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The role of oil futures intraday information on predicting US stock market volatility

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ABSTRACT

This study investigates the role of oil futures price information on forecasting the US stock market volatility using the HAR framework. In-sample results indicate that oil futures intraday information is helpful to increase the predictability. Moreover, compared to the benchmark model, the proposed models improve their predictive ability with the help of oil futures realized volatility. In particular, the multivariate HAR model outperforms the univariate model. Accordingly, considering the contemporaneous connection is useful to predict the US stock market volatility. Furthermore, these findings are consistent across a variety of robust checks.

1. Introduction

"*Measuring, forecasting, and controlling risk are at the heart of financial, economic theory and practice*" (Bollerslev et al., 2018). However, accurately forecasting stock market volatility is still an enormous challenge. Modeling and forecasting volatility using high-frequency (intraday) data have received more attention by scholars, for example, Andersen et al. (2007), Patton and Sheppard (2015), Liu et al. (2018), Ma et al. (2019a, 2019b, 2019c), Cai et al. (2019), Sun et al. (2019), and Qiu et al. (2019). One of the reasons for it is that high-frequency data can easily be acquired with the rapid development of computer technology and data storage. Andersen and Bollerslev (1998) propose realized volatility (RV), which is used to measure the "latent" volatility. The RV has some apparent advantages compared to traditional measures, such as "observable" and non-parameter. More importantly, the RV itself can contain much more intraday information. Also, and its prediction models have superior performance in forecasting volatility compared to traditional low-frequency models.

Considering the importance of the US stock market to the world stock markets (Rapach et al., 2013; Buncic and Gisler, 2016), we focus on forecasting US stock market volatility. To the best of knowledge, many studies (e.g., Dimpfl and Jank, 2016; Ma et al., 2019b; Liang et al., 2020; Vo and Tran, 2020) have investigated the predictive ability of the US stock market volatility. Notably, this paper is different from the abovementioned studies. It focuses on exploring the role of oil market intraday information on the US stock market volatility.[1]

There are several motivations for this research. First, oil is an important commodity for the US economy. The early studies emphasize the effects of oil price shocks on macro-economic indicators, which are the unemployment rate and inflation (e.g.,

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[1] Consistent with several previous studies, we use S&P 500 index to represent the US stock market.

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Hamilton, 1983; Mork, 1989; Hutchison, 1993; Cologni and Manera, 2008). As the oil market and macroeconomy have interconnection, several studies (e.g., Kling, 1985; Sadorsky, 1999; Jones and Kaul, 1996) naturally investigate the oil-stock market correlations, for example, the correlation between oil price volatility and stock market returns, and the correlation between oil shocks and returns.[2]

More importantly, there is a controversial opinion on whether oil futures prices have an impact on the US stock market volatility. For example, Bachmeier and Nadimi (2018) indicate that oil price volatility does not help predict stock return volatility using out-of-sample tests (e.g., the S&P 500, industry-level returns for 49 sectors, and the CRSP value-weighted index). Also, Vo (2011), Angelidis et al. (2015), Kang et al. (2015), and Xu et al. (2019) support this view. However, Christoffersen and Pan (2018) empirically show that oil price fluctuation is a reliable predictive indicator for the overall stock market after the financialization of commodity futures markets in 2004–2005.[3] Driesprong et al. (2008) and Wang et al. (2018) suggest that the oil price has predictive power over the stock return volatility. It is worthy to note that the above studies have primarily concerned with investigating links between oil and stock markets using low-frequency (e.g., monthly, daily) data. Also, we find that there are few studies to directly investigate the role of oil futures intraday information on US stock market volatility. In this research, we use a popular model, the heterogeneous autoregressive model (HAR-RV) proposed by Corsi (2009), to evaluate the predictive ability of oil futures intraday information. That helps to understand if the high-frequency data is useful to determine the relationship between the oil and stock markets.

Several studies (Degiannakis and Filis, 2017; Ma et al., 2019a) empirically show that stock market volatility impacts on future oil price volatility. For example, Degiannakis and Filis (2017) provide empirical evidence that using different "information channels" (e.g., stock market) increases the predictive ability of the oil price RV. Ma et al. (2019a) empirically demonstrate that jumps, cojumps, and jumps intensity between oil and US markets significantly increase the forecasting accuracy of oil market volatility. Moreover, some existing studies (e.g., Vo, 2011; Mensi et al., 2013; Souček and Todorova, 2013; Phan et al., 2016) point out that there are substantial cross-market volatility effects in both markets. Importantly, Souček and Todorova (2013) exhibit that the instantaneous correlation is increasing between equity and energy futures. To this end, to understand the interaction effects between the oil futures and US stock markets, we not only use the univariate prediction models but also construct the multivariate models.

The contributions of this research are threefold. First, we employ a straightforward technique to exploit the influence of oil futures intraday information on predicting the US stock market volatility using high-frequency data. That can provide a clear conclusion on whether oil futures intraday information is useful to predict the US stock volatility. Second, very few studies have evaluated the role of oil futures intraday information on the US stock market volatility using the multivariate models. In this paper, we use the univariate and multivariate models to investigate the role of oil futures on the US stock market. We find that multivariate models, taking into account the contemporaneous connection, can have higher accuracies. This finding helps us to offer a clear answer and provide some insights into volatility forecasting when two markets have interaction effects. Third, we further investigate the middle-term and long-term predictability of oil futures prices, and that extends and enriches our findings. Moreover, we also explore the effect of oil futures price intraday information for different fluctuation conditions.

