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Oil and the short-term predictability of stock return volatility[☆]

Yudong Wang[a,*], Yu Wei[b], Chongfeng Wu[c], Libo Yin[d]

[a] School of Economics and Management, Nanjing University of Science and Technology, China
[b] School of Finance, Yunnan University of Finance and Economics,, China
[c] Antai College of Economics and Management, Shanghai Jiao Tong University, China
[d] School of Finance, Central University of Finance and Economics, China

A R T I C L E   I N F O

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A B S T R A C T

The goal of this paper is to show that crude oil volatility is predictive of stock volatility in the short-term from both in-sample and out-of-sample perspectives. The revealed predictability is also of economic significance, as shown by examining the performance of portfolios constructed on the oil-based forecasts of stock volatility. Results from robustness tests suggest that oil volatility provides different information from traditional macro variables. Further analysis shows that simple linear regression is sufficient for capturing predictive relationships between oil and stock volatility. Oil volatility is found to predict return volatilities of a significant number of industry portfolios during recent periods.

1. Introduction

Since the seminal work of Schwert (1989a), economic sources of financial volatility have been investigated extensively (e.g., Asgharian et al. (2013); Choudhry et al. (2016); Christiansen et al. (2012); Diebold and Yilmaz (2008); Engle and Rangel (2008); Engle et al. (2013); Nonejad (2017); Paye (2012)). This interest stems from the fact that financial volatility is a crucial input in risk management, portfolio allocation and asset pricing. Financial volatility is also found to successfully predict business cycles, providing early signals of upcoming recessions (Chauvet et al., 2015). However, a recent paper by Paye (2012) shows that although some variables such as treasury spread and default returns can theoretically affect stock volatility, it is difficult to find an individual variable that can predict stock volatility. In detail, adding any macro variables to the benchmark autoregressive model cannot significantly improve out-of-sample forecasting performance. The failure of individual fundamental variables in forecasting stock volatility is further confirmed by more comprehensive analyses conducted by Christiansen et al. (2012), unless some modeling issues such as parameter instability and model uncertainty are addressed (Nonejad, 2017).

In this paper, we show that a new variable, crude oil volatility, can be strongly predictive of stock volatility. We demonstrate that oil volatility improves the short-horizon predictability of stock volatility over the autoregressive benchmark model. This predictability is significant during various sample periods. Our investigation complements studies of modeling and forecasting volatility by providing a new fundamental determinant of stock volatility. Our findings are helpful for understanding the economic sources of changes in stock volatility.

Various studies have investigated the relationship between oil and stock volatility (see, e.g., Degiannakis et al. (2014); Arouri et al. (2011, 2012); Creti et al. (2013)). Most papers take an in-sample perspective using multivariate GARCH models. However, it

[☆] All the authors contribute to the paper equally.
[*] Correspondence to: Xiaolingwei Street 200, Xuanwu District, Nanjing 210094, China.
E-mail addresses: wangyudongnj@126.com (Y. Wang), cfwu@sjtu.edu.cn (C. Wu), yinlibowsxbb@126.com (L. Yin).

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is commonly understood that good *in-sample* performance does not imply that the predictive model displays superior *out-of-sample* performance. We contribute to the literature by paying attention to the ability of oil to predict stock volatility from an *out-of-sample* perspective. We employ a parsimonious predictive regression based on realized volatility to provide forecasts, the superiority of which over the GARCH has been well documented in the literature.

Our paper is closely related to Driesprong et al. (2008), who find that changes in oil prices predict stock returns *in-sample*. We complement their work by showing that oil volatility can also predict stock volatility both *in-sample* and *out-of-sample*. This paper is also linked to Chen et al. (2010), who show that commodity prices cannot predict asset prices such as exchange rate. We provide a novel example whereby the volatility of a special commodity, crude oil, is shown to have predictive power over stock return volatility. We extend the idea of Chen et al. (2010) to a volatility case and obtain different results.

We use daily data spanning January 1990 to December 2015 for the S&P 500 index and prices of West Texas Intermediate (WTI) and Brent oils. We use simple predictive regressions for realized volatility of stock index and take past oil volatility as a predictor in addition to lagged stock volatility. The squared daily returns in each month are summed to construct monthly realized volatility. Our in-sample results indicate significant Granger causality from oil volatility to stock volatility. An increase in current month's oil volatility can result in a significant increase in next month's stock volatility. WTI oil volatility provides greater in-sample predictive power than Brent oil volatility; possibly and plausibly because WTI oil is more closely related to the U.S. economy.

We use both recursive and rolling estimation window to generate one-step-ahead out-of-sample forecasts of stock volatility for January 1996 through December 2015. We compare the out-of-sample forecasting performance of oil models for stock volatility with the benchmark autoregressive model to detect the information content of oil. In addition to the standard regression, we impose an economic constraint on the coefficient of oil volatility in the forecasting procedure. In detail, according to standard economic theory, oil price uncertainty should have positive effects on stock uncertainty. If the sign of the oil volatility coefficient is not consistent with economic theory (i.e., negative), we abandon the oil model forecasts and instead use the benchmark alternatives. The similar parameter restriction method has hitherto been applied in stock return forecasting studies (Campbell and Thompson, 2008; Pettenuzzo et al., 2014). The rationale is that the "abnormal" coefficient sign implies that the variable of interest is not a determinant of the dependent variable. The incorporation of irrelevant variables in the predictive regression is likely to cause overfitting, manifesting itself as improved in-sample performance but inferior out-of-sample performance.

Following the literature (Paye, 2012; Goyal and Welch, 2008), we use the out-of-sample R^2 (ΔR^2_{OOS}) to evaluate out-of-sample performance. This criterion measures the percentage decrease in the mean squared predictive error (MSPE) of the model of interest relative to the MSPE of the benchmark model. A positive ΔR^2_{OOS} implies that the model of interest produces more accurate forecasts. The Clark and West (2007) statistic is used to test the equivalence of MSPEs between two nested models. We find significant predictability from WTI oil to stock volatility over each of a variety of sample periods. Imposing economic constraints on coefficients improves predictive ability moderately when a rolling window is used.

We also explore the economic significance of the volatility predictability. We consider an investor with mean–variance utility who allocates his/her wealth between the stock index and risk-free Treasury bill, where the volatility forecast is a key input in computing optimal *ex-ante* stock index weights. The usefulness of volatility forecasts is evaluated by observing portfolio performance. We compare the utility of a portfolio constructed on volatility forecasts of oil models with the utility of an alternative constructed on benchmark forecasts. Our results indicate that accounting for oil volatility information improves portfolio performance. Notably, the percent increase in portfolio utility of oil model relative to that of the benchmark model is as high as 79% during the 2001–2005 period.

To explore whether oil volatility information has been covered by macro variables considered in the literature, we use 12 fundamental variables reflecting stock market activity to carry out the robustness analysis. These fundamental variables are regularly used in studies of return and volatility forecasting (Rapach et al., 2010; Neely et al., 2014; Christiansen et al., 2012; Zhu and Zhu, 2013). We put these variables in the benchmark of autoregressive model and investigate whether oil volatility information still improves the predictive ability of these amended models. Our empirical results indicate that the reduction of MSPE is significant after taking advantage of oil information for different benchmark models. Furthermore, we also consider the uncertainty variables developed by Ludvigson et al. (2015) and Jurado et al. (2015). The out-of-sample predictability from oil to stock volatility becomes weaker after using economic uncertainty as a control variable. Nevertheless, significant predictability still exists during more recent periods. Therefore, the revealed out-of-sample predictability is generally robust to alternative benchmarks. Oil information does not substantively overlap with traditional macro information.

Our empirical analysis is further extended to nonlinear models. We consider two types of nonlinear relationships including asymmetric oil models and regime switching models. In summary, we find little evidence supporting the superiority of nonlinear models over linear specifications in forecasting stock volatility. Our forecasting exercise is also conducted for longer horizons. We find significant predictability for horizons of 3 and 6 months. However, the predictability disappears for longer horizons. A plausible explanation for this is that the response of stock prices to oil information completes within a short period of time (Wang et al., 2013). Oil volatility is further found to predict the return volatilities of a significant number of portfolios during more recent periods.

