269^{***}	-0.0217^{***}	-0.0290^{***}	-0.0263^{***}	-0.0211^{***}	-0.0258^{***}
7 Days	-0.0330^{***}	-0.0315^{***}	-0.0254^{***}	-0.0339^{***}	-0.0308^{***}	-0.0247^{***}	-0.0301^{***}
8 Days	-0.0378^{***}	-0.0360^{***}	-0.0291^{***}	-0.0388^{***}	-0.0352^{***}	-0.0283^{***}	-0.0345^{***}
9 Days	-0.0427^{***}	-0.0406^{***}	-0.0328^{***}	-0.0437^{***}	-0.0397^{***}	-0.0319^{***}	-0.0388^{***}
10 Days	-0.0475^{***}	-0.0452^{***}	-0.0365^{***}	-0.0486^{***}	-0.0441^{***}	-0.0354^{***}	-0.0432^{***}
Panel B: one-sided t-statistics							
1 Day	−34.1487	−32.9990	−28.5391	−29.3112	−31.9685	−22.0064	−25.4974
2 Days	−34.2228	−33.0626	−28.6225	−29.3317	−32.0105	−22.0485	−25.5065
3 Days	−34.2994	−33.1262	−28.7002	−29.3524	−32.0544	−22.0803	−25.5196
4 Days	−34.3780	−33.1815	−28.7724	−29.3738	−32.0945	−22.1065	−25.5229
5 Days	−34.4611	−33.2424	−28.8482	−29.3977	−32.1321	−22.1298	−25.4990
6 Days	−34.5145	−33.2789	−28.9058	−29.3752	−32.1456	−22.1522	−25.4804
7 Days	−34.5680	−33.3145	−28.9615	−29.3507	−32.1596	−22.1676	−25.4702
8 Days	−34.6214	−33.3537	−29.0170	−29.3374	−32.1789	−22.1782	−25.4472
9 Days	−34.6701	−33.3914	−29.0723	−29.3243	−32.1963	−22.1889	−25.4314
10 Days	−34.7199	−33.4283	−29.1255	−29.3173	−32.2129	−22.2002	−25.4141
Panel C: out-of-sample R^2 statistics							
1 Day	32.6729	30.4309	10.4269	27.8045	34.0170	18.7710	26.3209
2 Days	32.8428	30.5794	10.5313	27.9066	34.1389	18.8856	26.4134
3 Days	33.0248	30.7318	10.6380	28.0120	34.2618	18.9878	26.5067
4 Days	33.2121	30.8817	10.7424	28.1203	34.3802	19.0821	26.5942
5 Days	33.4001	31.0323	10.8422	28.2269	34.4972	19.1722	26.6736
6 Days	33.5786	31.1766	10.9399	28.3251	34.6066	19.2613	26.7569
7 Days	33.7582	31.3191	11.0382	28.4216	34.7141	19.3471	26.8427
8 Days	33.9328	31.4584	11.1341	28.5200	34.8191	19.4239	26.9229
9 Days	34.1022	31.5933	11.2286	28.6169	34.9191	19.4981	27.0016
10 Days	34.2641	31.7206	11.3180	28.7125	35.0143	19.5705	27.0795

Notes: This table reports the regression results based on long time horizon from overnight to ten days apart. Three panels are shown in this table, describing the slope coefficients, t-statistics in-sample R^2 statistics and out-of-sample R^2 statistics estimated from the long-horizon model (15). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

4.4. Predictability during expansions and recessions

Economic cyclical periods can have an effect on the predictability of markets. As literature suggests (Neely et al., 2014), the predictability of stock market sees some different results during business expansions and recessions. To take a further insight into the ability of oil VRP to forecast stock realized volatility, we use OECD-dated business cycle to definite the business expansions and recessions and then calculate the R^2 statistics in Eq.(9) for different economic periods in both in-sample regressions and out-of-sample forecast tests.

Table5 reports the R^2 statistics computed for business expansions and recessions, respectively. The R^2 statistics for economic recessions are all greater and R^2 statistics for economic expansions are all less than the full-sample R^2 statistics as the benchmark. All the R^2 statistics for economic recession times are positive while some of the R^2 statistics for economic expansion times are negative, indicating the explanatory power of oil volatility risk premium mainly comes from its predictive power at economic recession periods. Six out of seven R^2 statistics for economic expansions even exceed 40% while four out of seven R^2 statistics for economic recessions are <0.

Overall, the predictability of stock realized volatility based on oil volatility risk premium is stronger during economic recessions than that during economic expansions. The higher the R^2 statistics for economic recessions all exceed the full-sample benchmark while for economic recessions all below.

4.5. Predictability under the circumstances of high/low volatility level

It is also of interest to investigate the predictive power of oil VRP during different volatility level of the both stock markets and oil markets. To classify high and low stock market volatility level, we set the median of stock realized volatility as the benchmark and compare it with all the stock realized volatility indexes. The higher ones are defined as high stock volatility and the lower ones are defined as low stock volatility. The high/low volatility of oil is also classified in this way, which means the higher oil market volatility are defined as high oil VRP and the lower ones are defines as low oil volatility. Here we use the high/low volatility indicator to separate the data spanning and calculating the R^2 statistics during different level of volatility. Since we focus on the predictability of the stock volatility, we use out-of-sample tests here to calculate the R^2 statistics and make comparison to identify the high/low volatility effect. The comparison results are illustrated in Table6.