This paper discovers some crucial findings. In-sample results show that oil RV can slightly increase the goodness-of-fit of the model, implying that oil RV may be a predictive indicator of the US stock market. Surprisingly, the impact of oil price volatility on different horizons varies. Moreover, the out-of-sample test determines that including oil RV can improve the forecasting performance, indicating that oil RV is useful to predict the US stock market volatility. Also, the multivariate HAR model outperforms the univariate HAR model in predicting stock market volatility. It implies that the contemporaneous connection between the US stock and oil markets can help forecast the US stock market. Hence, investors and policymakers should pay attention to the oil price risk, especially when oil price volatility is high. Our conclusions are consistent across a variety of robust checks, such as the direction-of-change test, different realized measurements, different predictive windows, and different forecast models. Finally, the multivariate HAR model with oil intraday information helps forecast the S&P 500 futures index. However, for long-horizon forecasts, oil intraday information is not useful.

2. Models

2.1. Benchmark model

Corsi (2009) proposes a heterogeneous autoregressive RV model based on the heterogeneous market hypothesis, called the HAR-RV model. This model contains three components, short-, middle- and long-term volatilities, and these components represent the different behaviors. The HAR-RV model has been investigated extensively. Because the HAR-RV model can easily be calibrated and has some apparent advantages, including understanding the stylized facts (e.g., long memory) and good predictability. Therefore, in this study, the HAR-RV model is the benchmark model, which can be expressed as,

[3] The idea, oil price fluctuation does not have influence on future stock market volatility, is supported by some studies, such as Vo (2011), Angelidis et al. (2015), Kang et al. (2015), and Xu et al. (2019).

Table 1
Description of the models employed in this research.

Model	Model name	Equation (Main)	Description
Model 0	HAR-RV	Equation (1)	Corsi (2009)
Model 1	HAR-RV-OIL	Equation (2)	Oil market information is added to the HAR-RV model.
Model 2	VHAR-RV-OIL-DCC	Equations (2)–(5)	Multivariate realized volatility model.

Notes: In this paper, we do not exhibit all the components of the multivariate model. For example, the VHAR-RV-OIL-DCC model can be seen in Eqs. (2)–(5), but in Eq. (2), RV_t^{oil}, $RV_{t-5,t}^{oil}$, and $RV_{t-22,t}^{oil}$ can be determined by using the model $RV_{t,t+1}^{oil} = \beta_0 + \beta_1 RV_t + \beta_2 RV_{t-5,t} + \beta_3 RV_{t-22,t} + \gamma_1 RV_t^{oil} + \gamma_2 RV_{t-5,t}^{oil} + \gamma_3 RV_{t-22,t}^{oil} + \varepsilon_{t+1}$. In this model, the oil market volatility is the dependent variable, and then the model in Eq. (2) is combined with the DCC model to develop a new model, VHAR-RV-OIL-DCC, and it is applied to predict the US stock market volatility.

$$RV_{t,t+1} = \beta_0 + \beta_1 RV_t + \beta_2 RV_{t-5,t} + \beta_3 RV_{t-22,t} + \varepsilon_{t+1}, \tag{1}$$

where $RV_t = \sum_{i=1}^{M} r_{t,j}^2$, M is observations in a trading day, $RV_{t-5,t} = (RV_{t-4} + RV_{t-3} + \ldots + RV_t)/5 RV_{t-22,t} = (RV_{t-21} + \ldots + RV_t)/22$, and ε_{t+1} is the error.

2.2. Predictive models including oil market information

To this end, we use the HAR-RV model to exploit the effect of oil price volatility information and then add oil RV to the HAR-RV model based on the works of Buncic and Gisler (2016) and Degiannakis and Filis (2017). Having oil price volatility information, we propose a predictive model, called the HAR-RV-OIL model, which is given below,

$$RV_{t,t+1} = \beta_0 + \beta_1 RV_t + \beta_2 RV_{t-5,t} + \beta_3 RV_{t-22,t} + \gamma_1 RV_t^{oil} + \gamma_2 RV_{t-5,t}^{oil} + \gamma_3 RV_{t-22,t}^{oil} + \varepsilon_{t+1}, \tag{2}$$

where the superscript of specific variables, “oil”, indicates that the values of those variables are obtained from the oil market information. For example,RV_t^{oil} is the daily RV, $RV_{t-5,t}^{oil}$ is the weekly RV, and $RV_{t-22,t}^{oil}$ is the monthly RV.

2.3. The VHAR model and proposed models

We further use the multivariate realized volatility model to predict the volatility of the US market due to three main reasons: (a) The studies of Vo (2011), Mensi et al. (2013), and Phan et al. (2016) have examined that the stock market volatility can significantly influence the oil price volatility; (b) the volatility of volatility (VOV) can raise the predictability of the linear models such as the HAR-RV (e.g., Corsi et al., 2008; Ma et al., 2017); and (c) There is a cross-market volatility effect. Our models (e.g., HAR-RV-OIL) may have an endogenous problem. Additionally, we may ignore the internal connection between the two markets. Hence, we put forward an extension of the HAR model, which is a multivariate model and called the vector HAR (VHAR) model. We use the dynamic conditional correlation (DCC) model suggested by Engle (2002) to construct the multivariate HAR model. Consequently, we build a new multivariate model,[4] called VHAR-RV-OIL-DCC model. The variance-covariance matrix can be written,