The predictability of stock volatility revealed by oil volatility can be explained by information transmissions from oil to stock markets. Crude oil is a core input in modern industry. Oil price shocks can certainly lead to changes in stock prices by affecting real economic activities (Hamilton, 1983; Kilian, 2009), current and future cash flows (Jones and Kaul, 1996) and monetary policy (Bernanke et al., 1996). In addition to transmissions of price information, there are three channels for transmitting oil volatility information to stock volatility. The first is the business cycle channel. It has been well documented in the literature that stock volatility is always higher when the economy undergone a recession (Schwert, 1989b; Hamilton and Lin, 1996). Because of the great importance of crude oil for the real economy, the large increase in oil price (i.e., high volatility) is an important factor driving business cycles. For example, Hamilton (2013) finds that all but one of the 11 postwar recessions were associated with high oil price volatilities.

The second is the risk premium channel. The economic model of Mele (2007) reveals that macro variables such as price–dividend ratios capturing time-varying risk premia are primary candidates for understanding and forecasting volatility. The theory of investment under uncertainty and real option advocates that current uncertainty about oil prices depresses future investment and consumption (e.g., Henry (1974); Bernanke (1983); Brennan and Schwartz (1985)). More recently, Elder and Serletis (2010) find that high oil price volatility has negative effects on real output, durable consumption and fixed investment. The risks associated with these variables are major fundamentals of stock risk premia.

The third channel is related to financialization of commodities (Tang and Xiong, 2012; Cheng and Xiong, 2013). Over the last decade, commodity futures have become a popular asset class for portfolio investors, just like stocks and bonds. Crude oil is one of the most important commodities. Oil futures prices are weighted most heavily in some popular commodity price indices such as S&P Goldman Sachs Commodity Index and the Dow-Jones UBS Commodity Index (DJ-UBS). Investors' asset reallocations between commodity indices and stocks results in volatility spillovers between oil and stock markets.

The remainder of this paper is organized as follows. Section 2 presents the methodology, including the predictive regressions, parameter restriction and the forecast evaluation method. Section 3 briefly describes the empirical data. We report the in-sample and out-of-sample results in Sections 4 and 5, respectively. Section 6 extends our analysis to nonlinear models. Section 7 reports the forecasting results for longer horizons. Section 8 documents the performance of oil in forecasting industry volatility. Finally, Section 9 concludes the paper.

2. Methodology

2.1. Realized volatility

The goal of this paper is to use oil return volatility to predict stock volatility. The regression-based approaches to modeling conditional volatility always build upon the ex-post measures of variance. Following the literature (e.g., Taylor (1986); Schwert (1989a); Paye (2012)), we sum the squared daily returns to construct the proxy for the variance of stock and oil returns at the monthly frequency. For a specific month t, the realized volatility is defined as:

$$RV_t = \sum_{j=1}^{M} r_{t,j}^2,\ t = 1, 2, \dots, T, \tag{1}$$

where M is the number of business days in each month, and $r_{t,j}$ denotes the jth daily return of the tth month. According to the arguments of Andersen and Bollerslev (1997), Andersen et al. (2001), and Andersen et al. (2003), this "realized volatility" contains less noise and is a better measure of ex-post variance than the squared monthly returns. The realized volatility is also employed in the recent literature on the predictive relationships between macroeconomic variables and stock volatility (see, e.g., Paye (2012); Christiansen et al. (2012)).

The original realized volatility defined by (1) is leptokurtic. We model and forecast volatility using the predictive regressions, the parameters of which are estimated via the ordinary least squares (OLS). However, it is well known that the statistical inference based on OLS is misleading when the errors are non-Gaussian. Motivated by this fact, we follow Paye (2012) in using the natural logarithms of realized volatility, $V_t = \log\left(RV_t\right)$, the distribution of which is approximately Gaussian according to the finding of Andersen et al. (2001).

2.2. Predictive regressions

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

$$V_{t+1} = \omega + \sum_{i=0}^{p-1} \alpha_i V_{t-i} + \varepsilon_{t+1}, \tag{2}$$

where $V_t = \log\left(RV_t\right)$, the error term ε_{t+1} is assumed to follow an independent and identically normal distribution. Following Paye (2012), the lag order p is set equal to 6 when using monthly data. The use of such long lag length is to sufficiently capture the strong autocorrelation in stock volatility.

To investigate the predictive content of oil volatility, we extend the AR(6) benchmark by incorporating a log realized volatility of crude oil as an additional predictor:

$$V_{t+1} = \omega + \sum_{i=0}^{p-1} \alpha_i V_{t-i} + \beta V_{t,oil} + \varepsilon_{t+1}, \tag{3}$$

where $V_{t,oil}$ is the oil volatility in the tth month. The parameter β captures the effects of oil market volatility on future stock volatility. We obtain the parameter estimates in (3) using the OLS. The null hypothesis of no predictability, $\beta = 0$, can be tested using the standard t-statistic. In order to take into account the possible presence of serial correlation in the data, we employ the Newey–West covariance correction for serial correlation when computing the t-statistics.

We use predictive regressions to generate out-of-sample volatility forecasts based on both techniques of rolling and recursive estimation windows. Specifically, we divide the total sample of T observations for each oil and stock volatility series into an in-sample part containing the first M observations and the out-of-sample part containing the remaining T-M observations. The first out-of-sample forecast of stock volatility based on oil volatility is given by,

$$\hat{V}_{M+1} = \hat{\omega}_M + \sum_{i=0}^{p-1} \hat{\alpha}_{i,M} V_{M-i} + \hat{\beta}_M V_{M,oil}, \tag{4}$$

where $\hat{\omega}_M$, $\hat{\alpha}_{i,M}$ and $\hat{\beta}_M$ are the OLS estimates of ω, α_i and β in (3), respectively. These estimates are obtained by regressing $\{V_t\}_{t=p+1}^{M}$ on a constant, $\{V_t\}_{t=j}^{M-p+j-1}$ for $j = 1, 2, \ldots, p$, and $\{V_{t,oil}\}_{t=p}^{M-1}$. The second out-of-sample forecast is given by,

$$\hat{V}_{M+2} = \hat{\omega}_{M+1} + \sum_{i=0}^{p-1} \hat{\alpha}_{i,M+1} V_{M-i+1} + \hat{\beta}_{M+1} V_{M+1,oil}. \tag{5}$$

For the recursive estimation window method, the parameter estimates $\hat{\omega}_{M+1}$, $\hat{\alpha}_{i,M+1}$ and $\hat{\beta}_{M+1}$ are obtained by regressing $\{V_t\}_{t=p+1}^{M+1}$ on a constant, $\{V_t\}_{t=j}^{M-p+j}$ for $j = 1, 2, \ldots, p$, and $\{V_{t,oil}\}_{t=p}^{M}$. Going forward like this through the end of out-of-sample period, a series of T-M forecasts of stock return volatility is generated. For the rolling estimation window, the first forecast is exactly the same to the first forecast based on recursive window. Differently, after adding a new observation rolling window method should drop the most distant one to do parameter estimation. In this way, when the estimation window rolls forward, the window size is fixed. For example, the parameter estimates $\hat{\omega}_{M+1}$, $\hat{\alpha}_{i,M+1}$ and $\hat{\beta}_{M+1}$ in (5) are obtained by regressing $\{V_t\}_{t=p+2}^{M+1}$ on a constant, $\{V_t\}_{t=j+1}^{M-p+j}$ for $j = 1, 2, \ldots, p$, and $\{V_{t,oil}\}_{t=p+1}^{M}$.

2.3. Parameter restriction

The predictive ability of an individual model is argued to suffer from the problem of model uncertainty (Avramov, 2002; Rapach et al., 2010). In detail, it is less possible that oil volatility is relevant to stock volatility all the time. During the period of time when stock volatility is not affected by past oil price fluctuations, the inclusion of irrelevant variable in the predictive regression is likely to cause overfitting, a situation that the in-sample performance is improved but out-of-sample performance is deteriorated. To reduce the effect of model uncertainty on forecasting performance, we use a parameter restriction method which imposes economic constraints on the signs of parameter estimates of predictive regressions. This method has been applied in recent studies on stock return forecasting (see, e.g., Campbell and Thompson (2008); Pettenuzzo et al. (2014)).

The standard economic theory suggests that higher oil return volatility cause higher stock volatility. The explanation is that because of the great importance of crude oil for the U.S. economy, an increase in oil volatility leads to higher macroeconomic uncertainty (Elder and Serletis, 2010), resulting in larger stock volatility. The volatility spillover from oil to stock has been also well documented in the literature (see, e.g., Arouri et al. (2011)). Therefore, the coefficient of oil volatility β in (3) is restricted to be positive. In detail, if the sign of the estimated coefficient $\hat{\beta}_t$ conditioned on the information available until the t-month is consistent with the economic theory (i.e., $\hat{\beta}_t > 0$), we use (3), the model with oil volatility, to produce stock volatility forecast in the $(t+1)$th month; otherwise, we use the benchmark model to generate forecast in the $(t+1)$th month. This parameter restriction procedure is reasonable in practice because it is more rational for economic forecasters to abandon the forecasts when the predictive model reveals "abnormal" in-sample predictive relations.