Panel A of Table6 reports the R^2 statistics calculated for different levels of stock volatility. Three rows ofR^2 statistics are all positive in value, suggesting the predictive power of oil predictor model outperforms historical average whether in high or low stock market volatility. What's more, the R^2 statistics for low stock volatility times are significantly greater than those for high stock volatility times, representing a stronger predictive power at low volatility times. Generally, the R^2 statistics at low stock volatility times are several percentiles bigger than those for the full sample and tens of percentiles bigger than those for the high stock volatility times. During low stock volatility times, six out seven R^2 statistics exceed 7% and the biggest one even reaches 47%, which shows a strong explanatory power.

Table5
Results for testing predictive strength during cyclical expansion and recession.

	DAX_t	CAC_t	MIB_t	$S\&P_t$	$FTSE_t$	$NIKKEI_t$	$S\&P/TSX_t$
R^2_{EXP}	26.9491	11.4992	−14.8148	12.3694	19.4969	−16.9297	16.7760
R^2_{REC}	43.3734	49.4120	46.1846	41.6339	46.0700	41.2203	35.1214
R^2	32.6320	30.3952	10.4163	27.7594	33.9902	18.7552	26.2931

Notes: This table reports the different R^2 statistics during cyclical expansion and recession periods. The first row documents the R^2 statistics during economic expansion times, the medium row documents the R^2 statistics during economic recession times and the bottom row gives the overall R^2 statistics as a standard of comparison.

Table6
Results for testing predictive strength during high/low volatility periods.

	DAX_t	CAC_t	MIB_t	$S\&P_t$	$FTSE_t$	$NIKKEI_t$	$S\&P/TSX_t$
Panel A: out-of-sample R^2 during high/low stock realized volatility							
R^2_{HIGH}	22.5142	26.2798	10.3902	27.1943	31.8722	20.3081	21.0274
R^2_{LOW}	46.8976	44.9321	11.8449	30.0581	40.6254	7.2553	47.0890
R^2	32.6320	30.3952	10.4163	27.7594	33.9902	18.7552	26.2931
Panel B: out-of-sample R^2 during high/low oil volatility							
R^2_{HIGH}	14.7808	26.2637	28.5417	20.2898	24.8307	25.6163	17.2403
R^2_{LOW}	61.1368	44.5968	−58.3966	64.9895	69.5202	−44.0142	67.9802
R^2	32.6320	30.3952	10.4163	27.7594	33.9902	18.7552	26.2931

Notes: This table reports the different R^2 statistics during high and low volatility times. Two panels with three rows are shown in the table. Panel A displays out-of-sample R^2-during high/low stock realized volatility and panel B displays out-of-sample R^2 during high/low oil volatility, in each of which the first row documents the R^2 statistics during high volatility times, the medium row documents the R^2 statistics during low volatility times and the bottom row gives the overall R^2 statistics as a standard of comparison.

Panel B of Table6 reports the R^2 statistics computed for different levels of the oil market volatility. Two out of seven R^2 statistics for low oil market volatility periods are negative, signifying the poorer performance of the predictor compared to historical average method. Similar with the results in panel A, the R^2 statistics during low oil volatility periods are mostly greater than the full-sample R^2 statistics, five of seven of which are even >40%. Therefore, the ability of oil market volatility to forecast stock volatility performs better at low oil volatility periods.

To sum up, the predictability of stock volatility based on the oil VRP performs better at low volatility times. Out-of-sample R^2 statistics for lower stock realized volatility or lower oil market volatility periods are greater than those for high volatility periods, thus indicating a stronger predictive power. In particular, the R^2 statistics during low volatility times can even reach 60%, which can lead to a considerable economic effect.

4.6. Predictive power in an incremental framework

Apart from the conventional tests of the predictor's ability, it is also of interest to capture its predictive power in an incremental model. We employ the framework proposed by Chen et al. (2016):

$$SRV_t = \alpha + \varphi \Delta SRV_{t-1} + \beta OV_{t-1} + \varepsilon_t \tag{16}$$

where ΔSRV_{t-1} denotes the innovation in stock realized volatility. Table7 reports the results estimated based on model (16). Panel A reports the in-sample results. It can be seen that when the information of daily stock volatility change is incorporated, the slope coefficients of oil VRP are the level of 0.004 or so, all of which are estimated with one basis point of deviation. Looking at the standard and the one-sided (upper tail) t-statistics, we find the confidence level of this predictive power far exceeds 99%, signifying the economic significance of oil VRP's ability. Noticeably, the in-sample R^2 statistics, which is placed on the bottom line in panel A, are close to 0.2 (20%), if not above, representing a strong explanatory power.

The out-of-sample results are reported in Panel B. For sake of comparing the additional predictive power of oil volatility risk premium, we compute the mean squared forecast error (MSFE) statistics based on two ways, where the one is calculated for using ΔSRV_{t-1} alone to forecast stock realized volatility, recorded as MSFE0, and the other is calculated for using both ΔSRV_{t-1} and OV_{t-1} as predictors, recorded as MSFE1. Using these two MSFEs we obtain the out-of-sample R^2 statistics, which is displayed in the bottom line of the panel. It can be seen the R^2 statistics are all positive and five of them are even >30%, that is to say, after incorporating the information of oil VRP, the predictability of stock realized volatility improves to a considerable degree, again suggesting the forecasting ability of oil VRP to predict stock realized volatility.

Table7
Predictive results for the incremental model.