$$H_t = D_t R_t D_t, \tag{3}$$

where $D_t = \mathrm{dig}\left(h_{11,t}^{1/2}, \cdots, h_{NN,t}^{1/2}\right)$, and $h_{ii,t}$ is any univariate GARCH model. According to Engle (2002), below is the correlation matrix,

$$R_t = \mathrm{dig}\left(q_{11,t}^{-1/2}, \cdots, q_{NN,t}^{-1/2}\right) Q_t \mathrm{dig}\left(q_{11,t}^{-1/2}, \cdots, q_{NN,t}^{-1/2}\right), \tag{4}$$

where $Q_t = (q_{ij,t})$, which can be expressed as,

$$Q_t = (1 - \delta_1 - \delta_2)\overline{Q} + \delta_1 Q \eta_{t-1} \eta_{t-1}' + \delta_2 Q_{t-1}, \tag{5}$$

where $\overline{Q}$is the unconditional variance matrix of η_t,which is $\varepsilon_{i,t}/\sqrt{h_{ii,t}}$, and δ_1 and δ_2 are nonnegative scalar parameters that satisfy the condition $\delta_1 + \delta_2 < 1$. Similar to Engle (2002), Caporin and McAleer (2012), Wang and Wu (2012), and Souček and Todorova (2013), the DCC model is estimated by a two-step method. In the first step, individual GARCH models are estimated, and in the second step, correlation coefficients are estimated. The proposed VHAR-RV-OIL-DCC model is used to predict the

[4] We build a new model, which is very similar to the HAR-RV-OIL. The main difference is that, we use oil RV to substitute the US RV as a dependent variable in Eq. (2). Then, we use them to combine with the DCC model and construct VHAR-RV-OIL-DCC model, and then forecast the US stock market volatility.

Table 2
Statistics for realized measures.

Variables	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Q (5)	ADF
RV^{US}	1.283	3.123	9.777***	161.379***	2717411.627***	4719.384***	-23.272***
RV^{oil}	2.871	4.252	4.103***	24.819***	157962.334***	7027.095***	-19.916***

Notes: RV^{US} and RV^{oil} represent the US stock and oil markets realized volatility and Std. Dev. is the abbreviation for the standard deviation. Asterisks *** and ** denote the rejection of the null hypothesis at 1% and 5% significance levels, respectively. The values of the mean and standard deviation are multiplied by 10000.

volatility of the US market. This model can also obtain the dynamic correlations and covariances that are different from the ones obtained from individual predictive models.

Table 1 presents the details of the models investigated in this paper.

3. Data

Liu et al. (2015) indicate that 5-min RV is the most appropriate measure in empirical forecasting exercises.[5] Since previous works, such as Haugom et al. (2014), Degiannakis and Filis (2017), and Zhang et al. (2019a), have employed the 5-min sampling frequency as a rule of thumb, we also use the same sampling frequency in our empirical studies. The WTI futures contract and the US stock market data (e.g., S&P 500) are collected from Thomson Reuters Tick History Database (TRTH) between January 1, 2007 and April 30, 2017. We clean the data by eliminating the days with too few transactions and obtain the oil market data for 2643 trading days, and the US stock market data for 2573 trading days. For the multivariate HAR model, matching the trading days for both markets, we obtain the data for 2560 common trading days.[6]

Table 2 shows descriptive statistics of the US and oil RVs. From Table 2, we observe that the statistical results are in agreement with many studies. At the 99% confidence level, the series (RV^{US} and RV^{oil}) are remarkably right-skewed and also leptokurtic. Moreover, the Jarque-Bera statistic test suggests that the US and oil RVs are not normally distributed. Additionally, using the Ljung-Box test, we examine the null hypothesis of no autocorrelation up to the 5th order. The result shows that the null hypothesis is rejected for both RVs, and it implies that RVs are serially correlated. Lastly, at the 99% confidence level, the ADF test suggests that the RVs are stationary.

Fig. 1 depicts magnitudes of the US stock and oil RVs from January 1, 2007 to April 30, 2017. We observe that during the 2008 financial crisis, the US stock and oil markets have large fluctuations. Comparing to the US stock market, oil prices have larger turbulences, which are supported by standard deviations presented in Table 1.

4. Empirical analysis

4.1. The estimated results through the in-sample period

Several empirical studies, including Aït-Sahalia and Mancini (2008) and Paye (2012), show that the log of the RV follows a Gaussian distribution. Hence, we use the logarithmic realized measurements to estimate the models and forecast the US stock market volatility. Table 3 presents the in-sample period for both benchmark and competing models. For both univariate and multivariate HAR models, we observe that daily, weekly, and monthly coefficients of stock market RVs are remarkable. It strongly suggests that the realized volatilities have long-memory. Moreover, the oil market RVs have mixed impacts, especially the long-term oil RV. The monthly oil RV can significantly impact on the future stock market RV. For the univariate models, we observe that the adjusted R-square values of the HAR-RV-OIL model slightly increase. It shows that oil market volatility contains valuable information. Furthermore, we use the LM ARCH test, which is presented in Engle (1982), to examine the ARCH effects of the univariate models. Table 3 presents the results showing that, for these models, there are the ARCH effects at the 1% significance level. These results further support us in studying the multivariate HAR using the DCC model. Finally, the results, $\delta_1 + \delta_2 < 1$, show that the DCC model is stable and can be used to model and forecast the US stock market volatility.