2.4. Forecast evaluation

To evaluate the forecast quality, we follow Campbell and Thompson (2008) and Rapach et al. (2010) using out-of-sample R^2, i.e., the percent reduction of mean squared predictive error (MSPE) of the model of interest relative ($MSPE_{\text{model}}$) to the MSPE of benchmark model ($MSPE_{\text{bench}}$), defined as

$$\Delta R^2_{OOS} = 1 - \frac{MSPE_{\text{model}}}{MSPE_{\text{bench}}}, \tag{6}$$

where $MSPE_i = \frac{1}{T-M}\sum_{t=M+1}^{T}\left(V_t - \hat{V}_{t,i}\right)^2 (i = \text{model, bench})$; V_t and $\hat{V}_{t,i}$ are, respectively, the true value and forecast of log realized volatility. The autoregressive model of log RV is taken as the benchmark model to be compared with. A positive ΔR^2_{OOS} implies that the forecasts from the model of interest have lower MSPE than the benchmark model, implying the greater forecasting accuracy.

Furthermore, we use the Clark and West (2007) method to test the null hypothesis that the benchmark forecast MSPE is less than or equal to competing forecast MSPE against one-sided (upper-tail) alternative hypothesis that the benchmark forecast MSPE is greater than the competing forecast MSPE. This statistic is a correction of Diebold and Mariano (1995) statistic and is demonstrated to be suitable for nested models. The Clark and West (2007) statistic is computed by defining,

$$f_t = \left(V_t - \hat{V}_{t,bench}\right)^2 - \left(V_t - \hat{V}_{t,model}\right)^2 + \left(\hat{V}_{t,bench} - \hat{V}_{t,model}\right)^2. \tag{7}$$

The t-statistic from the regression of f_t on a constant is the MSPE-adjusted statistic.

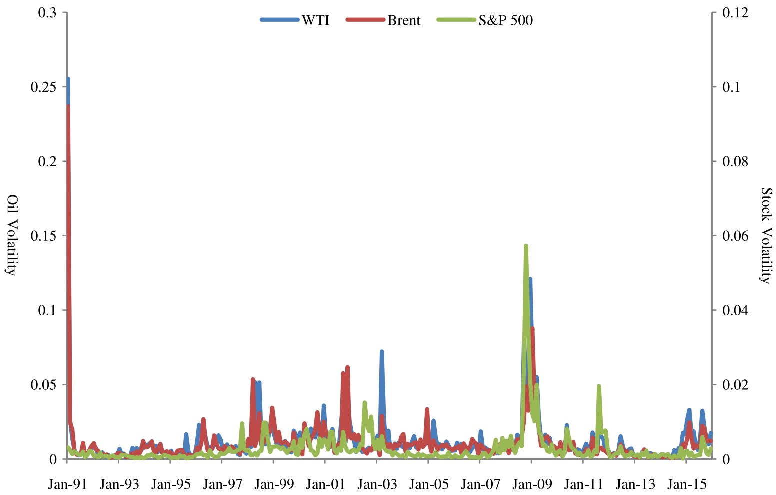

Fig. 1. Oil and stock volatilities. Notes: This figure provides graphical representation of realized volatilities of oil and stock index returns. The left vertical axis labels oil volatility, while the right vertical axis labels stock volatility.

3. Data

We collect daily price data of S&P 500 index from *Yahoo!* Finance (finance.yahoo.com). We use the prices of two oils, West Texas Intermediate (WTI) crude oil and Brent oil, which are available at the website of Energy Information Administration.[1] Both prices are the benchmark of international oil pricing but have slight differences. WTI oil price reflects more information about U.S. domestic oil supply and demand, while Brent price is more global and is the benchmark price of oil traded in the Europe and Africa.[2] Our data cover the sample period for January 1991 through December 2015.

Daily price data are employed to construct the monthly realized volatility. Fig. 1 illustrates the graphical representations of stock and oil volatility during our sample period. We can obtain some meaningful findings by looking at the evolution of oil and stock volatility. First, oil return volatility is about 3–4 times larger than stock volatility. Second, some large volatilities of crude oil always occurred together with or even before large stock volatilities. For example, the Iraqi invasion of Kuwait in 1990 and the subsequent Gulf War caused the monthly oil volatility of about 25% in January 1991, the largest value during our sample period. Stock volatility during this period is also higher than the volatility during the next years of early 1990s. The monthly stock volatility in October 2008 reached the historical summit of 5.7%. Notably, WTI oil volatility achieved its historical summit after 1991 in September 2008, one month before the time when the U.S. stock market crashed. Of course, the financial crisis caused the extremely fluctuated stock prices in later 2008. Hamilton (2009) nevertheless noted some avenues by which high oil prices contributed directly to the financial crisis itself. These meaningful findings motivate us to find whether oil volatility can provide useful information regarding future stock volatility.

4. In-sample results

According to the results from Inoue and Kilian (2004), in-sample predictability is a necessary condition for out-of-sample predictability. It would be unreasonable to find out-of-sample predictability in the absence of in-sample predictability. Table 1 displays the estimated coefficients of the predictive regression with oil volatility expressed by (3), as well as the t-statistics based on the Newey–West covariance correction for serial correlation. We also report the increase in R^2 for the regression with oil volatility relative to the benchmark of AR(6) model, expressed as a percentage.

The coefficient estimates of α_1 and α_2 are positive and highly significant, suggesting the stylized fact of volatility persistence. Being of our interest, the coefficient estimate of β is significantly positive at 10% level, regardless of whether WTI or Brent oil volatility is included in the predictive model, indicating the in-sample predictability from oil to stock volatility. The coefficient estimate of β is 0.107 and 0.072 for WTI and Brent oil volatility, respectively. Therefore, one percent increase in current month's WTI (Brent) oil volatility will lead to 0.072 (0.107)% increase in next month's volatility of S&P 500 returns. The percent increase in R^2 after adding WTI and Brent oil volatility to the benchmark regression is 1.200 and 0.536, respectively. These values are greater than the increase in R^2 due to the inclusion of most macroeconomic variables in predictive regressions reported in Table 3 of Paye (2012) paper, implying that oil volatility can provide greater predictive content than most popular predictors for stock volatility.

[1] www.eia.gov.

[2] In the literature of oil and the real economy, the refiner acquisition cost (RAC) of imported oil is considered the oil price most relevant to the U.S. economic activity. However, RAC price is available at the monthly frequency and is always published with a delay of about two or three months, which is not suitable for market participants to do real-time risk management or asset allocation. Therefore, we do not use RAC to forecast stock volatility.

Table 1
In-sample estimation results. This table reports the in-sample estimation results for the predictive regressions for monthly stock volatility with oil volatility. The specification of the predictive model is given by, $V_{t+1} = \omega + \sum_{i=0}^{p-1} \alpha_i V_{t-i} + \beta V_{t,oil} + \varepsilon_{t+1}$, where V_t and $V_{t,oil}$ are the natural logarithm of monthly realized volatility of stock and oil returns, respectively. The maximum lag order is set as $p = 6$. We report the estimate of the slope coefficient, as well as the corresponding heteroskedasticity-adjusted t-statistic based on the Newey–West method. We also show the percent increase in R^2 of the model of interest relative to that of the benchmark of AR(6) (i.e., the predictive regression with $\beta = 0$). The asterisks *, **, *** denote rejections of null hypothesis at 10%, 5% and 1% significance levels, respectively.

