Journal of Economic Studies

Modeling and forecasting oil price risk: the role of implied volatility index

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Modeling and Forecasting Oil Price Risk: The Role of Implied Volatility Index

Abstract

Purpose: While numerous empirical studies have tried to model and forecast the oil price volatility over the years, such attempts using the crude oil volatility index (OVX) rarely exist. In order to conceal this void, the present article investigates whether including OVX in the realized volatility (RV) models improve the accuracy of predictions.

Design/Methodology/Approach: At the empirical stage, we employ several measures to frame the RV of crude oil futures returns. In particular, we use three different range-based RV estimators recommended by Parkinson (1980), Rogers and Satchell (1991) and Alizadeh et al. (2002) respectively.

Findings: Our findings reveal that the information content of crude oil volatility index helps to provide more accurate volatility predictions in comparison to the base-line RV model which contains only historical oil volatilities. Besides, the forecast encompassing test further suggests that the modified RV model (when OVX is introduced in the base-line RV model) forecast encompasses the conventional RV forecast in majority of the cases.

Practical implications: Since forecasting oil price volatility plays a vital role in portfolio optimization, derivatives pricing, optimum asset allocation decisions and risk management, the findings of our study thus carry important implications for energy economists, investors and policymakers.

Originality/Value: This paper adds to the existing literature, since it is one of the initial studies to explore whether OVX is informative about the realized variance of the US oil market returns. Our findings recommend that the information content of oil implied volatilities should be taken into account when modeling the US oil market volatility. In addition, range-based measures should be utilized while estimating the realized volatility.

Keywords: Oil price volatility; OVX; range-based RV measures; RV models; WTI oil price futures; Forecast encompassing.

1. Introduction

Oil embodies a prominent role in the international economy as it continues to remain world's leading fuel accounting for 32.9% of global energy consumption[1]. Variations in crude oil price are thus likely to bring uncertainty for the global economic development and growth. Since oil market is reported to be one of the most volatile markets, several researchers have examined how and to what extent oil price volatility affects the overall economy. For example, Bouri (2015a) argues that oil price shocks can spill over into equity markets leading to immediate disturbances in financial markets and distant disruptions of economic activities. Vo (2011) also demonstrates that an increment in oil price leads to higher production costs which affect inflation, consumer confidence and hence economic growth. In addition, Chiou and Lee (2009) contend that if oil price has an impact on real output, an increase in oil price will depress aggregate stock prices suggesting a significant association between oil prices and equity market returns. Besides, Zhang and Tu (2016) report that metal industry is highly oil-intensive and hence oil price volatility certainly affects the metal markets and hence the overall economy. Therefore, crude oil is considered a key commodity for the national and international economies.

Considering the significance of the relationship between oil market and the overall economy, it is essential to minimize the negative impact of oil price fluctuations. To do so, it is very important to accurately predict the oil price direction, although forecasting the crude oil price is a hard task due to its intrinsic difficulty and practical applications (Xie et al., 2006). Nevertheless, researchers are always in search of precise methodologies in order to estimate the prices of this widely used energy commodity with accuracy. Consequently, predictions of oil price volatility have received significant attention in the literature. Important contributions include Morana

[1] This information is sourced from www.bp.com

(2001), Cortazar and Schwartz (2002), Fong and See (2002), Lanza et al. (2005), Coppola (2008), Kang et al. (2009), Vo (2009) and others. Morana (2001), for example, documents how the GARCH properties of oil price changes can be employed to forecast the oil price distribution over short-term horizons. The author employs a semi-parametric method to forecast the volatility of Brent crude oil prices. More recently, Kang et al. (2009) compare a number of GARCH models to predict the volatility of Brent, WTI and Dubai crude oil prices. The results show that for Brent and Dubai, the fractionally integrated GARCH model performs better than the other GARCH models, while the component GARCH model is found to outperform the rest in case of WTI crude oil.

Unlike the studies cited above, the present paper aims to forecast the oil price volatility using the information content of a newly published crude oil volatility index (OVX) from the Chicago Board Options Exchange (CBOE). Although numerous studies argue that the performance of volatility models can be substantially improved with the inclusion of VIX (Taylor, 2008), the crude oil volatility index has not received much attention in forecasting oil price variation. This is surprising, since OVX is a market-determined forecast which is quite similar to the implied volatility index in the stock market (Ji and Fan, 2016). For example, Maghyereh et al. (2016) contend that as volatilities are derived from market option prices, they are forward looking and thus they represent the markets' consensus on the expected future uncertainty. Besides, other researchers such as Liu et al. (2013) suggest that the use of OVX in predicting future realized volatility of crude oil prices will be potentially fruitful[2]. Nonetheless, predictions of oil price

[2] Earlier studies document that the information content of commodity market implied volatility index improves the volatility forecasts based on realized volatilities. Luo and Ye (2015), for example, report that the CBOE Silver ETF Volatility Index (VXSLV) is suitable for predicting the volatility of the Shanghai silver futures market. More

volatility using OVX are almost non-existent. The only exception includes Haugom et al. (2014) who document, using a heterogeneous auto-regressive (HAR) model, that the day-ahead and week-ahead volatility forecasts of oil futures can be significantly improved by including information from the crude oil implied volatility index.