	DAX_t	CAC_t	MIB_t	$S\&P_t$	$FTSE_t$	$NIKKEI_t$	$S\&P/TSX_t$
Panel A: in-sample results							
ΔSRV_{t-1}	-2.6218^{***}	-1.7323^{*}	-0.8898	-2.7379^{**}	-1.6493	-0.4467	-2.0752^{*}
	(0.7566)	(0.6968)	(0.7253)	(0.8077)	(0.7468)	(0.5653)	(0.8596)
	[−3.3267]	[−1.9949]	[−1.2065]	[−2.6494]	[−1.4187]	[−0.7007]	[−1.81676]
OV_{t-1}	-0.0047^{***}	-0.0045^{***}	-0.0036^{***}	-0.0048^{***}	-0.0044^{***}	-0.0035^{***}	-0.0043^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
	[−33.5808]	[−31.2399]	[−27.585]	[−28.7511]	[−30.1252]	[−21.9117]	[−25.2792]
R^2	0.2257	0.2352	0.1399	0.2585	0.2739	0.1877	0.2266
Panel B: out-of-sample results							
MSFE0	0.0056	0.0062	0.0085	0.0097	0.0063	0.0074	0.0091
MSFE1	0.0037	0.0043	0.0076	0.0070	0.0042	0.0060	0.0067
OOS_R^2	33.1854	30.5319	10.3836	28.0387	34.0774	18.7614	26.4221

Notes: This table reports the in-sample and out-of-sample prediction results based on model (16). Panel A reports the in-sample results, where *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Numbers in parentheses are standard error of mean corresponding to each coefficient. The t-values calculated from the one-sided (upper-tail) hypothesis test are shown in the brackets. R^2 statistics are shown in the bottom row of each panel. Panel B depicts the out-of-sample forecast results, in which MSFE0 denotes the MSFE for using ΔSRV_{t-1} alone to forecast stock realized volatility and MSFE1 denotes the MSFE for using both ΔSRV_{t-1} and OV_{t-1} as predictors. OOS_R^2 is then given by: $OOS\_R^2 = 1 - MSFE1/MSFE0$ and shown in the form of percentage.

4.7. Predictive power with control variables

Numerous literature provides a series of variables which can influence stock markets in terms of stock returns and stock market volatility. To identify whether the predictive power of oil volatility is affected by these variables, we use these variable as control variables to test the forecast effectiveness of oil volatility risk premium. Parsimoniously, we compute the in-sample and out-of-sample R^2 statistics to evaluate the predictive power of oil volatility risk premium.

$$SRV_t = \alpha + \sum_{i=1}^{p} \omega_i SRV_{t-i} + \varphi CL_{t-1} + \varepsilon_t, \tag{17}$$

Table8
Predictive results with control variables.

	DAX_t	CAC_t	MIB_t	$S\&P_t$	$FTSE_t$	$NIKKEI_t$	$S\&P/TSX_t$
Panel A: in-sample R^2 statistics							
DP	0.1207	0.0493	0.0133	0.0557	0.0540	0.0025	0.0359
	0.4242	0.4019	0.2933	0.4444	0.4531	0.3075	0.3778
EP	0.5216	0.4295	0.1156	0.5346	0.5284	0.3943	0.4468
	0.5680	0.5090	0.2356	0.6034	0.6040	0.4330	0.5091
B/M	0.0293	0.0016	0.0243	0.0214	0.0167	0.0076	0.0725
	0.3914	0.4007	0.2868	0.4415	0.4496	0.2992	0.4085
TBL	0.0700	0.1251	0.3289	0.0440	0.0531	0.0944	0.0001
	0.4326	0.4915	0.5228	0.4647	0.4811	0.3701	0.3797
LTY	0.0127	0.0004	0.1377	0.0077	0.0094	0.0041	0.0254
	0.3863	0.4081	0.4249	0.4393	0.4489	0.2992	0.3829
NTIS	0.0006	0.0256	0.0297	0.0670	0.0784	0.0617	0.1416
	0.3953	0.3988	0.2394	0.4562	0.4713	0.3195	0.4439
RF	0.0700	0.1251	0.3289	0.0440	0.0531	0.0944	0.0001
	0.4326	0.4915	0.5228	0.4647	0.4811	0.3701	0.3797
INFL	0.0273	0.0356	0.0574	0.0284	0.0297	0.0528	0.0279
	0.3872	0.4020	0.2551	0.4408	0.4505	0.3148	0.3788
LTR	0.0014	0.0013	0.0002	0.0025	0.0026	0.0009	0.0014
	0.3861	0.3986	0.2346	0.4397	0.4492	0.3000	0.3773
SVAR	0.0166	0.0169	0.0135	0.0221	0.0157	0.0178	0.0195
	0.3859	0.3982	0.2346	0.4407	0.4490	0.3010	0.3779
EPU	0.0361	0.0205	0.1902	0.2316	0.0130	0.1248	0.0124
	0.3864	0.4240	0.4022	0.5118	0.4595	0.3466	0.3777
Panel B: out-of-sample R^2 statistics							
DP	5.6910	−16.2433	−32.2451	4.7756	13.3824	−54.1120	23.6803
EP	15.5078	18.8580	14.1038	18.5890	25.0879	−0.5291	17.0423
B/M	37.5864	13.5547	−41.8740	16.3848	28.1997	−70.6468	21.5539
TBL	59.9351	59.9652	6.1931	53.6058	62.0441	21.9790	40.8294
LTY	43.5907	31.2588	−34.3048	33.4881	43.0862	−22.5830	37.7654
NTIS	39.1765	5.5203	−52.8073	18.1084	25.7667	−49.9759	26.1340
RF	59.9351	59.9652	6.1931	53.6058	62.0441	21.9790	40.8294
INFL	49.2816	24.3774	−41.2054	32.0377	41.9770	−34.6090	40.4500
LTR	43.6699	12.2013	−47.2774	22.6408	32.4179	−69.8634	34.6388
SVAR	44.0020	12.3512	−46.4752	22.8190	32.1659	−67.9542	34.8132
EPU	59.9360	47.6047	−19.4652	50.8925	62.1276	−23.0352	61.3188