4.2. Evaluated results through the out-of-sample period

In this subsection, we pay more attention to the predictability of competing models through the out-of-sample period. Such performance comparison is more useful to scholars and investors because the ability of the model to predict the future with higher accuracy is more important than the ability to analyze the past. The rolling method is prevalent to forecast future volatility. Therefore, for both benchmark and competing models, we use the same approach to predict future volatility. In this

[5] Andersen et al. (2003) find that using the 5-min sampling frequency can provide the balance between market microstructure noise and measurement accuracy.

[6] Notably, we drop the first 22 days' information and then have 2538, which is 2560-22, trading days' data to forecast the US stock market volatility.

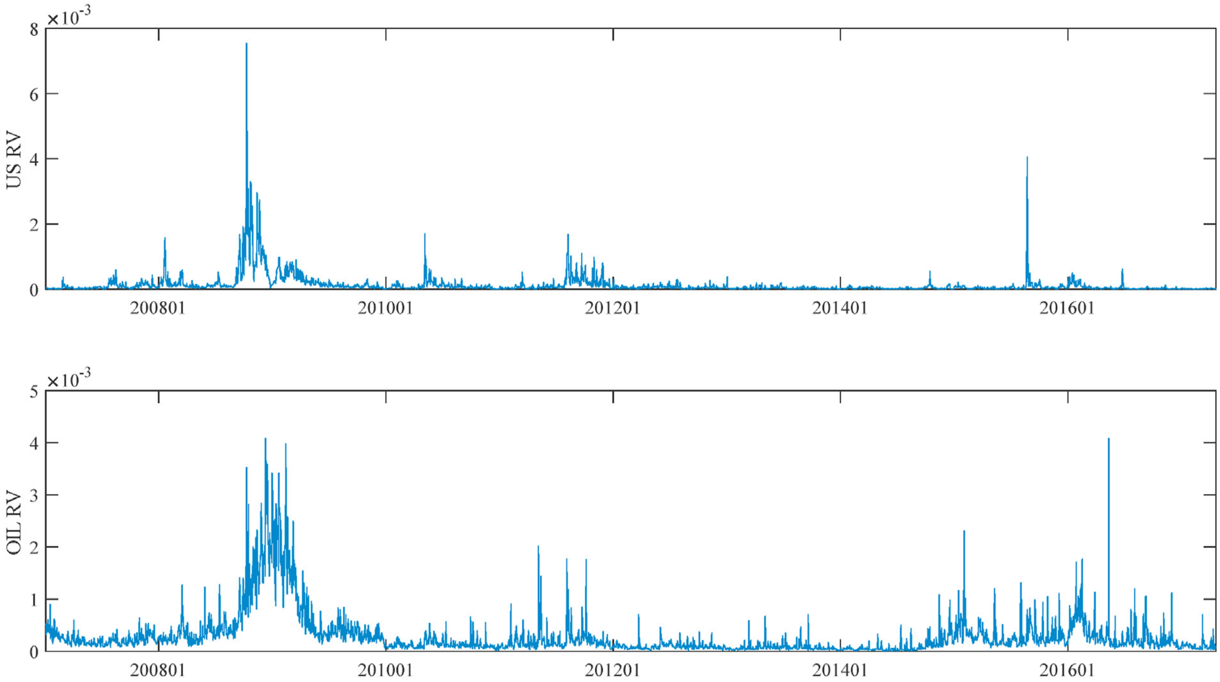

Fig. 1. The magnitudes of the US stock RV and oil RV.

research, based on the data that we obtained, we select the length of the fixed window of 1838 days and the out-of-sample period of 700 days.

We employ R^2_{OOS} to assess the superiority of the models (Models 0–2). The details of the R^2_{OOS} can be found in Christoffersen and Pan, 2018 and Ma et al. (2018). R^2_{OOS} is defined as

$$R^2_{oos} = 1 - \frac{\sum_{t=1}^{B}\left(\mathrm{RV}_t - \widehat{\mathrm{RV}}_{t,i}\right)^2}{\sum_{t=1}^{B}\left(\mathrm{RV}_t - \widehat{\mathrm{RV}}_{t,0}\right)^2},\ i = \text{“Model1”}, \text{“Model2”}, \tag{6}$$

where $B = 700$ days, RV_t is the real volatility of day t, $\widehat{\mathrm{RV}}_{t,i}$is the forecast based on model i through the out-of-sample period, and $\widehat{\mathrm{RV}}_{t,0}$ is the forecast by the benchmark model, which is the HAR-RV model. If the value of R^2_{oos}exceeds zero, the competing model outperforms the benchmark model and vice versa. Furthermore, we employ the MSPE-adjusted statistic to evaluate whether the forecasting performance of competing and benchmark models has any significant difference (Clark and West, 2007).