	WTI oil volatility		Brent oil volatility	
	Coefficient	t-stat	Coefficient	t-stat
Parameter estimation results				
ω	−0.811**	−2.508	−0.857***	−2.637
α_1	0.464***	5.849	0.480***	6.073
α_2	0.165***	2.724	0.165***	2.717
α_3	0.091	1.449	0.091	1.451
α_4	−0.101	−1.399	−0.097	−1.320
α_5	0.097	1.480	0.097	1.465
α_6	0.078	1.486	0.076	1.446
β	0.107**	2.298	0.072*	1.704
Percent increase of R^2				
ΔR^2	1.200		0.536	

Table 2
Out-of-sample forecasting results, recursive window. This table reports the forecasting results for the predictive regressions with oil volatility. We present the results from the regression given by, $V_{t+1} = \omega + \sum_{i=0}^{p-1} \alpha_i V_{t-i} + \beta V_{t,oil} + \varepsilon_{t+1}$, where V_t and $V_{t,oil}$ are the natural logarithm of monthly realized volatility of stock and oil returns, respectively. The maximum lag order is set as $p = 6$. The forecasts are generated using a recursive window with the initial sample covers the period of 60 months. The table reports the out-of-sample R^2, defined by the percent reduction of mean squared predictive error (MSPE) of the oil model relative to that of the benchmark of AR(6). The p-values of Clark and West (2007) (CW) tests for the equivalence of MSPEs between oil model and the benchmark model are given in the parentheses. The asterisks *, ** and *** indicate rejections of null hypothesis at 10%, 5% and 1% significance levels, respectively.

	1996–2015		2001–2015		2006–2015		2011–2015	
	Without restriction	With restriction	Without restriction	With restriction	Without restriction	With restriction	Without restriction	With restriction
WTI	0.826*	0.826*	1.460**	1.460**	2.172**	2.172**	3.666**	3.666**
	(0.093)	(0.093)	(0.045)	(0.045)	(0.023)	(0.023)	(0.025)	(0.025)
Brent	−0.133	−0.071	0.380	0.460	0.754	0.839*	1.523*	1.523*
	(0.443)	(0.404)	(0.196)	(0.164)	(0.111)	(0.090)	(0.091)	(0.091)

5. Out-of-sample results

It has been shown in extensive literature that a good in-sample performance does not gauge that the predictive model displays superior performance from an out-of-sample perspective. For example, a relatively large number of studies on stock return forecasting documents that many single predictive models perform poorly out-of-sample (see, e.g., Goyal and Welch (2008); Rapach et al. (2010)). The results in Paye (2012) show that some variables related to macroeconomic uncertainty, time-varying expected stock returns and credit conditions indeed can predict stock volatility in-sample but any individual predictive models involving these variables is difficult to beat the benchmark of autoregressive model out-of-sample. Actually, market participants are more interested in the out-of-sample performance of a predictive model because they are more concerned about how well they can do in the future using this model. Motivated by these facts, we pay more attention to the predictive content of oil volatility from an out-of-sample perspective. In detail, we investigate whether adding oil volatility to the benchmark model can improve the forecasting accuracy. Accordingly, we compare the out-of-sample performance of the model (3) with the benchmark of autoregressive model (2).

5.1. Out-of-sample forecasting performance of oil volatility models

We generate volatility forecasts for January 1996 through December 2015 and evaluate the forecasting performance over a variety of sample periods. The volatility forecasts of regressions with WTI and Brent oil volatility are illustrated in Figs. 2 and 3, respectively. Table 2 reports the evaluation results of the predictive regression with and without parameter restriction based on the recursive estimation window. We give the values of out-of-sample R^2, as well as the p-values of CW test for the equivalence of MSPEs of two nested models.

We first look at the forecasting performance of WTI oil volatility. The values of ΔR^2_{OOS} suggest that the inclusion of WTI oil volatility in the right-hand side of predictive regression can lead to a reduction of MSPE of 0.826% in the full out-of-sample period. The p-value of CW test suggests that the improvement of forecasting accuracy is significant. The ΔR^2_{OOS} values are even larger during more recent subperiods, indicating that the predictive ability of oil volatility becomes stronger over time. We can find that

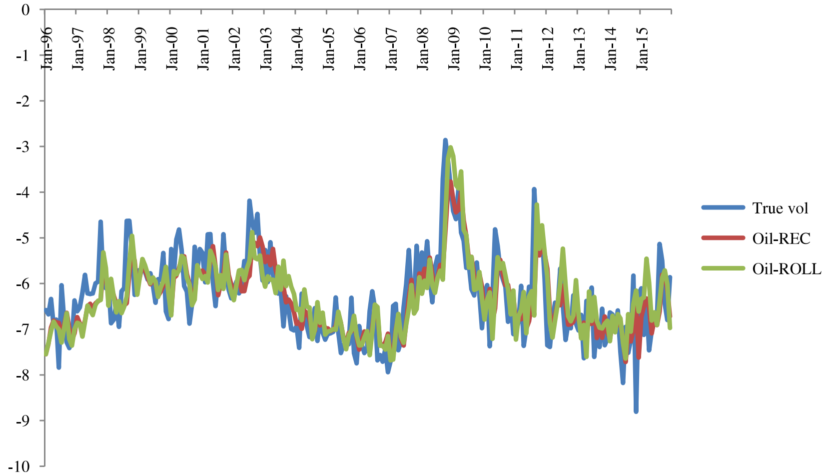

Fig. 2. WTI oil forecasts of stock volatility based on rolling and recursive windows. "True vol", "Oil-REC" and "Oil-ROLL" represents true volatility, volatility forecasts from recursive window and forecasts from rolling window, respectively. We use the predictive regressions with WTI oil volatility.

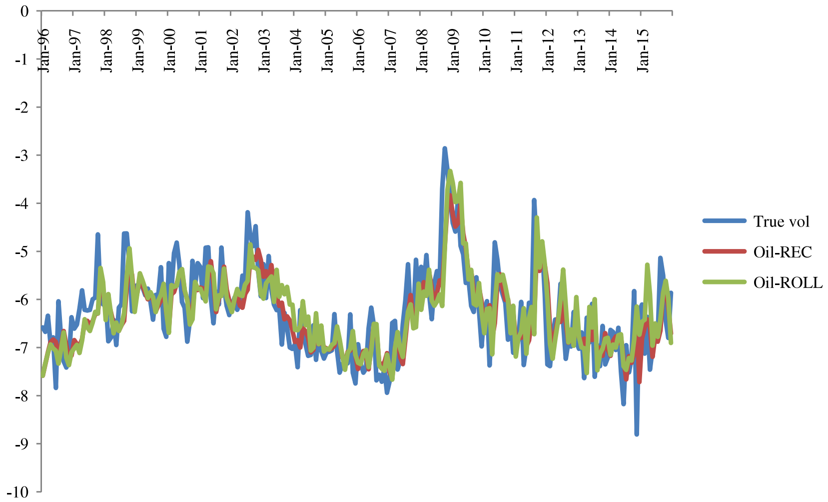

Fig. 3. Brent oil forecasts of stock volatility based on rolling and recursive windows. "True vol", "Oil-REC" and "Oil-ROLL" represents true volatility, volatility forecasts from recursive window and forecasts from rolling window, respectively. We use the predictive regressions with Brent oil volatility.

the forecasting results of the restricted and unrestricted models with WTI oil volatility are exactly the same. The reason is that the coefficient estimates of oil volatility are positive all the time.

The forecasting performance of the model with Brent oil volatility is a bit weaker. The evidence is that ΔR^2_{OOS} is negative over the full 1996–2015 sample period. The plausible explanation is that Brent oil price is determined by oil market situation in the Europe and Africa, and is less relevant to the U.S. economy than WTI price. The unrestricted model can significantly beat the benchmark of AR(6) during the 2011–2015 period but it cannot outperform the benchmark model during 2001–2015 or 2006–2015 subperiods. Interestingly, we find that during the 2006–2015 period the predictability becomes significant after imposing economic constraints on the slope coefficient of oil volatility, signaling the benefit of forecasting gains from parameter restriction.

Table 3 reports the forecasting results based on rolling window. We can find that the predictive regressions with oil volatility can significantly beat the benchmark model, regardless of whether WTI or Brent oil is included. This evidence indicates the strong predictive content of oil volatility for stock volatility. The revealed predictability is stronger over more recent periods. During 2011–2015 period the percent decrease of MSPE, i.e., out-of-sample R^2, is as high as 6%. The parameter restriction can improve the predictability greatly over some specific sample periods. For example the ΔR^2_{OOS} value of WTI (Brent) oil volatility model in the whole out-of-sample period increases from 0.581% to 1.368% (from 0.090% to 1.489%) after imposing economic constraint. Overall, we find the existence of significant predictability from oil volatility to stock volatility and the predictability is more prominent when WTI oil is employed.