In order to extend this scarce literature, the present study uses the information content of the implied oil volatility (IV) index for modeling and forecasting the realized variance of WTI crude oil futures prices. Our paper differs from Haugom et al. (2014) in that we have used various range-based measures to estimate the realized volatility (RV) of oil market returns, while the former considers the RV measure based on squared returns. This can be considered as an important contribution, since several researchers (Alizadeh et al., 2002; Viteva et al., 2014) argue that range-based volatility estimators are better than squared returns in capturing the underlying volatility process. For instance, Alizadeh et al. (2002) contend that range-based volatility measures are more robust to the microstructure noise caused by the bid/ask bounce. We also extend the study by Haugom et al. (2014) by applying the forecast encompassing test to determine whether the use of OVX is of assistance. That is, the test allows us to examine if the underlying IV index is informative about the variation in crude oil futures market.

In order to estimate the oil price risk, we have applied three different range-based RV measures proposed by Parkinson (1980), Rogers and Satchell (1991) and Alizadeh et al. (2002). We then consider these measures in three different RV models. The first one is simply the base-line RV

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recently, Luo et al. (2016) show that the information content of the CBOE Gold ETF Volatility Index (GVZ) plays a major role in forecasting realized volatility of the Shanghai gold futures market.

specification which includes only the lagged RV as an independent variable, while the second one examines if OVX alone is sufficient to explain the volatility crude oil futures returns. The third and final model includes both lagged RV along with the lagged OVX as the independent variables. Our findings, in short, suggest that the oil volatility index contains additional information to that provided by the base-line RV model and the economic value of that further evidence appears to be phenomenal. The results thus recommend the application of OVX when modeling and forecasting volatility of the US oil market.

The rest of the paper will proceed as follows. Section 2 briefly reviews the related literature. Section 3 outlines the various realized volatility specifications. Section 4 describes the data we have considered in our empirical analysis. The results are discussed in Section 5. Section 6 concludes.

2. Related Literature

A growing body of literature pays a special attention to modeling and forecasting the oil price volatility considering its huge importance on the global and regional economies. Cortazar and Schwartz (2002), for instance, propose a parsimonious three-factor approach of the term structure of oil futures prices that can be easily estimated from available futures price data. The model is executed using daily prices of all futures contracts traded at the New York Mercantile Exchange between 1991 and 2001. The findings of the in-sample and out-of-sample tests show that the model fits the data extremely well. Fong and See (2002) forecast the volatility of crude oil futures prices using a Markov regime switching model over the period 1992-1997. The regime switching approach is based on the ARCH/GARCH model allowing for jumps in the conditional variance between regimes. The Out-of-sample tests document that the regime switching model performs remarkably better than the non-switching models regardless of evaluation criteria. While exploring the association among ten prices series of heavy crude oils and fourteen price series of petroleum products in Europe and Americas during the period 1994–2002, Lanza et al. (2005) analyze the crude oil and product price dynamics using cointegration and error correction models (ECM). They also consider the ECM specification to predict crude oil prices over the horizon January 2002–June 2002. The study further compares the forecasting performance of ECM with a naïve model in first differences which does not exploit any cointegrating relation.

Xie et al. (2006) suggest a new method for crude oil price forecasting based on support vector machine (SVM). To evaluate the forecasting ability of SVM, the study compares its performance with those of ARIMA and BPNN. The findings reveal that SVM outperforms the other two methods and is a fairly good candidate for the crude oil price prediction. Sadorsky (2006) applies several different univariate and multivariate statistical models to estimate the forecasts of daily volatility in petroleum futures price returns. The out-of-sample forecast results show that the TGARCH model fits well for heating oil and natural gas volatility, while the GARCH model fits well for crude oil and unleaded gasoline volatility. The author also documents that models like state space, vector autoregression and bivariate GARCH do not outperform the single equation GARCH models. Coppola (2008) examines the long-run relationship between spot and futures oil prices using the cointegration tests and the vector error correction model (VECM). In addition, the author considers the random walk model (RWM) as a benchmark. The study finds that the futures market information can explain a sizable portion of oil price movements and that the VECM outperforms the RWM in forecasting price movements of 1-month futures contracts. Alizadeh et al. (2008) estimate the constant and dynamic hedge ratios in the New York

Mercantile Exchange oil futures markets and assessing their hedging performance. In doing so, the authors introduce a Markov regime switching vector error correction model with GARCH error structure. The in and out-of-sample tests show that state dependent hedge ratios are able to provide significant reduction in portfolio risk.