Notes: This table summarizes the in-sample and out-of-sample R^2 statistics for the predictive model with control variables. Two panels are included in this table, describing the in-sample R^2 statistics the out-of-sample results R^2 statistics respectively. For each row in panel A, the first line shows the R^2 statistics for model (17) and the second line shows the R^2 statistics for model (18) for sake of comparing the predictive power before and after incorporating the information of oil volatility risk premium. Panel B reports the R^2 statistics using an out-of-sample predictive framework, in which the R^2 statistics are given by: $R^2 = 1 - \frac{MSFE_{(18)}}{MSFE_{(17)}}$, where $MSFE_{(18)}$ denotes the mean squared forecast error (MSFE) based on model (18) and $MSFE_{(17)}$ denotes the mean squared forecast error (MSFE) based on model (17). Consistent with the basic out-of-sample tests, the R^2 statistics are shown in the form of percentage.

$$SRV_t = \gamma + \sum_{i=1}^{p} \omega_i SRV_{t-i} + \delta CL_{t-1} + \theta OV_{t-1} + \varepsilon_t, \quad (18)$$

where CL_{t-1} denotes the control variables. In the process, 11 control variables are employed as explanatory variable one by one, respectively.

Table8 displays the in-sample and out-of-sample R^2 statistics estimated from models (17) and (18). Panel A reports the in-sampleR^2 statistics, in which the first line of each row shows theR^2 statistics for model (17) and the second line shows theR^2 statistics for model (18). Clearly can be seen that when incorporating the information of oil volatility risk premium, theR^2 statistics for the predictive framework see significant increase by dozens of basis points, suggesting that the predictive power of the model are economically significantly improved. Panel B of Table8 summarizes the out-of-sample R^2 statistics for these two models. Different from the out-of-sampleR^2 statistics using historical average as the benchmark, the out-of-sampleR^2 statistics here is calculated by setting model (17) as the benchmark and comparing the mean squared forecast error (MSFE) of model (17) and model (18) to compute the R^2 statistics since we focus more on the predictive power of oil volatility risk premium. For all G7 countries, theR^2 statistics are nearly all positive in value for any control variables, indicating the information of oil volatility risk premium do help predict the stock realized volatility. Remarkably, ten variables show that the out-of-sample R^2 statistics can be >20% and the maximum ofR^2 statistics can even exceed 62%, which strongly supports that capturing oil volatility risk premium to predict stock volatility outperforms using control variables alone as a predictor.

5. Link to real economy

In this section, we conduct a forecasting analysis of future economic fundamentals using oil VRP and attempt to provide an explanation for the predictive ability of oil VRP to forecast stock volatilities.

Paye (2012) argues that stock volatilities are driven by global risk perception, the world business cycle, and traditional macroeconomic variables. In light of this, we investigate links between the predictive ability of oil VRP and real economy in terms of global risk, macro uncertainty, and observable fundamental variables. In specific, we consider the economic policy uncertainty (EPU) for G7 countries, the producer price index (PPI), consumer price index (CPI), ADS indicator proposed by Aruoba etal. (2009), the macroeconomic uncertainty (MACU) and financial uncertainty (FINU) for h = 1,3, 12 months proposed by Jurado et al. (2015), unemployment rate, industrial production index and TED spread of the U.S. and Chicago Fed National Activity Index (CFNAI). Byusing a number of important economic indicators immediately upon release to get an updated view of the overall level of economic activity, it is designed to track real business conditions at monthly frequency.

Both in-sample and out-of-sample analysis are performed based on:

$$MAC_t = \alpha + \beta OV_{t-1} + \varepsilon_t, \quad (19)$$

where MAC_t denotes the macroeconomic variables at time t. Due to the limitation of macro data spanning, here we employ a monthly data frequency to perform regressions.

Table9 illustrates the in-sample and out-of-sample analysis results. For in-sample regressions, 16 out of 20 macroeconomic variables can be forecast by oil volatility risk premium at a >95% confidence level, among which 13 macroeconomic variables even can be predicted at a 99% confidence level, signifying the strong predictive power of oil volatility to the real economy. Looking at the corresponding one-sided (upper tail) t-statistics, we can see most of them have absolute values of >2, which represents the forecasting ability of oil volatility risk premium to these macroeconomic variables are economically significant. The fourth column reports the in-sample R^2 statistics, corresponding to each macroeconomic variable. The right side of the table summarizes the out-of-sample tests results. Comparing the mean squared forecast error (MSFE) for historical average benchmark, which is shown in the fifth column of the table, and the mean squared forecast error for oil volatility risk premium predictive framework, which is shown in the sixth column of the table, we can see an obvious reduction for all the macroeconomic variables. The MSFE-adjusted statistics are reported in the

Table9
Results for the foresting power of oil volatility to forecast real economy.