Table 3
Out-of-sample forecasting results, rolling window. This table reports the forecasting results for the predictive regressions with oil volatility. We present the results from the regression given by, $V_{t+1} = \omega + \sum_{i=0}^{p-1} \alpha_i V_{t-i} + \beta V_{t,oil} + \varepsilon_{t+1}$, where V_t and $V_{t,oil}$ are the natural logarithm of monthly realized volatility of stock and oil returns, respectively. The maximum lag order is set as $p = 6$. The forecasts are generated using a rolling window with each window covers a period of 60 months. The table reports the out-of-sample R^2, defined by the percent reduction of mean squared predictive error (MSPE) of the oil model relative to that of the benchmark of AR(6). The p-values of Clark and West (2007) (CW) tests for the equivalence of MSPEs between oil model and the benchmark model are given in the parentheses. The asterisks *, ** and *** indicate rejections of null hypothesis at 10%, 5% and 1% significance levels, respectively.

	1996–2015		2001–2015		2006–2015		2011–2015	
	Without restriction	With restriction	Without restriction	With restriction	Without restriction	With restriction	Without restriction	With restriction
WTI	0.581**	1.368**	1.461**	2.165**	2.454**	2.701**	5.977**	5.977**
	(0.039)	(0.035)	(0.028)	(0.029)	(0.032)	(0.029)	(0.023)	(0.023)
Brent	0.090*	1.489**	0.891**	2.185**	1.707**	2.723**	4.766**	4.766**
	(0.061)	(0.034)	(0.042)	(0.027)	(0.049)	(0.027)	(0.026)	(0.026)

5.2. Portfolio exercise

Comparing with the statistical gains of volatility predictability, market investors care more about the economic gains. To evaluate the economic significance, we take the volatility forecasts as the key determinant of portfolio optimization by maximizing investor utility following Fleming et al. (2001, 2003) and Guidolin and Timmermann (2005, 2007). The usefulness of volatility forecasts is evaluated by observing the portfolio performance. We consider a mean–variance investor who allocates his or her wealth between stock index and risk-free asset following the majority of stock return forecasting literature (see, e.g., Guidolin and Na (2006); Neely et al. (2014); Rapach et al. (2010)) and recent studies of volatility forecasting (Wang et al., 2016). The utility from investing in this portfolio is:

$$U_t\left(r_t\right) = E_t\left(w_t r_t + r_{t,f}\right) - \frac{1}{2}\gamma var_t(w_t r_t + r_{t,f}), \tag{8}$$

where w_t is the weight of stock in this portfolio, r_t is the stock return in excess of risk-free rate, and γ denotes the risk aversion degree. For the risk-free rate $r_{t,f}$, we use 3-month Treasury bill rate. $E_t(\cdot)$ and var_t are, respectively, the conditional mean and variance given the information available at the tth month.

Maximizing $U_t\left(r_t\right)$ respect to w_t yield the ex-ante optimal weight of stock index at the $(t+1)$th month:

$$w_t^* = \frac{1}{\gamma}\left(\frac{\hat{r}_{t+1}}{\hat{\sigma}_{t+1}^2}\right), \tag{9}$$

where $\hat{r}_{t+1}$ and $\hat{\sigma}_{t+1}^2$ denote the mean and volatility forecasts of stock excess returns, respectively. We use the same historical average forecast which is the well-known benchmark model in stock return forecasting analysis. Goyal and Welch (2008) find that it is difficult for an individual model to significantly outperform this benchmark out-of-sample. In this way, the portfolio performance differs depending on the various volatility forecasts.

Obviously, the optimal weight depends on the risk aversion degree γ. A higher value of γ implies that stock receives lower weight in the portfolio. We use $\gamma = 3$ in portfolio analysis; the results are qualitatively similar for reasonable γ values. The optimal weight is restricted between 0 and 1.5 to preclude short sales and to prevent more than 50% leverage following the literature (e.g., Rapach et al. (2010); Neely et al. (2014)).

The portfolio return can be written as:

$$R_{t+1} = w_t^* r_{t+1} + r_{t+1,f}. \tag{10}$$

We use the popular criterion of certainty equivalent return (CER) to evaluate portfolio performance:

$$CER_p = \hat{\mu}_p - \frac{\gamma}{2}\hat{\sigma}_p^2, \tag{11}$$

where $\hat{\mu}_p$ and $\hat{\sigma}_p^2$ are the mean and variance of portfolio returns over the sample period, respectively.

Table 4 reports the percent increase in utility of portfolio formed by predictive regression with oil volatility relative to that formed by benchmark model. When using recursive window, the utility gains are about 3% in the whole out-of-sample period. During the other three subperiods, the increase in utility is about 7.7%-8.8% after adding oil volatility to the benchmark model. The economic gains from the information of oil volatility are larger for more recent periods. When using rolling window, the improvement of portfolio performance is more prominent. The increase in utility is about 10% during the whole sample period. This value is as high as 66% during the 2001–2015 period for unrestricted models and even higher using economic constraints (79%). Overall, our results based on portfolio exercise suggest that accounting for oil market information is also quite helpful for asset allocation.

5.3. Robustness tests

It is possible whether forecast improvement can be obtained by adding oil volatility to the benchmark model is sensitive to omitted variables in models (2) and (3). To examine this question, we also consider following benchmark model to do robustness check:

$$V_{t+1} = \omega + \sum_{i=0}^{p-1}\alpha_i V_{t-i} + \theta z_t + \varepsilon_{t+1}, \tag{12}$$

Table 4
Performance of portfolio. This table provides the performance of portfolio formed by volatility forecasts. Each period a mean–variance investor allocates wealth between stock and T-bill based on return and volatility forecasts. In this framework, the stock index is assigned the weight $w_t^* = \left(\frac{1}{\gamma}\right)\left(\frac{\hat{r}_{t+1}}{\hat{\sigma}^2_{t+1}}\right)$, where γ denotes the risk aversion degree. We use the popular historical average return forecasts and use $\gamma = 3$. The optimal weight of stock is restricted between 0 and 1.5. The portfolio performance is evaluated based on certainty equivalent return (CER). We show the percent increase of portfolio utility of the oil model relative to that of the benchmark model AR(6).

	1996–2015		2001–2015		2006–2015		2011–2015	
	Without restriction	With restriction	Without restriction	With restriction	Without restriction	With restriction	Without restriction	With restriction
Panel A: Portfolio results based on recursive window								
WTI	3.110	3.110	7.704	7.704	7.084	7.084	8.795	8.795
Brent	2.864	2.838	7.311	7.230	5.336	5.287	6.216	6.216
Panel B: Portfolio results based on rolling window								
WTI	9.487	8.281	57.52	44.52	16.59	16.97	17.36	17.36
Brent	10.23	15.45	66.06	79.15	28.91	30.18	35.41	35.41

where z_t is a vector with non-oil macro variables. As an alternative to these benchmarks, we add an oil volatility variable:

$$V_{t+1} = \omega + \sum_{i=0}^{p-1} \alpha_i V_{t-i} + \theta z_t + \beta V_{t,oil} + \varepsilon_{t+1}. \tag{13}$$

The sets of potential macro variables z_t should be very large. In detail, to determine whether each of n variables is included in the model, one can obtain $2^n - 1$ potential sets of macro variables. We follow Rapach et al. (2010) and Paye (2012) in using single popular predictors.

Following Christiansen et al. (2012), we use 12 macroeconomic variables for stock market activity suggested by Goyal and Welch (2008). These popular predictor variables are the dividend–price ratio (DP), dividend yield (DY), earning–price ratio (EP), book-to-market ratio (BM), net equity expansion (NITS), Treasury bill rate (TBL), long-term yield (LTY), long-term return (LTR), default yield spread (DFY), default return spread (DFR), inflation (INFL) and value-weighted stock index return (SR).[3] The 3rd–14th rows in Table 5 report the forecasting results of the models with WTI volatility based on a recursive window.[4] We find that the incorporation of oil volatility in almost all benchmark models with these popular predictor variables significantly improves predictive ability. The revealed predictability is also stronger over more recent sample periods.

Furthermore, Ludvigson and Ng (2007) use a large and near-exhaustive set of economic variables for forecasting stock market volatility,[5] using factor analysis to deal with the large dimension problem. We use the aforementioned 12 macroeconomic variables as the control benchmark case, which may not be as complete as those put forward by those authors. By extension, Ludvigson et al. (2015) and Jurado et al. (2015) proposed three uncertainty variables: "financial uncertainty", "macro uncertainty" and "real uncertainty", applying factor analysis for a large data set including crude oil prices. We also use these three uncertainty variables as control variables to explore the robustness of predictability[6] from oil to stock volatility. The last three rows in Table 5 present the out-of-sample forecasting results of model (13) relative to (12) when these three uncertainty variables are taken as control variables.[7] For the full out-of-sample period, the out-of-sample R^2 values are positive, but the forecasting gains become insignificant. However, for three more recent sub-periods, ΔR^2_{OOS} values remain positive and statistically significant at least at the 10% level. In comparison with the figures in Table 2, the ΔR^2_{OOS} values decrease to different extents during each of three subsample periods after adding the three uncertainty measures as control variables. These results suggest that oil price volatility indeed provides predictive information regarding stock volatility that partly overlaps with the three new uncertainty variables. This is expected because oil price uncertainty can affect economic uncertainty (Elder and Serletis, 2010), which contains important information about stock volatility (Ludvigson and Ng, 2007).