Cheong (2009) aims to investigate the time-varying volatility of two major crude oil markets, the West Texas Intermediate (WTI) and Europe Brent, using a flexible ARCH model which takes into account the stylized volatility facts such as clustering volatility, asymmetric news impact and long memory volatility among others. The empirical results suggest that although both the estimation and diagnostic evaluations are in favor of an asymmetric long memory ARCH model, only the WTI models provide superior in the out-of-sample forecasts. On the other hand, from the empirical out-of-sample forecasts, the study shows that the simplest parsimonious generalized ARCH provides the best forecasted evaluations for the Brent crude oil data. While incorporating regime-switching into the stochastic volatility (SV) framework in order to forecast oil price volatility, Vo (2009) finds a clear evidence of regime-switching in the oil market. In addition, incorporating regime-switching into the SV framework significantly enhances the forecasting power of the SV model. The author also reports that the regime-switching stochastic volatility model is capable of capturing major events affecting the oil market. Moreover, Agnolucci (2009) compares the predictive ability of two approaches which can be used to forecast volatility: GARCH-type models where forecasts are obtained after estimating time series models and an implied volatility model where forecasts are obtained by inverting one of the models used to price options. Besides, the study also investigates whether volatility of the oil futures are affected by asymmetric effects, whether parameters of the GARCH models are influenced by the distribution of the errors and whether allowing for a time-varying long-run mean in the volatility produces any improvement on the forecast obtained from GARCH models.

A recent work by Hou and Suardi (2012) considers a nonparametric method to model and forecast oil price return volatility. Focusing on two crude oil markets, Brent and West Texas Intermediate (WTI), the study reports that the out-of-sample volatility forecast of the nonparametric GARCH model offers superior performance relative to an extensive class of parametric GARCH models. More recently, Haugom et al. (2014) utilize the information content of the CBOE crude oil volatility index when forecasting realized volatility in the WTI futures market. The study also considers other market variables, such as volume, open interest, daily returns and bid-ask spread among others. The in and out-of-sample forecasting tests reveal that econometric models based on realized volatility can be improved by including OVX and other variables.

3. Methodology

3.1. Measuring realized volatility

One of the key purposes of the present study is to investigate how the variation in range-based realized volatility measures affects the relationship between the RV of oil returns and OVX. To this end, we employ three different range-based estimators proposed by Parkinson (1980) (henceforth RVP), Rogers and Satchell (1991) (henceforth RVRS) and Alizadeh, Brandt and Diebold (2002) (henceforth RVABD).

The major benefit of using ranged-based RV measures is that they are superior in computing volatility than simply squaring daily returns. For example, Parkinson (1980) and Alizadeh et al. (2002) argue that that range-based volatility is superior to the usual log absolute returns or squared-returns-based volatility measures as it is more efficient, less noisy and more robust to bid–ask spreads. Besides, the RVRS estimator considers opening and closing prices in addition to high and low prices to capture any jumps during the non-trading times (Viteva et al., 2014).

Following Parkinson (1980), our first RV measure is given by:

$$RVP_t = \frac{1}{4\ln 2}[\ln(high)_t - \ln(low)_t]^2 \tag{1}$$

where $high_t$ and low_t refer to the highest and lowest prices on a trading day *t*.

Rogers and Satchell (1991) suggest the following one:

$$RVRS_t = \ln\left(\frac{high_t}{open_t}\right)\ln\left(\frac{high_t}{close_t}\right) + \ln\left(\frac{low_t}{open_t}\right)\ln\left(\frac{low_t}{close_t}\right) \tag{2}$$

where $open_t$ and $close_t$ denote the opening and closing prices on a trading day *t*.

Our third and final measure, RVABD, is defined as:

$$RVABD_t = \frac{high_t - low_t}{close_t} \tag{3}$$

In total, we consider three different volatility estimators to measure the realized variance of the underlying oil market.

3.2. RV models

In this study, we run a series of predictive regressions for assessing the impact of the information content of OVX on the realized volatility of the crude oil futures market. We begin with defining the base line RV model which assumes the following form:

$$RV_{t+1} = \beta_0 + \beta_1 RV_t + \varepsilon_{t+1} \tag{4}$$

where, RV_{t+1} signifies the realized volatility of the crude oil futures price on day *t*+1.

In order to examine the predictive power of the crude oil implied volatility index in explaining the realized variance of oil futures returns, we aim to estimate the following specification:

$$RV_{t+1} = \beta_0 + \beta_1 OVX_t + \varepsilon_{t+1} \tag{5}$$

We shall call specification (5) as OVX alone approach in our analysis. Now, in order to assess whether OVX contains information for future oil market volatility, it is sufficient to test $H_0\colon \beta_1 = 0$. That is, if β_1 is statistically different from zero, we conclude that the implied volatility index has significant influence over the oil price uncertainty.

We further investigate whether we should consider the inclusion of oil volatility index in the conventional RV model. To be specific, we make an attempt to assess if OVX carries any additional information to that provided by the historical volatilities of oil returns. To do so, we estimate the following extended RV model which contains both lagged RV and OVX:

$$RV_{t+1} = \beta_0 + \beta_1 RV_t + \beta_2 OVX_t + \varepsilon_{t+1} \tag{6}$$

We continue to repetitively estimate the above models using different range-based measures of realized volatility.