Out-of-sample evaluations are reported in Table 4 using R^2_{OOS} test. We have several compelling findings. First, regarding the univariate model, we observe that the R^2_{OOS} value of the HAR-RV-OIL model is 0.554%, indicating that it remarkably outperforms the benchmark model. Specifically, the improvement of the HAR-RV-OIL model is 0.554%, suggesting that oil price volatility information can include valuable information to predict the US stock market volatility. Second, for the multivariate model, theR^2_{OOS} value of the VHAR-RV-OIL-DCC model is larger than zero. This observation implies that this model is a powerful tool to forecast volatility. Third, comparing the univariate model to the multivariate model, we notice that the R^2_{OOS} value of the VHAR-RV-OIL-DCC (multivariate) model is larger than the R^2_{OOS} value of the univariate model. For example, for the HAR-RV model, the improvement of VHAR-RV-OIL-DCC is 0.637% (from 0 to 0.637%). However, for the HAR-RV-OIL model, the improvement of VHAR-RV-OIL-DCC is 0.083% (from 0.554% to 0.637%). These results show that the contemporaneous links between US stock and oil markets may help predict the US stock market volatility.

4.3. *Robust tests*

4.3.1. *Direction-of-change*

We employ the Direction-of-Change (DoC) test as our alternative test to evaluate the benchmark and competing models. The DoC test is vital to design trading strategies and manage a portfolio. It may provide a fraction of the forecast that has appropriately determined the upward or downward movement of the volatility. The fraction of the forecast can be described as follows:

Table 3
In-sample period results of the benchmark and competing models.

	HAR-RV	HAR-RV-OIL	VHAR-RV-OIL-DCC
β_0	-0.645***	-0.415**	-0.458***
β_1	0.339***	0.319**	0.311***
β_2	0.407***	0.423**	0.445***
β_3	0.195***	0.127**	0.108**
γ_1		0.0488	0.047
γ_2		-0.073	-0.108
γ_3		0.130**	0.159*
δ_1			0.000
δ_2			0.987***
ARCH	9.697***	8.996***	
Adj.R^2	0.695	0.698	

Notes: Asterisks ***, **, and * represent the rejection of null hypothesis at the 1%, 5%, and 10% significance levels, respectively. The abbreviation Adj.R^2 denotes the adjusted R-square. ARCH is the ARCH test proposed by Engle (1982). The coefficients of VHAR-RV-OIL-DCC model are only reported for the dependent variable of the US stock market volatility, $\mathrm{RV}_{t,t+1} = \beta_0 + \beta_1 \mathrm{RV}_t + \beta_2 \mathrm{RV}_{t-5,t} + \beta_3 \mathrm{RV}_{t-22,t} + \gamma_1 \mathrm{RV}_t^{\mathrm{oil}} + \gamma_2 \mathrm{RV}^{\mathrm{oil}}_{t-5,t} + \gamma_3 \mathrm{RV}^{\mathrm{oil}}_{t-22,t} + \varepsilon_{t+1}$. Specifically, we do not provide the results of the GARCH component and the dependent variable, oil RV, $\mathrm{RV}^{\mathrm{oil}}_{t,t+1} = \beta_0 + \beta_1 \mathrm{RV}_t + \beta_2 \mathrm{RV}_{t-5,t} + \beta_3 \mathrm{RV}_{t-22,t} + \gamma_1 \mathrm{RV}_t^{\mathrm{oil}} + \gamma_2 \mathrm{RV}^{\mathrm{oil}}_{t-5,t} + \gamma_3 \mathrm{RV}^{\mathrm{oil}}_{t-22,t} + \varepsilon_{t+1}$. Regarding the omitted estimations, the readers can request them from authors. These models are converted to logarithmic form.

Table 4
Out-of-sample period results of univariate and multivariate forecasting models.

Models	R^2_{OOS} (%)	MSPE-adjust	*p*-value
HAR-RV-OIL	0.554**	1.900	0.029
VHAR-RV-OIL-DCC	0.637**	1.850	0.032

Notes: Asterisk ** represents the rejection of the null hypothesis at the 95% confidence level. The HAR-RV is the benchmark.

$$p_{ti} = \begin{cases} 1, if \mathrm{RV}_t > \mathrm{RV}_{t-1} and\ \hat{\sigma}_m^2 > \mathrm{RV}_{t-1} 1, if \mathrm{RV}_t \le \mathrm{RV}_{t-1}\ and\ \hat{\sigma}_m^2 \le \mathrm{RV}_{t-1} 0\ otherwise., \end{cases} \tag{7}$$

where p_{ti}, represents that model i correctly determines the movement of the volatility. Based on Equation (7), the success ratio (SR), which indicates that model i has correctly determined the movement of the volatility, is given by,

$$SR_i = \frac{\sum_{t=1}^{M} p_{ti}}{M} \times 100, \tag{8}$$

A test provided in Pesaran and Timmermann (2009) is used to estimate the differences of the volatility movement under the null hypothesis of no accuracy of the volatility movement. Table 5 presents the results obtained from the DoC test. Notably, the null hypothesis, at the 1% significance level, is rejected by all the models. Table 5 also exhibits that the success ratio values of the models are more significant than 0.5. This result implies that these models have a powerful ability to predict the US stock market volatility. For the magnitudes of the SR, the values of HAR-RV-OIL and VAHR-RV-OIL-DCC models are higher than the value of the benchmark model. Notably, the SR values of HAR-RV-OIL and VAHR-RV-OIL-DCC models increase by 0.286% and 0.429%, respectively, compared to the SR value of the HAR-RV model. The increasing SR values provide empirical evidence that oil market information and the multivariate structures (internal links) between the US stock and oil markets can help improve the forecast accuracy.

Table 5
Out-of-sample period results using the Direction-of-Change (DOC) approach.