We can also confirm that oil price volatility information cannot be substituted by any of these uncertainty variables. Plausible explanations for this are twofold. First, Jurado et al. (2015) use monthly WTI oil prices when constructing the uncertainty variable. Differently, we use daily price data to compute realized volatility. According to arguments in the literature (Andersen and Bollerslev, 1997; Andersen et al., 2001), realized volatility is a better proxy for unobserved volatility and contains much less noise than the volatility proxy computed using monthly returns directly (e.g., squared monthly returns). If we use monthly oil price data, more useful predictive information in higher-frequency daily data may be omitted. As supporting evidence, our non-reported results indicate that the predictability of stock volatility disappears when the squared monthly return is used as the proxy for true oil volatility. Second, Jurado et al. (2015) use factor analysis to draw out salient information from a large data set; the principal component they use may account for major but not all specificities of oil information.

[3] The detailed description of these macro variables can be seen in Goyal and Welch (2008). We thank Amit Goyal for providing these data via his homepage (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html).

[4] For brevity, we do not report results for the predictive regressions with Brent volatility. The results based on a rolling forecasting window are also consistent in quality.

[5] We thank an anonymous referee for this constructive suggestion.

[6] Data associated with these three uncertainty variables are available via Sydney Ludvigson's homepage (https://www.sydneyludvigson.com/data-and-appendixes/).

[7] We use the log differences of the uncertainty for consistency.

Table 5
Out-of-sample forecasting results, alternative benchmarks. This table reports the forecasting results for the predictive regressions with oil volatility. We present the results from the regression of the specification $V_{t+1} = \omega + \sum_{i=0}^{p-1} \alpha_i V_{t-i} + \beta V_{t,oil} + \theta z_t + \varepsilon_{t+1}$, where V_t and $V_{t,oil}$ are the natural logarithm of monthly realized volatility of stock and oil returns, respectively. z_t denotes a vector with macro variables, the symbols of which are listed in the first column. The maximum lag order is set as $p = 6$. The forecasts are generated using a recursive window with the initial length of 60 months. We give the out-of-sample R^2, defined by the percent reduction of mean squared predictive error (MSPE) of the oil model relative to the benchmark model without oil volatility, $V_{t+1} = \omega + \sum_{i=0}^{p-1} \alpha_i V_{t-i} + \theta z_t + \varepsilon_{t+1}$. The first 12 macroeconomic variables are suggested by Goyal and Welch (2008). The last three variables FU, MU and RU are financial uncertainty, macro uncertainty and real uncertainty, respectively (see, e.g., Ludvigson and Ng, 2007; Ludvigson et al., 2015). The p-values of Clark and West (2007) (CW) tests for the equivalence of MSPEs between oil model and the benchmark model are given in the parentheses. The asterisks *, ** and *** indicate rejections of null hypothesis at 10%, 5% and 1% significance levels, respectively.

Macro variable	1996–2015		2001–2015		2006–2015		2011–2015	
	Without restriction	With restriction	Without restriction	With restriction	Without restriction	With restriction	Without restriction	With restriction
DP	1.269**	1.269**	1.859**	1.859**	2.701**	2.701**	4.378**	4.378**
	(0.044)	(0.044)	(0.030)	(0.030)	(0.014)	(0.014)	(0.023)	(0.023)
DY	1.230**	1.230**	1.840**	1.840**	2.654**	2.654**	4.336**	4.336**
	(0.048)	(0.048)	(0.030)	(0.030)	(0.015)	(0.015)	(0.022)	(0.022)
EP	1.570**	1.570**	2.126**	2.126**	3.223***	3.223***	4.846**	4.846**
	(0.028)	(0.028)	(0.023)	(0.023)	(0.008)	(0.008)	(0.017)	(0.017)
BM	1.164*	1.164*	1.974**	1.974**	2.681**	2.681**	4.406**	4.406**
	(0.053)	(0.053)	(0.021)	(0.021)	(0.014)	(0.014)	(0.019)	(0.019)
NTIS	0.714	0.714	1.270*	1.270*	2.047**	2.047**	3.410**	3.410**
	(0.111)	(0.111)	(0.061)	(0.061)	(0.027)	(0.027)	(0.031)	(0.031)
TBL	0.742	0.779	1.681**	1.729**	2.245**	2.245**	3.806**	3.806**
	(0.111)	(0.104)	(0.032)	(0.029)	(0.026)	(0.026)	(0.028)	(0.028)
LTY	0.918*	0.918*	1.520**	1.520**	2.088**	2.088**	3.608**	3.608**
	(0.075)	(0.075)	(0.039)	(0.039)	(0.028)	(0.028)	(0.029)	(0.029)
LTR	0.833*	0.833*	1.499**	1.499**	2.186**	2.186**	3.687**	3.687**
	(0.088)	(0.088)	(0.040)	(0.040)	(0.021)	(0.021)	(0.023)	(0.023)
DFY	0.984*	0.984*	1.411**	1.411**	2.153**	2.153**	3.667**	3.667**
	(0.065)	(0.065)	(0.049)	(0.049)	(0.024)	(0.024)	(0.025)	(0.025)
DFR	0.844*	0.844*	1.543**	1.543**	2.271**	2.271**	3.912**	3.912**
	(0.094)	(0.094)	(0.037)	(0.037)	(0.018)	(0.018)	(0.018)	(0.018)
INFL	0.807*	0.807*	1.489**	1.489**	2.163**	2.163**	3.678**	3.678**
	(0.095)	(0.095)	(0.042)	(0.042)	(0.022)	(0.022)	(0.025)	(0.025)
SR	0.815*	0.815*	1.481**	1.481**	2.146**	2.146**	3.619**	3.619**
	(0.091)	(0.091)	(0.039)	(0.039)	(0.021)	(0.021)	(0.023)	(0.023)
FU	0.062	0.280	0.870*	1.026*	1.249*	1.298*	2.394**	2.394**
	(0.324)	(0.238)	(0.084)	(0.057)	(0.063)	(0.056)	(0.049)	(0.049)
MU	0.314	0.512	0.950*	1.225**	1.487**	1.537**	2.545**	2.545**
	(0.196)	(0.138)	(0.071)	(0.034)	(0.037)	(0.033)	(0.034)	(0.034)
RU	0.713	0.730	1.303*	1.406**	1.974**	1.726**	3.150**	3.150**
	(0.106)	(0.102)	(0.051)	(0.038)	(0.025)	(0.038)	(0.029)	(0.029)

6. The nonlinear oil-stock volatility relationship

We have found the predictability of stock volatility using the simple linear regression with oil volatility which assumes the linear predictive relationship. If the oil-stock relationship is nonlinear, the linear models are misspecified and are likely to generate less accurate forecasts. Due to this motivation, we investigate whether some nonlinear models are better candidates for stock volatility forecasting. We consider two specifications accounting for different types of nonlinearity in the lead–lag linkages between oil and stock volatility, asymmetric effect and regime change.

6.1. Asymmetric effect

The asymmetric effect of oil price on the real economy is initially documented by Mork (1989). The author finds that the effect of increase in oil price on the U.S. GDP is significantly negative, whereas the effect of oil price decrease is minor. Therefore, it is possible that the effect of oil shocks on stock market activity is asymmetric. Because oil price increases (i.e., positive returns) are always associated with higher volatilities, we isolate the impact of oil volatility due to positive returns using two regressions based on different volatility measures. The first model takes an indicator of positive return as an additional variable:

$$V_{t+1} = \omega + \sum_{i=0}^{p-1} \alpha_i V_{t-i} + \beta V_{t,oil} + \delta V_{t,oil} I(r_{t,oil} > 0) + \varepsilon_{t+1}, \tag{14}$$

where I (.) is an indicator function which is equal to 1 when the condition in the parentheses is satisfied and zero otherwise.