4. Data

The crude oil volatility index, an important tool for trading oil price volatility, is published by the Chicago Board Options Exchange (CBOE) from the middle of 2007. The OVX considers real-time bid/ask quotes of nearby and second nearby options with at least 8 days to expiration, and weights these options to derive a constant, a 30-day estimate of the expected volatility of crude oil prices (Liu et al., 2013).

Moreover, the data on crude oil futures come from NYMEX. To be specific, price for the crude oil futures is for the nearest expiration contract on NYMEX. Our sample period starts in 10 May 2007 and ends in 30 June 2016, providing a total of 2303 data points. All the information is extracted from the Thomson Reuters DataStream database.

Fig.1 demonstrates the crude oil volatility index for the whole sample period. The figure exhibits several major spikes in OVX during the sample period considered. The first one occurs in the second half year of 2008, during the global financial crisis, when WTI oil prices drop drastically, and OVX reaches its historical high (Ji and Fan, 2016). It is noteworthy that these hikes are the consequences of either economic or political events. For instance, the spike arising in OVX during the beginning of 2011 can be accredited to the Libyan war for which the oil price uncertainty increases evidently (Liu et al., 2013).

Now Table 1 displays the descriptive statistics for both series. The findings reveal that crude oil futures prices show negative skewness, while OVX is negatively skewed. Besides, we find that both indices have kurtosis higher than 3, implying that each series has a leptokurtic distribution with asymmetric tails. Furthermore, the Jarque-Bera test rejects the null hypothesis of normality on every occasion.

Moreover, Table 2 reports the summary statistics for various RV measures. The application of Dickey-Fuller along with the Phillips-Perron unit root tests indicates that the all RV time series are stationary during the sample period. In addition, the autocorrelation over 10 lags suggests that none of these RV indices reveals long memory.

[Fig. 1 about here]

[Table 1 about here]

[Table 2 about here]

5. Empirical results

5.1. In-sample fitting

5.1.1. Full period analysis

Table 3 reports the estimation results of our volatility models which are specified in Equations 4-6. Panel A shows the findings for the base-line RV approach, Panel B contains the same when only OVX is used as the independent variable, and the outcomes of Panel C are based on the extended RV model that comprises both historical as well as implied oil volatilities as the explanatory variables.

The findings of Panel A show that the lagged RV in each case is statistically significant at 1% level suggesting strong persistence in the realized volatility dynamics. While adding the implied volatility index (see the results shown in Panel C), it is also found to be highly significant at 1% level, albeit the coefficient size is generally smaller compared to that of RV. Thus the lagged RV remains the main variable when both the historical along with the implied oil volatilities are considered in the realized variance model. Moreover, the outcomes of Panel B also confirm that OVX is highly significant for all the measures estimating the realized variance of oil market returns. The impact is positive implying that a rise in oil price uncertainty makes the crude oil futures market more volatile. Our results further reveal that the RV measure suggested by Alizadeh et al. (2002) produces higher R^2 value than the rest.

One important and interesting finding is that OVX demonstrates better predictive power compared to the historical volatility of oil returns. For example, when the variance of oil market is proxied by RVABD, the R^2 values provided by the base line as well as the OVX alone models amount to 0.410 and 0.553 respectively. The R^2 values shown in Panel C also verdict that OVX provides further evidence beyond what is contained in the historical volatilities. Hence the introduction of OVX improves the explanatory power of the RV model. We thus conclude that the information content of OVX could be extremely beneficial for modeling the realized variance of crude oil futures market.

[Table 3 about here]

5.1.2. Subsample analysis

We present the results of our subsample analyses in Tables 4 and 5. Table 4 reports the findings for Subsample I, while the numbers displayed in Table 5 are based on Subsample II. Now

Subsample I refers to the crisis period (2 January, 2008 to 30 June, 2009), while subsample II indicates the post crisis period (1 July, 2009 to 30 June, 2016). Such sub-period investigations will help us to assess the effect of the global financial crisis on the relationship between realized and implied oil volatilities. It is noteworthy that we define the period of the global financial crisis following the NBER (National Bureau of Economic Research) guidance[3].

While observing the estimates exhibited in Tables 4 and 5, we document several exciting findings. First, during the crisis period, the magnitudes of all the OVX-coefficients have increased, while for the post crisis period, on the other hand, the corresponding coefficient sizes are lower than when fitting the RV model to the whole or crisis period sample. For example, if the realized variance is computed using the measure suggested by Alizadeh et al. (2002), the estimated coefficients of OVX are equal to 0.00098, 0.00099 and 0.00097 for the full period, crisis period as well as post crisis period respectively. The results displayed in Panel C of all the three tables also conclude the same. These findings simply indicate that the association between oil price uncertainty and the realized volatility of crude oil futures returns appears to have strengthened during the global financial crisis era.

Second, the findings of Table 4 reveal that when both historical and implied volatilities are used to model the future oil market volatility, the lagged RV is found to be statistically insignificant in each case, while OVS is still highly significant at 1% level. Thus during the crisis period, the implied volatility index seems to be a more important variable than the oil market's own past volatility shock in explaining the variations in crude oil futures prices.