Model name	SR (%)	Stat. value	*p*-value
HAR-RV	64.092***	7.530	0
HAR-RV-OIL	64.378***	7.855	0
VHAR-RV-OIL-DCC	64.521***	7.951	0

Notes*:* SR denotes the success ratio. The asterisk *** indicates at the 1% significance level.

Table 6
Out-of-sample period results based on the HAR-TJ model using out-of-sample R^{21} test.

Models	R^2_{OOS} (%)	MSPE-adjust	p-value
HAR-TJ	1.407**	1.767	0.039
HAR-TJ-OIL	1.388**	1.702	0.044
VHAR-TJ-OIL-DCC	1.551**	1.831	0.034

Notes: Asterisk ** indicates the rejection of the null hypothesis at the 95% confidence level.

4.3.2. Different predictive models

Considering the importance of jumps on volatility forecasting, we examine the influence of oil market information using the HAR-TJ model, which is presented in Corsi et al. (2010). The HAR-TJ model is also a popular predictive model in the literature.[7] Hence, we choose the HAR-TJ model and its extensions to draw an analogy with the HAR-RV model. We add the oil market volatility to the HAR-TJ model and then develop the HAR-TJ-OIL model. Also, we integrate the DCC with the HAR-TJ model to construct another model called the VHAR-TJ-OIL-DCC model. Due to the scarcity of the space, we only provide the expression of the HAT-TJ model,

$$\mathrm{RV}_{t,t+1} = \beta_0 + \beta_1 \mathrm{TC}_t + \beta_2 \mathrm{TC}_{t-5,t} + \beta_3 \mathrm{TC}_{t-22,t} + \beta_4 \mathrm{TJ}_t + \varepsilon_{t+1}, \tag{9}$$

where$\mathrm{TC}_t = I(\mathrm{CT_z}_t \le \Phi_\alpha)*\mathrm{RV}_t + I(\mathrm{CT_z}_t > \Phi_\alpha)*\mathrm{C_TBPV}_t$ and$\mathrm{TJ}_t = \max(\mathrm{RV}_t - \mathrm{C_TBPV}_t,\ 0)*I(\mathrm{CT_z}_t > \Phi_\alpha)$. Additionally, $\mathrm{C\_TBPV}_t$ is the corrected threshold bi-power variation and $\mathrm{CT\_z}_t$ is the statistical value of the jumps test. The detailed procedures can be found in Corsi et al. (2010). The competing models (e.g., HAR-TJ and its extensions) and the benchmark model are compared, and the results are presented in Table 6. We observe that the improvement of these models ranges from 1.388% to 1.551%. In general, the multivariate HAR model beats the benchmark and competing models, and that directly indicates that the contemporaneous connections between the oil and US stock markets can comprise more valuable information to predict the US stock market volatility.

4.3.3. Different rolling windows

Choosing diverse estimated and predictive sample sizes may result in distinct empirical results (Rapach et al., 2013). Therefore, the number of days in the out-of-sample period influences the predictive ability of the benchmark and competing models. We choose a couple of rolling windows, such as 600 and 800 days, to implement the robustness checks. Table 7 shows the empirical results. Panel A (Panel B) of Table 7 shows the empirical results of 600 (800) days. The results show some interesting findings: a) for the univariate model (HAR-RV), the improvements are 0.567% and 0.513% for different windows, and that strongly suggests that the oil market information is useful to predict the US stock market volatility; b) from Table 7, we notice that the VHAR-RV-OIL-DCC model can significantly outperform the benchmark model and the R^2_{OOS} value of the VHAR-RV-OIL-DCC model is more significant than that of the other models. This finding reinforces our conclusions and provides direct evidence that our conclusions are robust. We examine the influence of the oil RV on the US stock market volatility using univariate and multivariate models. That provides some insights into forecasting stock market volatility.

4.3.4. Realized kernel

In the section, we employ realized kernel (RK) (Barndorff-Nielsen et al., 2008), as an alternative to the actual volatility, since the RK is vigorous to market microstructure noise. Several studies also have a similar treatment (e.g., Wang et al., 2015; Zhang et al., 2019b). The RK is defined as,

$$\mathrm{RK}_t = \sum_{u=-H}^{H} K\left(\frac{u}{u+1}\right)\gamma_u, \gamma_u = \sum_{w=|u|+1}^{n} r_{t,w} r_{t,w-|u|}. \tag{10}$$

In the above expression, Parzen kernel function, $k(y)$, is expressed by,

$$K(\mathrm{y}) = \begin{cases} 1 - 6y^2 + 6y^3 & 0 \le y \le 1/2, \\ 2(1-y)^3 & 1/2 \le y \le 1, \\ 0 & y > 1. \end{cases} \tag{11}$$

We strictly follow the choice of H from Barndorff-Nielsen et al. (2009). Table 8 presents the out-of-sample empirical results using actual market volatility. It can be seen that HAR-RV models with the oil market information have more considerable improvement, indicating that the oil market information can increase the accuracy of the forecast of the US stock market volatility. Specifically, Panel A indicates that the R^2_{OOS} value of the HAR-RV-OIL model improves by 3.464%, and the R^2_{OOS} value

[7] Corsi et al. (2010) disclose that the C_Tz test is significantly powerful, for example, in a situation where jumps are very frequent, such as the case of high-frequency data.

Table 7
Out-of-sample comparison results with diverse rolling windows.