The second model capturing asymmetric effect is based on the decomposition of realized volatility. We use the methodology of Patton and Sheppard (2015) which decomposes monthly realized variance into a component that relates only to positive daily returns and a component that relates only to negative daily returns. This specification of this model is given by:

$$V_{t+1} = \omega + \sum_{i=0}^{p-1} \alpha_i V_{t-i} + \beta^+ V^+_{t,oil} + \beta^- V^-_{t,oil} + \varepsilon_{t+1}, \tag{15}$$

Table 6
Out-of-sample forecasting results of nonlinear models. The table reports the forecasting results for the nonlinear predictive regressions with oil volatility. We present the results from the three regressions of the specifications Asymmetric model 1: $V_{t+1} = \omega + \sum_{i=0}^{p-1} \alpha_i V_{t-i} + \beta V_{t,oil} + \delta V_{t,oil} I\left(r_{t,oil} > 0\right) + \varepsilon_{t+1}$ Asymmetric model 2: $V_{t+1} = \omega + \sum_{i=0}^{p-1} \alpha_i V_{t-i} + \beta^+ V_{t,oil}^+ + \beta^- V_{t,oil}^- + \varepsilon_{t+1}$ Regime switching model: $V_{t+1} = \omega + \sum_{i=0}^{p-1} \alpha_i V_{t-i} + \beta_{s_t} V_{t,oil} + \epsilon_{t+1}, \epsilon_{t+1} \sim N\left(0, \sigma_{s_t}^2\right), s_t = (0,1)$ where V_t and $V_{t,oil}$ are the natural logarithms of monthly realized volatility of stock and oil returns, respectively. $V_{t,oil}^+$ and $V_{t,oil}^-$ are log semivariances related to positive and negative oil returns, respectively. The maximum lag order $p = 6$. The forecasts are generated using a recursive window with the initial length of 60 months for parameter estimation. We give the out-of-sample R^2, defined by the percent reduction of mean squared predictive error (MSPE) of the oil model relative to the benchmark of AR(6). The p-values of Clark and West (2007) (CW) tests for the equivalence of MSPEs between oil model and the benchmark model are given in the parentheses. The asterisks *, ** and *** indicate rejections of null hypothesis at 10%, 5% and 1% significance levels, respectively.

	1996–2015	2001–2015	2006–2015	2011–2015
Panel A: Forecasting results of Asymmetric model 1				
WTI	−0.158	0.457	0.771	1.970*
	(0.261)	(0.180)	(0.158)	(0.098)
Brent	−1.517	−0.452	−0.072	0.922
	(0.828)	(0.521)	(0.390)	(0.176)
Panel B: Forecasting results of Asymmetric model 2				
WTI	−0.497	0.430	0.460	−0.676
	(0.322)	(0.190)	(0.218)	(0.411)
Brent	−2.099	−1.893	−2.787	−4.988
	(0.268)	(0.443)	(0.639)	(0.790)
Panel C: Forecasting results of regime switching model				
WTI	0.726*	1.177*	2.115*	6.319**
	(0.051)	(0.065)	(0.062)	(0.025)
Brent	0.081*	−0.085	0.630	6.183**
	(0.078)	(0.145)	(0.139)	(0.018)

where $V_{t,oil}^+ = \log RS_{t,oil}^+$ and $V_{t,oil}^- = \log RS_{t,oil}^-$; $RS_{t,oil}^+$ and $RS_{t,oil}^-$ are the monthly realized semivariances of oil returns related to positive and negative returns, respectively. Here, the realized semivariance is defined as follows:

$$RS_{t,oil}^+ = \sum_{j=1}^{M} r_{t,j,oil}^2 I(r_{t,j,oil} > 0), \text{ and,}$$
$$RS_{t,oil}^- = \sum_{j=1}^{M} r_{t,j,oil}^2 I(r_{t,j,oil} < 0), \; t = 1, 2, \dots, T, \tag{16}$$

where $r_{t,j,oil}$ is the oil return on jth day of the tth month.

Table 6 reports the forecasting results of two asymmetric models. We find that the benchmark model of AR(6) cannot be significantly outperformed by regressions with WTI or Brent oil volatility for most cases. The only exception is that during 2011–2015 period the asymmetric regression (15) reveals the significant predictability with the out-of-sample R^2 of 1.97% when WTI volatility is used. The gains of predictability from asymmetric models measured by R_{OOS}^2 are lower than those from simple symmetric models. Therefore, accounting for the asymmetry in the predictive regressions cannot obtain more accurate forecasts and even worsens the forecasting performance. This evidence reinforces the finding in Kilian and Vigfusson (2013) that the regressions with symmetric oil price measure are good enough to capture the joint dynamics between oil price and macro variables.

6.2. Regime change

Because of some factors such as business cycle and occasional events, the effects of oil shocks on stock market experience regime shifts over time (Aloui and Jammazi, 2009; Chen, 2010). To address time-variation in the oil-stock volatility relationship, we consider a Marko regime switching model given by:

$$V_{t+1} = \omega + \sum_{i=0}^{p-1} \alpha_i V_{t-i} + \beta_{s_t} V_{t,oil} + \epsilon_{s_{t+1}}, \; \epsilon_{s_t} \sim i.i.d\, N\left(0, \sigma_{s_t}^2\right), \; s_t = (0,1). \tag{17}$$

For simplicity, our model just imposes regime switching on the coefficient of oil volatility and assumes that the intercept and autoregressive coefficient are regime-independent.

The lower part of Table 6 shows the forecasting results of regime switching model based on recursive window. We find that the relative forecasting performance between two-regime model and single-regime model depends on which sample period is considered

Table 7
Out-of-sample forecasting results for longer horizons. The table reports the longer-horizon forecasting results for the predictive regressions with oil volatility. We present the results from the regression given by, $V_{t+h} = \omega + \sum_{i=0}^{p-1} \alpha_i V_{t-i} + \beta V_{t,oil} + \varepsilon_{t+1}$, where V_t and $V_{t,oil}$ are the natural logarithm of monthly realized volatility of stock and oil returns, respectively; h denotes the forecasting horizon. The first column lists the names of oil variable. The maximum lag order is set as $p = 6$. The forecasts are generated using a recursive window with the initial estimation window covers a period of 60 months. The table reports the out-of-sample R^2, defined by the percent reduction of mean squared predictive error (MSPE) of the oil model relative to that of the benchmark of AR(6). The p-values of Clark and West (2007) (CW) tests for the equivalence of MSPEs between oil model and the benchmark model are given in the parentheses. The asterisks *, ** and *** indicate rejections of null hypothesis at 10%, 5% and 1% significance levels, respectively.

	1996–2015		2001–2015		2006–2015		2011–2015	
	Without restriction	With restriction	Without restriction	With restriction	Without restriction	With restriction	Without restriction	With restriction
Forecasting horizon $h = 3$								
WTI	2.101***	2.101***	0.018	0.018	2.473**	2.473**	3.741**	3.741**
	(0.009)	(0.009)	(0.102)	(0.102)	(0.014)	(0.014)	(0.035)	(0.035)
Brent	1.886***	1.886***	1.450**	1.450**	2.117**	2.117**	4.268**	4.268**
	(0.008)	(0.008)	(0.019)	(0.019)	(0.027)	(0.027)	(0.034)	(0.034)
Forecasting horizon $h = 6$								
WTI	2.156**	2.156**	0.731*	0.731*	1.334*	1.334*	9.045***	9.045***
	(0.010)	(0.010)	(0.082)	(0.082)	(0.097)	(0.097)	(0.001)	(0.001)
Brent	1.844***	1.844***	1.904**	1.904**	1.230*	1.230*	7.508***	7.508***
	(0.009)	(0.009)	(0.017)	(0.017)	(0.081)	(0.081)	(0.003)	(0.003)
Forecasting horizon $h = 9$								
WTI	0.408	0.408	−0.099	−0.099	−0.991	−0.991	3.618**	3.618**
	(0.143)	(0.143)	(0.284)	(0.284)	(0.640)	(0.640)	(0.034)	(0.034)
Brent	0.592	0.592	0.589	0.589	−1.473	−1.473	2.538*	2.538*
	(0.112)	(0.112)	(0.138)	(0.138)	(0.695)	(0.695)	(0.099)	(0.099)

for forecast evaluation and which oil volatility is incorporated in the model. For example, during the period of 2011–2015, regime switching model can achieve higher R^2_{OOS} values than single regime model (see Table 2), implying greater forecasting accuracy. During the whole period of 1996–2015, imposing regime switching on the regression with WTI volatility cannot improve predictive ability. As a contrast, the R^2_{OOS} of regression with Brent volatility turns from negative to significantly positive, indicating the gains of predictability from regime switching. During the other two periods of 2001–2015 and 2006–2015, regime switching model performs worse than single regime model. Therefore, whether regime change is helpful to obtain more accurate oil forecasts of stock volatility is rather mixed. The plausible explanation is that regime switching model can lead to overfitting when oil-stock volatility relationship is rather stable. In summary, the regime switching model is not a consistently better candidate than the single-regime regression for capturing oil-stock volatility relationship from the out-of-sample perspective.