[3] Bouri (2015b) also uses the same reference from NBER.

Third, like the full sample analysis, the sub-period investigations also show that OVX generally reveals better predictive power compared to the historical volatility of oil returns. The only exception is observed when the RV measure, proposed by Parkinson (1980), is employed during the post-crisis period. In this case, the R^2 value provided by the OVX alone model (0.337) is slightly lower than that obtained from the conventional RV model (0.360). All these results confirm our previous inference that OVX is remarkably informative about the realized variance of crude oil futures market.

On the whole, the empirical analysis reveals that the regression coefficients differ as the sample period changes. In addition, we document that the parameter estimates are sensitive to various changes in the RV measure. That is, applying several measures leads to different properties of the underlying regression process. Therefore, one could expect that the predictive content of realized volatility is affected by the alterations in both the model specification as well as the sample period. Nevertheless, our results are consistent in that OVX is a highly significant variable when modeling the volatility of crude oil futures returns and hence the information content of this IV index could be extremely useful for explaining the variation in oil market prices.

[Table 4 about here]

[Table 5 about here]

5.2. Out-of-sample forecast

In order to assess the prediction performance of various approaches considered in our empirical analysis, we use two popular loss functions: Root Mean Square Error and Mean Absolute Error. Our objective is to verify if the use of information content of crude oil volatility index improves the volatility forecasts. In doing so, we choose the in-sample estimation period from May 10, 2007 to December 31, 2014 and the out-of-sample forecast period from January 1, 2015 to June 30, 2016. It should be mentioned that the one-step-ahead forecasts for volatility are obtained in our analysis.

Now the loss functions are defined as:

$$\text{Root Mean Square Error: } RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(RV_{a,t} - RV_{f,t}\right)^2}$$

$$\text{Mean Absolute Error: } MAE = \frac{1}{n}\sum_{i=1}^{n}\left|RV_{a,t} - RV_{f,t}\right|$$

Within this framework, *n* denotes the number of forecast data points, $RV_{a,t}$ refers to the actual volatility on day *t* computed from different ranged-based RV measures and $RV_{f,t}$ stands for the volatility forecast for day *t* estimated using the RV models.

Table 6 exhibits the estimated RMSE and MAE values for different cases. These outcomes confirm that including OVX in the analysis improves the volatility forecasts on a regular basis. For example, in case of RVABD, the MAE statistics obtained from base-line RV model, OVX alone model and extended RV models amount to 0.0118, 0.0107 and 0.0105 respectively. Similar findings are documented in other cases as well. Thus the results confirm that models involving OVX generate more accurate out-of-sample volatility forecasts than does the base-line RV model.

[Table 6 about here]

5.3. Forecast encompassing

The forecast encompassing test, proposed by Chong and Hendry (1986), is used to investigate the relative forecasting performance. That is, the test assists us in gauging whether the forecast obtained from the extended RV model or OVX alone model conveys further evidence over a base-line RV approach. If our modified methodology provides no additional information, then the conventional RV model is said to 'encompass' the former (Kambouroudis and McMillan, 2016). In order to apply this forecast encompassing test, we estimate the following regression model:

$$RV_{t+1} = a + \theta_1 \widehat{RV_{1,t}} + \theta_2 \widehat{RV_{2,t}} + \epsilon_t \tag{7}$$

where, $\widehat{RV_{1,t}}$ indicates the base-line RV forecast and $\widehat{RV_{2,t}}$ signifies the modified RV forecast. In case, when $\theta_1 = 0$ and $\theta_2 \neq 0$, our refined model forecast encompasses that provided by the conventional RV specification. Similarly, the base-line RV model forecast encompasses its counterpart if $\theta_1 \neq 0$ and $\theta_2 = 0$. If both parameters have non-zero values, then the implied volatility index contains additional information to that delivered by the base-line model.

The results of the encompassing tests are displayed in Table 7. Panel A shows the results when the base-line forecast is compared with the OVX alone model forecast, while Panel B contains the comparison between base-line and extended RV model forecasts. Observing the numbers shown in Panel A, we report that both the base line as well as the modified RV forecast coefficients (θ_1 and θ_2) are found to be statistically significant and θ_1 is smaller than θ_2 in each case.

Next, Panel B provides more interesting outcomes. The findings show that the modified RV forecast encompasses the base line forecast in majority of the cases. That is, we do not even find a statistically significant $\theta_1$in two out of three cases. We obtain significant θ_1 only when the RV measure of Parkinson (1980) is used. These results hence indicate that the conventional RV forecasts are markedly improved when the crude oil implied volatility index is taken into account. The findings also suggest that energy economists, investors and policymakers should consider the information content of OVX when forecasting oil price volatility.