	In sample				Out of sample			
	Coef.	Std.	t-Value	R^2	$MSFE_{HA}$	$MSFE_{OV}$	$MSFE_{ADJ}$	R^2OS
EPU(GER)	-1.0630^{**}	0.5796	−2.1707	0.0175	4308.9630	4418.0239	0.8406	−2.5310
EPU(FRA)	1.0042	0.8683	1.3464	0.0070	11,772.5589	11,811.4119	0.5160	−0.3300
EPU(ITA)	−0.1785	0.3983	−0.4796	0.0011	1714.2055	2019.5392	−1.7636	−17.8120
EPU(US)	-1.5281^{***}	0.3724	−5.9422	0.0818	2225.9490	2139.1145	2.0802	3.9010
EPU(UK)	0.0709	0.8835	0.1007	0.0000	12,994.5245	13,358.1052	−0.0573	−2.7980
EPU(JPN)	-1.2894^{***}	0.3575	−4.1804	0.0644	1471.9598	1413.6843	2.4145	3.9590
EPU(CAN)	-1.7043^{**}	0.7396	−2.4268	0.0273	9234.7928	9400.6561	0.9258	−1.7961
PPI	1.2651^{***}	0.2623	5.0599	0.1096	1206.5055	1144.3775	2.3015	5.1494
CPI	0.8627^{***}	0.2139	4.1909	0.0792	795.9205	771.4477	1.6595	3.0748
ADS	0.0593^{***}	0.0064	5.4738	0.3098	0.9363	0.6173	3.7547	34.0736
MAC-1	-0.0084^{***}	0.0008	−7.3794	0.3897	0.0167	0.0099	5.9255	40.8034
MAC-3	-0.0087^{***}	0.0008	−7.4558	0.3966	0.0173	0.0101	6.0492	41.6091
MAC-12	-0.0051^{***}	0.0005	−7.3600	0.3661	0.0063	0.0038	6.2628	39.1085
FAN-1	-0.0169^{***}	0.0016	−10.2638	0.3647	0.0431	0.0218	4.8276	49.4792
FAN-3	-0.0134^{***}	0.0013	−10.6620	0.3652	0.0261	0.0130	4.9158	50.2795
FAN-12	-0.0047^{***}	0.0005	−11.7327	0.3621	0.0029	0.0014	5.2594	53.2172
UNE	-0.0290^{*}	0.0185	−1.9680	0.0129	6.0368	6.0553	0.7053	−0.3058
IND	0.3718^{***}	0.0421	9.7155	0.2922	28.3836	21.7990	4.6476	23.1985
TED	-0.0131^{**}	0.0044	−2.5062	0.0457	0.2578	0.2636	0.1889	−2.2555
CFANI	0.0692^{***}	0.0077	5.3263	0.3018	1.2204	0.7945	3.4458	34.8970

Notes: This table summarizes the in-sample and out-of-sample analysis results of testing the relationship between oil volatility risk premium and the real economy based on model (18). The macroeconomic variables include the economic policy uncertainty (EPU) for G7 countries, the producer price index (PPI), consumer price index (CPI), ADS indicator proposed by Aruoba etal. (2009), the macroeconomic uncertainty (MACU) and financial uncertainty (FINU) for h = 1,3, 12 months proposed by Jurado et al. (2015), unemployment rate, industrial production index and TED spread of the U.S. and Chicago Fed National Activity Index (CFNAI) as is listed in order in the table. The left four columns report the in-sample regression estimations including the slope coefficients of oil volatility risk premium, the corresponding standard error, the t-statistics based on the one-sided (upper tail) test and the in-sample R^2 statistics. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The right four columns report the out-of-sample evaluations including the mean squared forecast error (MSFE) for historical average (HA) and the predictive model based on oil volatility risk premium (OV), the MSFE-adjusted statistics proposed by Clark and West (2007) and out-of-sample R^2 statistics.

Table10
Out-of-sample test results for the predictability of stock implied volatility based on oil VRP.

	$FTSE_t$	$VDAX_t$	CAC_t	VJX_t	VIX_t	$VSTOXX_t$	$S\&P/TSX_t$
$MSFE_{HA}$	82.9364	87.0133	77.5737	126.6212	105.2875	90.6316	24.5712
$MSFE_{OV}$	51.6804	48.7809	47.4767	96.4573	66.1087	55.5463	15.1211
$MSFE_{ADJ}$	15.9271	16.3168	16.1332	11.3197	15.2344	15.3254	22.5202
OOS_R^2	37.6866	43.9385	38.7979	23.8222	37.2112	38.7120	38.4600
ENC_{NEW}	1169.9734	1654.5739	1284.8513	622.3486	1120.8987	1360.9217	937.4303
$\overline{(\hat{e})}^2_{HA}$	0.0855	0.4652	0.1915	2.5899	0.0078	0.4096	0.6901
$Var(\hat{e})_{HA}$	82.8508	86.5481	77.3821	124.0313	105.2797	90.2220	23.8811
$\overline{(\hat{e})}^2_{OV}$	0.0199	0.0461	0.6887	4.2335	0.3901	1.1224	0.2280
$Var(\hat{e})_{OV}$	51.6606	48.7348	46.7880	92.2238	65.7186	54.4239	14.8931
GW	37.9939	42.0207	37.2829	37.3243	42.5376	40.2541	20.8913