Models	R^2_{OOS} (%)	MSPE-adjust	*p*-value
Panel A (600 days)			
HAR-RV-OIL	0.567**	1.856	0.032
VHAR-RV-OIL-DCC	0.632**	1.864	0.031
Panel B(800 days)			
HAR-RV-OIL	0.513**	1.879	0.030
VHAR-RV-OIL-DCC	0.602**	1.827	0.034

Notes: Asterisk ** represents the rejection of the null hypothesis at the 95% confidence level.

Table 8
Out-of-sample empirical results using RK as actual US stock market volatility.

Models	R^2_{OOS} (%)	MSPE-adjust	*p*-value
Panel A			
HAR-RV-OIL	3.464**	1.971	0.024
VHAR-RV-OIL-DCC	3.437*	1.302	0.096
Panel B			
HAR-TJ-OIL	7.138**	1.894	0.029
VHAR-TJ-OIL-DCC	11.225***	2.526	0.006

Notes: Asterisks ***, **, and * denote the rejection of the null hypothesis at 1%, 5%, and 10% significance levels, respectively.

of the VHAR-RV-OIL-DCC model improves by 3.437%. Besides, we consider the HAR-TJ model and its extensions. In Table 8, Panel B indicates that the improvement of the HAR-TJ-OIL model is 7.138%, and the improvement of the VHAR-TJ-OIL-DCC model is 11.225[8] . In general, the oil market information and contemporaneous connections increase the predictive ability of the US stock market.

4.3.5. t-distribution and constant conditional correlation (CCC) model

We additionally consider two more robustness checks, such as *t*-distribution and CCC model (Bollerslev, 1990), and evaluate whether our conclusions are robust in different conditions. First, assumed that ε_{t+1} follows a *t*-distribution, which is different from the normal distribution assumed by the models in this paper. Panel A of Table 9 provides the R^2_{OOS} results. We observe that the improvement of the VHAR-RV-OIL-DCC is 0.642%, which is larger than that of the HAR-RV-OIL model, implying that the coherence between two markets can be useful to predict the US volatility. Moreover, we use the CCC model to capture coherence and then forecast the US stock market volatility. The CCC model is also applied in various fields, for example, Bauwens et al. (2006), Wang and Wu (2012), and Cabrera and Schulz (2016). The CCC model is significantly different from the DCC model since the CCC model assumes a constant conditional correlation, which is not time-varying. Panel B of Table 9 reports the empirical results showing that the multivariate HAR model exhibits a better forecast. That also reaffirms our findings.

4.3.6. The predictive models with considering the leverage effect

Corsi and Renò (2012) extend the work of Andersen et al. (2007) to account for the leverage effect in predictive models and indicate that the model with the leverage effect exhibits a more accurate predictive power. In this section, we control the leverage effect, $r^-_{t-1} = \min(r_{t-1},0)$, where r_{t-1} is the US stock market return. Table 10 reports the out-of-sample results using the MCS test. We find that the leverage effect can improve the predictability of the benchmark model. Compared to the univariate model, the multivariate HAR model outperforms the univariate HAR model, implying that the contemporaneous connections between the oil and US stock markets can be useful to forecast the US stock market volatility.

5. Further analysis

5.1. High oil volatility regime

To examine the predictive performance of oil futures prices at high and low volatility scenarios, we split the out-of-sample period into a couple of subsample periods depending on the average oil RV, which is determined by $\overline{\mathrm{RV}} = \frac{1}{2538}\sum_{t=1}^{2538} \mathrm{RV}_t^{\mathrm{oil}}$. Oil price volatility is called low when $\mathrm{RV}_t^{\mathrm{oil}} < \overline{\mathrm{RV}}$, whereas oil price volatility is called high when.$\mathrm{RV}_t^{\mathrm{oil}} \geq \overline{\mathrm{RV}}$[9] Thus, we re-evaluate the predictability of the benchmark and competing models. Table 11 shows the empirical results when the oil price volatility

[2] These relationships are supported by Degiannakis et al. (2017).

[8] More details on the HAR-TJ model and its extensions can be requested from authors.

[9] In this study, we choose different thresholds to define the high oil price volatility, such as exceeding 70%, 80%, and 90% oil RV, and find that our conclusions are very robust. Readers can request these robust results from the authors, if necessary.

Table 9
Out-of-sample results of univariate and multivariate forecasts based on *t*-distribution and CCC model.

Models	R^2_{OOS} (%)	MSPE-adjust	*p*-value
Panel A: t-distribution			
HAR-RV-OIL	0.554**	1.900	0.029
VHAR-RV-OIL-DCC	0.642**	1.862	0.031
Panel B: constant conditional correlation (CCC) model			
HAR-RV-OIL	0.554**	1.900	0.029
VHAR-RV-OIL-CCC	0.636**	1.861	0.031

Notes: Asterisk ** denotes the rejection of the null hypothesis at the 95% confidence level.

Table 10
Out-of-sample results in accounting the leverage effect.

Models	R^2_{OOS} (%)	MSPE-adjust	*p*-value
HAR-RV-OIL-retf	8.523*	1.463	0.072
VHAR-RV-OIL-retf-DCC	9.574*	1.448	0.074

Notes: Asterisk * represents the rejection of the null hypothesis at the 90% confidence level.

Table 11
Out-of-sample results when the oil price volatility is high.