[Table 7 about here]

5.4. Testing Asymmetric impacts of OVX

Until now, we have documented that OVX has a major impact over crude oil futures returns. It would be interesting to assess whether such impact is asymmetric. In order to reach our goal, we estimate the following model:

$$RV_{t+1} = \pi + k_1 \Delta OVX_t^+ + k_2 \Delta OVX_t^- + \epsilon_{t+1} \tag{8}$$

In Equation 8, $\Delta OVX_t^+ = \max(\Delta OVX_t, 0)$ and $\Delta OVX_t^- = \min(\Delta OVX_t, 0)$, where $\Delta OVX_t = OVX_t - OVX_{t-1}$. Testing $H_0: k_1 = k_2$ will then serve our purpose.

Table 8 exhibits the estimation results for Equation 8. The findings suggest that both ΔOVX_t^+ and ΔOVX_t^- are found to significantly affect the RV of oil returns on every occasion. We further report that null hypothesis of symmetric effect is rejected each time confirming that crude oil volatility index appears to have asymmetric impacts on the returns of crude oil futures market. In other words, the rise and fall in oil volatility index would have heterogeneous effects on the oil market realized volatility.

[Table 8 about here]

It is noteworthy that our findings are consistent with those reported by Haugom et al. (2014) who also show that inclusion of oil volatility index improves the R^2 value of the underlying RV model. That is, OVX contains additional information beyond what is embedded in the realized oil volatility. However, although Haugom et al. are the first to document the significance of using the information content of OVX in explaining oil market volatility, we extend their work in several aspects. First, the earlier study considers intra-day returns to estimate the realized oil volatility, while we use range-based measures to serve our purpose. While it is possible to estimate volatility more precisely using the intraday data, Dacorogna et al. (2001) argue that due to market microstructure effects, the volatility estimation from high frequency intra-day data is rather a complex issue. The range-based volatility proxy, on the other hand, is not only highly efficient, but also approximately Gaussian and robust to microstructure noise (Alizadeh et al., 2002). Second, unlike Haugom et al. (2014), we make use of the forecast encompassing test to assess whether considering OVX is beneficial. Applying this test suggests that the oil volatility forecasts are significantly improved when the base-line RV model is extended by including the oil volatility index, an indicator of oil market uncertainty. Third, we attempt to assess whether the global financial crisis has significant impact on the association between realized and implied oil volatilities. We document that the relationship between oil price uncertainty and the realized volatility of crude oil futures returns tends to be strengthened during the global financial crisis era. Finally, we aim at testing whether there exist any asymmetric associations between implied and realized oil volatilities. Such inspection allows us to determine whether positive OVX shocks affect the realized oil volatility more than the negative shocks. In addition, the existence of asymmetric relations, as evidenced by our empirical work, would shift market analysts from linear modeling to the application of non-linear models. Note that it is a difficult task to compare the results of our paper with those of previously published articles, since they do not consider the application of OVX. Nevertheless, it would be motivating to replicate the analyses of former studies which have been conducted after the introduction of oil volatility index.

6. Conclusion

Since oil is considered one of the most important production inputs in an economy, it is essential to reduce the oil price risk. Doing so requires precise predictions of the oil price direction. Despite the fact that a large number of scholarly works make decent attempts to find appropriate methods to forecast oil price volatility, there is no real consensus on the preferred approach. In this study, unlike the previous research, we investigate whether the variance of oil market returns can be explained using the information content of crude oil volatility index (OVX), a measure of oil price uncertainty. In doing so, we consider applying several range-based measures to frame the realized volatility (RV) of crude oil futures returns. Our main objective is to observe the predictive power of OVX when modeling the realized variance of oil market returns.

The major findings of our empirical research can be summarized as follows. First, OVX has a significant impact on the realized volatility of crude oil futures returns. The impact is positive implying that a rise in market uncertainty makes the oil price more volatile. Second, we find strong evidence that OVX contains extra information to that provided by the historical volatilities of oil returns. Third, the connection between realized and implied oil volatilities becomes firm during the period of global financial crisis. Forth, the impact of OVX on crude oil futures returns appears to be asymmetric. Finally, the forecast encompassing test suggests that the modified RV model (when OVX is introduced in the base-line RV model) forecast encompasses the conventional RV forecast in majority of the cases. To sum up, the inclusion of OVX provides some additional information not contained in the base line RV forecasts and the economic value of that extra evidence seems remarkable.

The precise predictions of oil price volatility play a vital role in portfolio optimization, derivatives pricing, optimum asset allocation decisions and risk management. The findings of our study are thus believed to convey important implications for traders and investors. Since various financial assets are traded on the basis of oil market, investors could use our results for making proper investment decisions and achieving better portfolio diversification benefits. In addition, financial institutions could utilize these outcomes to predict the future oil market trends and improve their hedging performances. To this end, the application of oil market VIX will improve the volatility forecasting and enhance market participants' ability to more accurately measure the price risk in global crude oil market.