Notes: This table reports the out-of-sample forecast results for using oil volatility risk premium to predict stock implied volatility. In line with the basic out-of-sample tests for the predictability of stock realized volatility, ten evaluations are reported in this table, in which $MSFE_{HA}$ denotes the mean squared forecast error (MSFE) for historical average, $MSFE_{OV}$ denotes the mean squared forecast error (MSFE) for predictive model, OOS_R^2 denotes the out-of-sample R^2 statistics, ENC_{NEW} denotes the encompassing test ENC statistics, GW denotes the statistics proposed by Giacomini and White (2006) and the remaining four denote the decomposition of MSFEs.

seventh column and the out-of-sample R^2 statistics are reported in the eighth column. Consistent with the MSFE reduction, most predictions produce a positive out-of-sample R^2 statistic with the maximum even >50%, indicating the predictability of those macroeconomic variables based on the volatility risk premium of oil outperforms the historical average method.

Overall, the oil VRP can forecast macroeconomic variables in both in-sample regressions and out-of-sample rolling forecast. This predictive power of oil VRP substantially explains the forecasting ability to predict stock market volatility.

6. Robustness check

The robustness of the oil VRP's predictive power is tested in this section. We employ alternative measures of oil volatility to retest the forecasting power of oil volatility risk premium.

Since this paper emphasizes the out-of-sample forecast ability of oil volatility, the out-of-sample test is performed using the recursive forecasting window proposed by Welch and Goyal (2008), of which the results are shown in Table10. The R^2 statistics in the fourth line all signal positive in value, indicating the predictive effectiveness of oil

Table11
Predictive results for the predictive power of oil realized and implied volatility.

	DAX_t	CAC_t	MIB_t	$S\&P_t$	$FTSE_t$	$NIKKEI_t$	$S\&P/TSX_t$
Panel A: using oil realized volatility to forecast stock realized volatility							
In-sample results							
OR_{t-1}	0.0027***	0.0030***	0.0026***	0.0036***	0.0033***	0.0031***	0.0036***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0002)
	[15.4005]	[18.7101]	[15.7173]	[22.6080]	[23.0258]	[22.9427]	[23.9642]
	[14.6097]	[15.9312]	[15.4308]	[16.0367]	[17.3856]	[15.1805]	[16.5500]
R^2	0.054	0.0783	0.0566	0.1104	0.1141	0.1133	0.1224
Out-of-sample results							
$MSFE_{HA}$	0.0056	0.0061	0.0085	0.0097	0.0063	0.0074	0.0091
$MSFE_{OV}$	0.0038	0.0043	0.0076	0.0070	0.0042	0.0060	0.0067
$MSFE_{ADJ}$	22.5972	18.1208	11.3840	18.6390	19.7152	13.3847	19.7931
OOS_R^2	32.6320	30.3952	10.4163	27.7594	33.9902	18.7552	26.2931
ENC_{NEW}	1119.8124	978.2649	367.9785	747.8204	1015.1088	523.0436	618.0859
$\overline{(\hat{e})}^2_{HA}$	0.0001	0.0002	0.0033	0.0001	0.0000	0.0003	0.0000
$Var(\hat{e})_{HA}$	0.0055	0.0060	0.0052	0.0096	0.0063	0.0071	0.0091
$\overline{(\hat{e})}^2_{OV}$	0.0000	0.0003	0.0036	0.0002	0.0001	0.0005	0.0001
$Var(\hat{e})_{OV}$	0.0037	0.0040	0.0041	0.0068	0.0041	0.0055	0.0066
GW	0.2898	0.2937	0.2023	0.3521	0.3146	0.2535	0.3330
Panel B: using oil implied volatility to forecast stock realized volatility							
In-sample results							
OI_{t-1}	0.0034***	0.0034***	0.0028***	0.0038***	0.0034***	0.0030***	0.0035***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
	[35.1139]	[38.7071]	[29.0124]	[43.9125]	[45.6451]	[38.5446]	[42.6136]
	[43.0520]	[46.3444]	[40.7551]	[40.9922]	[48.0562]	[29.9538]	[37.9449]
R^2	0.2303	0.2667	0.1696	0.3188	0.3359	0.2650	0.3059
Out-of-sample results							
$MSFE_{HA}$	0.0056	0.0061	0.0085	0.0097	0.0063	0.0074	0.0091
$MSFE_{OV}$	0.0038	0.0040	0.0074	0.0063	0.0036	0.0054	0.0000
$MSFE_{ADJ}$	22.1504	18.2751	12.8691	19.0016	19.9649	14.7922	20.3237
OOS_R^2	32.0323	35.2590	13.3466	34.7475	42.6976	27.7400	35.8858
ENC_{NEW}	1384.4292	1502.9712	596.8730	1260.0819	1780.4120	1027.7548	1143.0055
$\overline{(\hat{e})}^2_{HA}$	0.0001	0.0002	0.0033	0.0001	0.0000	0.0003	0.0000
$Var(\hat{e})_{HA}$	0.0055	0.0060	0.0052	0.0096	0.0063	0.0071	0.0091
$\overline{(\hat{e})}^2_{OV}$	0.0001	0.0001	0.0030	0.0001	0.0000	0.0004	0.0000
$Var(\hat{e})_{OV}$	0.0037	0.0038	0.0044	0.0062	0.0036	0.0049	0.0058
GW	0.2872	0.3164	0.2291	0.3939	0.3526	0.3083	0.3890