Models	R^2_{OOS} (%)	MSPE-adjust	*p*-value
HAR-RV-OIL	0.591**	1.964	0.025
VHAR-RV-OIL-DCC	0.640**	1.778	0.038

Notes: Asterisk ** represents the rejection of the null hypothesis at the 95% confidence level.

is high. However, Table 4 presents where the whole out-of-sample period. We find that the improvement of the HAR-RV-OIL and VHAR-RV-OIL-DCC models slightly increases, indicating that when oil price volatility is high, the influence of the oil market information on the stock market volatility enhances. For example, the improvement of the VHAR-RV-OIL-DCC model increases from 0.637% to 0.640%. Based on these empirical results, we suggest that investors and policymakers should pay attention to the oil price risk, especially when oil price volatility is high[10].

5.2. The oil intraday information and S&P 500 futures index

We are also interested in investigating if the oil intraday information is helpful for predicting the S&P 500 futures index, since it receives much attention, for example, Corsi et al. (2010), Souček and Todorova (2013), Frijns et al. (2016), and Tu et al. (2016). Particularly, we look into the impact of the oil intraday information on the one-step-ahead volatility of the S&P 500 futures index. The 5-min S&P 500 futures price data are obtained from TRTH database, including from January 1, 2007 to December 31, 2016.[11] To be consistent, we choose the last 700 days as an out-of-sample length. Table 12 shows the empirical results based on the out-of-sample R^2 (R^2_{OOS}). We find that the improvements of the HAR-RV-OIL and VHAR-RV-OIL-DCC models are 0.758% and 0.872%, respectively. It clearly indicates that oil intraday information can increase the accuracy of the forecast of the S&P 500 futures prices index, especially considering the contemporaneous connection. Although oil intraday information contains useful information to predict the US financial markets, very few studies explore the links between the S&P 500 futures and oil markets using high-frequency data. To some extent, this paper fills that gap in the literature.

5.3. Long-horizon forecasts

We investigate whether the multivariate model with oil intraday information can still outperform the univariate model (e.g., benchmark model) for long-term forecasting. To this end, we forecast one-week and one-month US stock market volatilities and also evaluate the ability of the models to predict the volatilities. We replace $\mathrm{RV}_{t,t+1}$ with $\mathrm{RV}_{t,t+h}$ for all predictive models, where h is equal to 5 and 22, respectively. For example, when $h=5$, $\mathrm{RV}_{t,t+5}=\frac{1}{5}(\mathrm{RV}_{t,t+1}+\ldots+\mathrm{RV}_{t,t+5})$. Table 13 demonstrates the out-of-sample empirical results based on diverse horizons. We observe that, in general, the oil intraday information does not comprise the predictive ability, and the multivariate structure model has an inferior performance for long-horizon forecasts.

[10] For the framework of the HAR-TJ model and its extensions, the improvement of the VHAR-TJ-OIL-DCC model increases from 1.551% to 2.163%.

[11] Based on the available permission, the S&P 500 futures data ends on December 31, 2016.

Table 12
Out-of-sample results of univariate and multivariate forecasts in the S&P 500 futures index.

Models	R^2_{OOS} (%)	MSPE-adjust	p-value
HAR-RV-OIL	0.758**	2.045	0.020
VHAR-RV-OIL-DCC	0.872**	1.631	0.051

Notes: Asterisk ** represents the rejection of the null hypothesis at the 95% confidence level.

Table 13
Out-of-sample empirical results based on different horizons.

Models	R^2_{OOS} (%)	MSPE-adjust	p-value
$h = 5$			
HAR-RV-OIL	1.901***	2.798	0.003
VHAR-RV-OIL-DCC	0.735	1.210	0.113
$h = 22$			
HAR-TJ-OIL	-5.834**	2.089	0.018
VHAR-TJ-OIL-DCC	-8.227***	2.377	0.009

Notes: Asterisks **, and *** denote the rejection of the null hypothesis at 5% and 10% significance levels, respectively.

6. Conclusions and implications

Having access to the high-frequency data, recent development in modeling and forecasting stock market volatility using intraday information is paramount by scholars and practitioners. In the same line of research, this study comprehensively examines the effect of oil market intraday volatility information on the US stock market volatility using univariate and multivariate models. Based on a series of empirical results, we conclude some noteworthy findings. First, oil market volatility can slightly increase the goodness-of-fit of the model through the in-sample period. It suggests that oil market volatility may contain valuable information for forecasting the US stock market volatility. Also, the impact of oil daily realized volatility (RV), weekly RV, and monthly RV varies. Second, out-of-sample results strongly show that the oil price volatility information improves forecasting the US stock market volatility. Third, our multivariate HAR model outperforms the univariate HAR model. It implies that the contemporaneous connections between the oil and US stock markets can help forecast the US stock market volatility. Fourth, investors and policymakers should pay attention to the oil risk when the oil price volatility is high. Additionally, our conclusions are consistent across a variety of robust checks, such as the direction-of-change test, different realized measurements, different predictive windows, and different forecast models. Finally, the multivariate HAR model with oil intraday information helps forecast the S&P 500 futures index. However, oil intraday information is not useful for long-horizon forecasts.

The findings of this study are beneficial to researchers, market participants, and policymakers because volatility is one of the critical inputs to portfolio selection, hedging strategies, and risk management. Finally, this research provides empirical evidence that oil market risk should not be overlooked when predicting the US stock market volatility and designing equity options, especially when oil risk is high. Based on the internal links between the US stock and oil markets, investors may use some hedging strategies to safeguard their assets when holding the oil and US equities.

Conflict of interest

The authors declare no conflict of interest.

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