The empirical findings could also assist policymakers to adopt effective strategies to moderate the impact of oil market uncertainty. A large oil-importing nation like the US could benefit from improving their strategic petroleum reserves and thus protect their economies from the adverse effect of oil price fluctuations. Previous studies (e.g., Maghyereh and Awartani, 2016; Zhang and Tu, 2016) also argue that oil reserve is essential for those countries which are highly dependent on imported oil. Moreover, the increased use of renewable energy could also stabilize the global oil market to some extent. In order to promote the environment-friendly biofuels, governments could tax fossil fuel usage (Sadorsky, 2012). Considering such steps would then drive those sectors, which heavily rely on fossil fuel, towards the employment of alternative or clean energies. Since it is quite challenging to develop an appropriate model for forecasting oil market volatility more precisely, taking all these policies into account might help to mitigate the oil price risk.

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Table 1: Descriptive statistics

	WTI futures price	OVX
Mean	81.573	37.606
Standard deviation	22.580	14.565
Skewness	-0.301	1.262
Kurtosis	2.564	5.203
Jarque-Bera	53.197***	1077.265***

Notes: *** indicates statistical significance at 1% level.

Table 2: Summary statistics for different RV measures

	RVABD	RVRS	RVP
Mean	0.0316	0.0001	0.0002
Standard deviation	0.0192	0.0003	0.0010
DF	-3.6952***	-3.7347***	-3.4330***
PP	-40.7778***	-48.0798***	-57.7227***
AC (1)	0.641	0.534	0.412
AC (10)	0.553	0.457	0.402

Notes: DF and PP represent the Dickey-Fuller and the Phillips-Perron unit root tests respectively. *** indicates statistical significance at 1% level.

Table 3: Full period estimation results

	RVABD	RVRS	RVP
Panel A: $RV_{t+1} = \beta_0 + \beta_1 RV_t + \varepsilon_{t+1}$			
Constant	0.01140***	0.00032***	0.00011***
RV	0.64098***	0.41165***	0.53400***
R^2	0.410	0.169	0.285
Panel B: $RV_{t+1} = \beta_0 + \beta_1 OVX_t + \varepsilon_{t+1}$			
Constant	-0.00529***	-0.00100***	-0.00035***
OVX	0.00098***	0.00004***	0.00002***
R^2	0.553	0.339	0.425
Panel C: $RV_{t+1} = \beta_0 + \beta_1 RV_t + \beta_2 OVX_t + \varepsilon_{t+1}$			
Constant	-0.00418***	-0.00090***	-0.00029***
RV	0.16316***	0.100215***	0.16975***
OVX	0.00082***	0.00004***	0.00001***
R^2	0.563	0.345	0.440

Notes: *** indicates statistical significance at 1% level.

Table 4: Crisis period estimation results

	RVABD	RVRS	RVP
Panel A: $RV_{t+1} = \beta_0 + \beta_1 RV_t + \varepsilon_{t+1}$			
Constant	0.02444***	0.00105***	0.00033***
RV	0.50337***	0.25630***	0.36607***
R^2	0.254	0.065	0.134
Panel B: $RV_{t+1} = \beta_0 + \beta_1 OVX_t + \varepsilon_{t+1}$			
Constant	-0.00544*	-0.00185***	-0.00062***
OVX	0.00099***	0.00006***	0.00002***
R^2	0.485	0.264	0.378
Panel C: $RV_{t+1} = \beta_0 + \beta_1 RV_t + \beta_2 OVX_t + \varepsilon_{t+1}$			
Constant	-0.00566*	-0.00016***	-0.00006***
RV	-0.02449	-0.02655	-0.05399
OVX	0.00101***	0.00006***	0.000002***
R^2	0.396	0.127	0.368

Notes: *** and * indicate statistical significance at 1% and 10% levels significantly.

Table 5: Post crisis period estimation results

	RVABD	RVRS	RVP
Panel A: $RV_{t+1} = \beta_0 + \beta_1 RV_t + \varepsilon_{t+1}$			
Constant	0.01079***	0.00017***	0.00007***
RV	0.62191***	0.53927***	0.59983***
R^2	0.387	0.291	0.360
Panel B: $RV_{t+1} = \beta_0 + \beta_1 OVX_t + \varepsilon_{t+1}$			
Constant	-0.00495***	-0.00052***	-0.00024***
OVX	0.00097***	0.00003***	0.00001***
R^2	0.468	0.342	0.337
Panel C: $RV_{t+1} = \beta_0 + \beta_1 RV_t + \beta_2 OVX_t + \varepsilon_{t+1}$			
Constant	-0.00311***	-0.00036***	-0.00013***
RV	0.26794***	0.29361***	0.38944***
OVX	0.00069***	0.00001***	0.000001***
R^2	0.502	0.398	0.431

Notes: *** indicates statistical significance at 1% level.