Notes: This table reports the predictability of oil volatility risk premium based on the realized volatility (OR) and implied volatility (OV) of oil, which is shown in panel A and panel B respectively. Both in-sample and out-of-sample results are reported as in the previous section of this paper. The asterisks, *, **, and ***, indicate significance at the 1%, 5%, and 10% levels, respectively.

volatility risk premium outperforms that of the historical average benchmark. What's more, all the out-of-sample R^2 statistics exceed 20% and the maximum gets to 44%, signifying a strong forecasting ability of oil volatility to stock implied volatility. The mean squared forecast error (MSFE) for historical average and oil volatility predictive framework are shown in the first and second row, respectively. Echoing the positive out-of-sample R^2 statistics, the MSFE sees a reduction for all the tests. The MSFE statistics for oil volatility predictive framework decrease by several percentiles compared to those for historical average. For further investigation, we decompose the MSFE statistics. From the results, we can see that, similar with the test results for stock realized volatility, the reduction in MSFE mainly comes from the decrease in forecast error variance.

Then, we use oil realized volatility and implied volatility as predictors to forecast stock realized volatility. In line with the empirical framework (4), both in-sample regressions and out-of-sample forecasts are performed and the results are depicted in Table11. Panel A of Table11 summarizes the predictive results of using oil realized volatility to explain stock realized volatility. The coefficients of oil realized volatility to forecast G7 stock realized volatility are shown in the first line of panel A, of which the corresponding standard errors and t-statistics, including standard and one-sided (upper tail) t-statistics, are shown below them. For all the G7 countries, the slope coefficients are 0.003 or so, which are followed with a standard error of one or two basis point. What's more, all the coefficients are labeled with three asterisks due to the 99% confidence level, indicating that all the G7 countries' stock realized volatility can be significantly forecast by oil realized volatility. The bottom row demonstrates the R^2 statistic for each regression, which shows that the explanatory power of the oil volatility risk premium is considerable. At first glance, it seems that the R^2 statistics appear too small. However, a monthly R^2 statistic near 0.5% is big enough to represent an economically significant predictive power as proposed by Campbell and Thompson (2008). For daily data, a smaller magnitude of R^2 statistic can stand for a strong effect. In the fourth line, seven R^2 statistics are all above 10% and the largest even exceeds 22%, indicating the explanatory power of this model is considerable enough. Looking at the out-of-results, we can see a reduction in MSFE statistics when using oil volatility as a predictor. Also consistent with the previous results, the reduction in MSFE mainly comes from the decrease in forecast error variance. Remarkably, the out-of-sample R^2 statistics reach dozens of percentiles, the maximum of which surprisingly exceeds 35%. Again, this magnitude of R^2 statistics represent a considerably economically significance of this predictive power. Panel B shows the test results for the predictive power of oil implied volatility. Similar conclusions can be obtained with panel A. Here we also use CFSE difference graphs to compare the forecasting accuracy of these predictive model with that of the historical average benchmark, which is shown in Figs. 3 and 4. We see similar trends in these plots with those generated by oil VRP models. Generally a sloping-up can be caught in each subplot in spite of some fluctuations. The curves depict positive forecasting error difference of HA over oil market volatility models, again suggesting the excessive predictive power covered by oil volatilities.

In general, the predictability of stock volatility can be based on both oil realized volatility and implied volatility.

7. Conclusions

Though a number of researchers have reported the widespread statistical correlation between oil factors and stock volatilities, there is little evidence on the out-of-sample forecasting ability of oil factors for stock volatilities. Our research therefore aims at investigating the predictability of the stock market volatility based on the volatility risk premium of oil (oil VRP).

In both the in-sample regressions and the out-of-sample forecasting exercises, we show that oil VRP can strongly predict daily stock volatilities of G7 major countries. These results hold up well for both realized volatilities and implied volatilities. Furthermore, the strength of the predictive evidence is substantial during relatively high and low level of stock market, while is substantially higher for recessions vis-á-vis expansions. Apart from the bivariate model, we also provide positive evidence by using a long-horizon framework and an incremental