7. Forecasting performance for longer horizons

This section investigates the forecasting performance of oil volatility model of stock volatility for longer horizons. The predictive model is given by:

$$V_{t+h} = \omega + \sum_{i=0}^{p-1} \alpha_i V_{t-i} + \beta V_{t,oil} + \varepsilon_{t+h}, \tag{18}$$

where h is the forecasting horizon.

Table 7 reports forecasting results for the horizons of 3, 6 and 9 months based on recursive window.[8] We can see that the predictability from oil to stock volatility changes over forecasting horizons. For the horizons of 3 and 6 months, both WTI and Brent oil volatility can predict stock volatility, evidenced by significantly positive out-of-sample R^2 during all periods. However, the predictability disappears in most cases for the horizon of 9 month. The absence of predictability for longer horizons can be explained by the finding in the literature that the responses of stock market activities to oil shocks complete within a certain period of time (Wang et al., 2013).

8. Forecasting return volatilities of industry portfolios

We have revealed significant predictability from oil to stock index volatility. This section examines whether oil volatility can also predict industry portfolio return volatilities.[9] We use the daily returns of 12 industrial portfolios to compute monthly industry volatility, which are available via the Kenneth French Data Library's website.[10] The forecasting results are reported in Table 8. In the full sample, significant stock predictability is found for 5 out of 12 industry portfolios when the restricted model is used. The

[8] To save space, we do not report results based on rolling window.

[9] We are grateful to an anonymous referee for this constructive suggestion.

[10] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table 8

Forecasting results for return volatilities of industry portfolios. The table reports the forecasting results for the predictive regressions with oil volatility for return volatilities of industry portfolios. We present the results from the regression given by, $V_{t+1} = \omega + \sum_{i=0}^{p-1} \alpha_i V_{t-i} + \beta V_{t,oil} + \epsilon_{t+1}$, where V_t and $V_{t,oil}$ are the natural logarithm of monthly realized volatility of industry portfolio returns and oil returns, respectively. The first column lists the names of industries. NoDur is consumer nondurables, Durbl is consumer durables, Manuf is manufacturing, Enrgy is energy related industries such as oil, gas, and coal extraction and products, Chems is chemicals and allied Products, BusEq is business equipment, Telcm is telephone and television transmission, Utils is utilities, Shops is wholesale, retail, and some services (laundries, repair shops), Hlth is healthcare, medical equipment, and drugs and Money is finance industries. The maximum lag order is set as $p = 6$. The forecasts are generated using a recursive window with the initial estimation window covers a period of 60 months. We give the out-of-sample R^2, defined by the percent reduction of mean squared predictive error (MSPE) of the oil model relative to that of the benchmark of AR(6). The *p*-values of Clark and West (2007) (CW) tests for the equivalence of MSPEs between oil model and the benchmark model are given in the parentheses. The asterisks *, ** and *** indicate rejections of null hypothesis at 10%, 5% and 1% significance levels, respectively.

Macro variable	1996–2015		2001–2015		2006–2015		2011–2015	
	Without restriction	With restriction	Without restriction	With restriction	Without restriction	With restriction	Without restriction	With restriction
NoDur	0.601	1.138*	1.218*	1.707**	2.238**	2.247**	4.193**	4.193**
	(0.121)	(0.060)	(0.064)	(0.025)	(0.025)	(0.024)	(0.022)	(0.022)
Durbl	0.127	0.013	1.084*	1.357**	2.152**	1.974**	1.430	1.430
	(0.172)	(0.216)	(0.070)	(0.039)	(0.031)	(0.038)	(0.148)	(0.148)
Manuf	0.642	0.836*	1.238*	1.608**	1.941**	2.134**	2.649*	2.649*
	(0.103)	(0.071)	(0.057)	(0.026)	(0.034)	(0.025)	(0.063)	(0.063)
Enrgy	−0.750	−0.764	−0.406	−0.064	−0.201	−0.088	0.238	0.238
	(0.728)	(0.804)	(0.761)	(0.485)	(0.566)	(0.485)	(0.330)	(0.330)
Chems	1.433**	1.660**	2.714***	3.051***	3.857***	4.002***	5.809***	5.809***
	(0.026)	(0.015)	(0.006)	(0.002)	(0.003)	(0.002)	(0.008)	(0.008)
BusEq	−0.091	0.294	0.141	0.443	0.347	0.547	1.450*	1.450*
	(0.446)	(0.171)	(0.305)	(0.147)	(0.230)	(0.150)	(0.091)	(0.091)
Telcm	−0.544	−0.272	0.217	0.562*	0.667	0.832*	1.898**	1.898**
	(0.524)	(0.412)	(0.239)	(0.080)	(0.100)	(0.061)	(0.043)	(0.043)
Utils	−0.410	−0.183	−0.026	0.202	1.032	0.417	1.871	1.871
	(0.256)	(0.194)	(0.305)	(0.202)	(0.119)	(0.183)	(0.102)	(0.102)
Shops	0.584	0.696*	1.029*	1.161*	1.595*	1.520*	2.568*	2.568*
	(0.108)	(0.088)	(0.079)	(0.059)	(0.053)	(0.059)	(0.068)	(0.068)
Hlth	−0.211	−0.046	−0.079	0.292	0.386	0.399	1.361	1.361
	(0.411)	(0.357)	(0.399)	(0.265)	(0.269)	(0.265)	(0.124)	(0.124)
Money	−0.015	0.004	0.548	0.689*	0.952*	0.894*	2.028*	2.028*
	(0.340)	(0.338)	(0.124)	(0.080)	(0.071)	(0.080)	(0.054)	(0.054)
Other	0.366	0.639*	1.149*	1.511**	1.999**	2.046**	2.822**	2.822**
	(0.143)	(0.073)	(0.055)	(0.020)	(0.021)	(0.019)	(0.041)	(0.041)

forecasting performance of oil during the recent three subsample periods is more encouraging. For example, the restricted model with oil volatility reveals significant stock volatility for 8 out of 12 industry portfolios. Consistent with the results for stock index volatility, the ΔR^2_{OOS} values become large during more recent periods. That is, the predictive ability of oil volatility for industry portfolio volatility becomes stronger over time.

Why does predictability disappear for some industries? Oil price shocks could be a systematic risk because they affect many industries and may not be diversifiable. Indeed, this may be the reason it can forecast market volatility, which is a measure of systematic risk. However, many firms may have used derivatives, like oil futures contracts, to hedge away the oil price risk. For these industries, using oil volatility fails to obtain more accurate forecasts of industry volatility. In addition, Hong et al. (2007) point out that the information of a significant number of industry portfolios leads the stock market by one or two months. Nevertheless, our subsample analysis suggests that oil volatility has significant predictive power that is stronger for the portfolio volatilities of most industries during more recent periods.

9. Conclusions

This paper examines the evidence for short-term predictability of U.S. stock volatility using crude oil volatility as predictor. We establish several findings. First, the slope coefficients in predictive regressions of stock volatility on the oil volatility are significantly positive via an in-sample analysis. Second, adding oil volatility to the benchmark of autoregressive model can significantly improve out-of-sample forecasting performance. Third, we establish the economic significance of the stock volatility predictability by showing that the portfolio constructed on oil-based forecasts of stock volatility displays a higher certainty equivalent return than the benchmark forecasts.

We examine the robustness of predictability by considering a wide range of alternative benchmark models with macro variables. Our results suggest that the predictability is not affected by the change of benchmark models to a large extent. Our finding gives a new factor explaining and forecasting stock return volatility.

We further extend the forecasting exercise in three dimensions. First, we use nonlinear models to capture the relationship between oil and stock volatility. However, we find little evidence supporting the superiority of nonlinear models over the simple linear models. Second, we do forecasting analysis for longer horizons. Our evidence indicates that oil cannot predict stock volatility for longer horizons of 9 months. Finally, we forecast industry portfolio return volatilities using oil volatility. The results show the existence of significant predictability for a significant number of portfolios during recent periods.

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