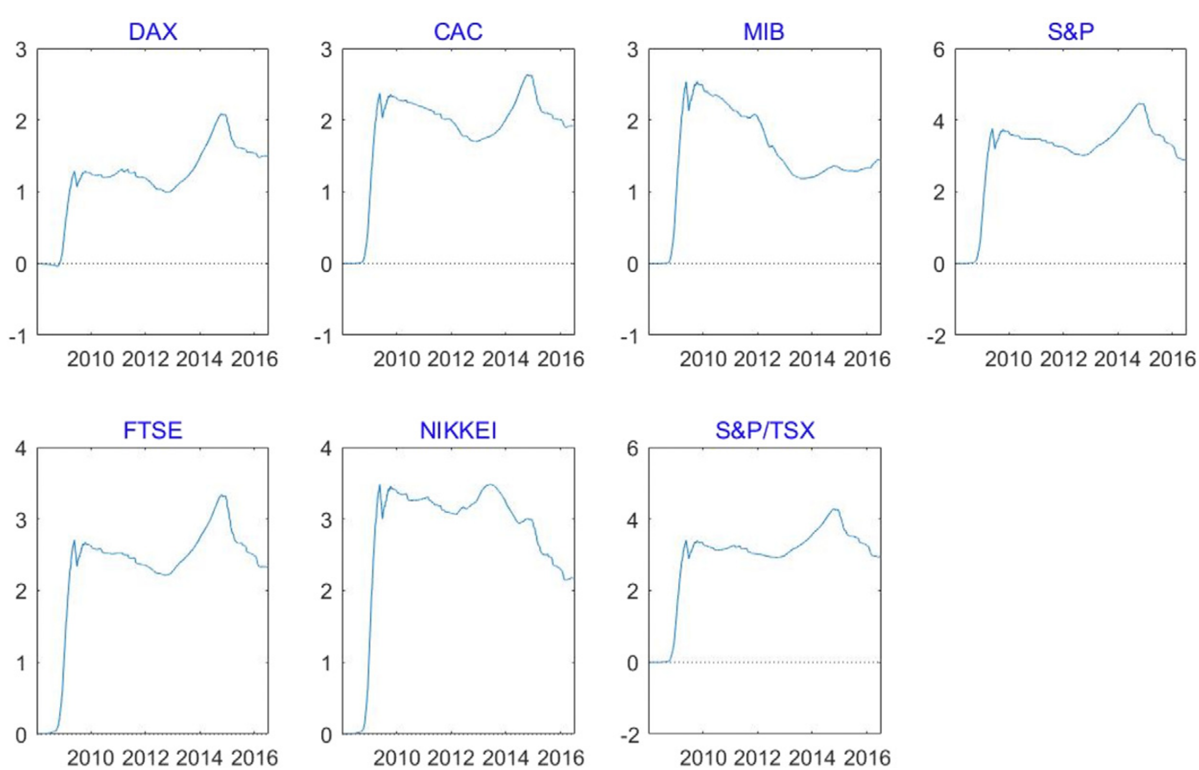

Fig.3. Cumulative square forecasting error (CSFE) graphs Notes: This figure depicts the differences of cumulative forecasting error (CSFE) over time between the historical average benchmark and oil realized volatility predictive model. The solid line exhibits these differences of CSFE and the dotted line shows the zero line for comparison.

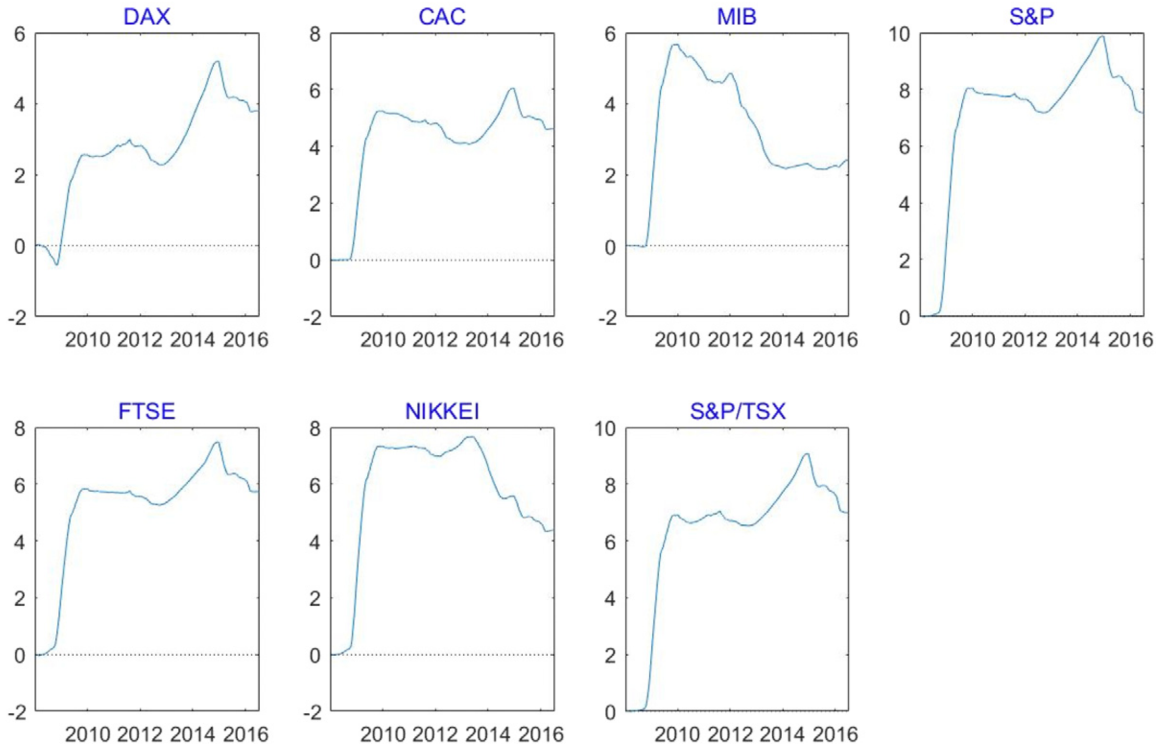

Fig.4. Cumulative square forecasting error (CSFE) graphs Notes: This figure depicts the differences of cumulative forecasting error (CSFE) over time between the historical average benchmark and oil implied volatility predictive model. The solid line exhibits these differences of CSFE and the dotted line shows the zero line for comparison.

model. What's more, the strength of the predictive is still significant even controlling for some popular macroeconomic variables. Overall, the substantial fluctuations in stock volatilities appear well captured by oil VRP.

To link oil VRP to economic activity, we find that oil VRP can effectively predict economic activity. These pieces of evidence provide an explanation for why oil VRP can predict stock volatilities.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2017.09.023.

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