Table 6: Out-of-sample forecasts

Models ↓	RVABD		RVRS		RVP	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
$RV_{t+1} = \beta_0 + \beta_1 RV_t + \varepsilon_{t+1}$	0.0158	0.0118	0.0007	0.0004	0.0003	0.0002
$RV_{t+1} = \beta_0 + \beta_1 OVX_t + \varepsilon_{t+1}$	0.0147	0.0107	0.0006	0.0004	0.0002	0.0001
$RV_{t+1} = \beta_0 + \beta_1 RV_t + \beta_2 OVX_t + \varepsilon_{t+1}$	0.0143	0.0105	0.0006	0.0004	0.0002	0.0001

Table 7: Forecasting encompassing test results

RV measures ↓	θ_1			θ_2		
	Estimate	S.E.	*p*-value	Estimate	S.E.	*p*-value
Panel B: Base-line vs OVX alone models						
RVABD	0.2294***	0.0874	0.00	0.9937***	0.1120	0.00
RVP	0.4795***	0.1052	0.00	0.9063***	0.1259	0.00
RVRS	0.1106*	0.0601	0.06	0.4122***	0.0451	0.00
Panel B: Base-line vs extended RV models						
RVABD	0.0013	0.1062	0.98	1.1435***	0.1289	0.00
RVP	0.2589**	0.1261	0.04	1.0235***	0.1421	0.00
RVRS	0.0250	0.0656	0.70	0.4511***	0.0489	0.00

Notes: ***, ** and * indicate statistical significance at 1%, 5% and 10% levels respectively.

Table 8: Testing the asymmetric impacts of OVX

	RVABD	RVRS	RVP
Constant	0.02609***	0.00030***	0.00014***
ΔOVX_t^+	0.00543***	0.00020***	0.00008***
ΔOVX_t^-	-0.00309***	-0.000167***	-0.00005***
$H_0: k_1 = k_2$	34.98***	3.02***	4.90***

Notes: These results are obtained by estimating the following equation $RV_{t+1} = \pi + k_1 \Delta OVX_t^+ + k_2 \Delta OVX_t^- + \epsilon_{t+1}$. The last row reports the value of *t*-statistic for testing $H_0: k_1 = k_2$. *** indicates statistical significance at 1% level.

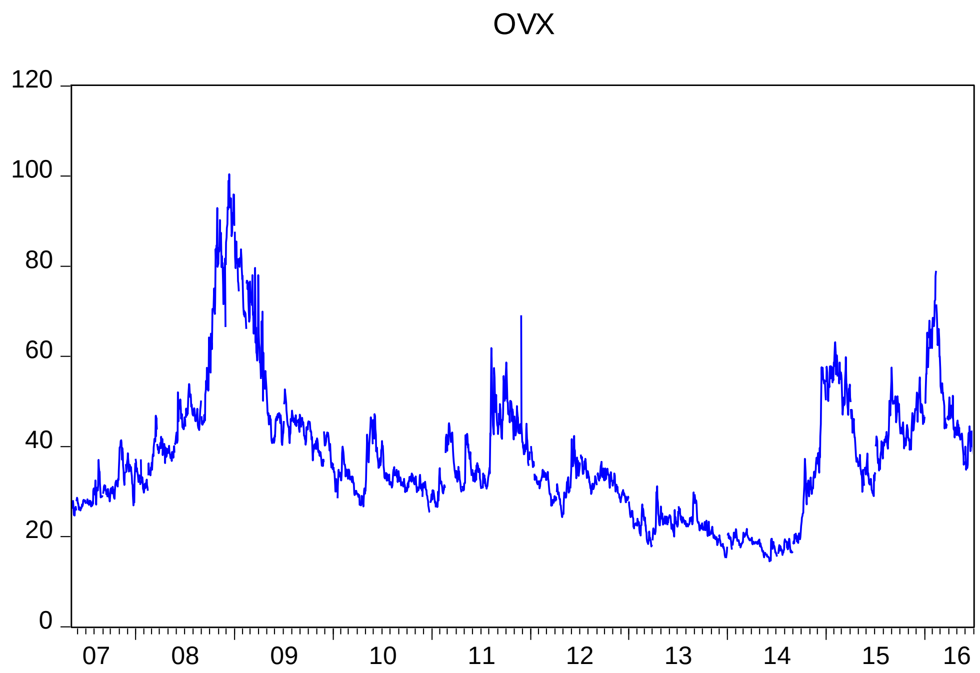

Fig. 1: Crude oil volatility index from 10/05/2007-30/06/2016

Modeling and Forecasting Oil Price Risk: The Role of Implied Volatility Index

Abstract

Purpose: While numerous empirical studies have tried to model and forecast the oil price volatility over the years, such attempts using the crude oil volatility index (OVX) rarely exist. In order to conceal this void, the present article investigates whether including OVX in the realized volatility (RV) models improve the accuracy of predictions.

Design/Methodology/Approach: At the empirical stage, we employ several measures to frame the RV of crude oil futures returns. In particular, we use three different range-based RV estimators recommended by Parkinson (1980), Rogers and Satchell (1991) and Alizadeh et al. (2002) respectively.

Findings: Our findings reveal that the information content of crude oil volatility index helps to provide more accurate volatility predictions in comparison to the base-line RV model which contains only historical oil volatilities. Besides, the forecast encompassing test further suggests that the modified RV model (when OVX is introduced in the base-line RV model) forecast encompasses the conventional RV forecast in majority of the cases.

Practical implications: Since forecasting oil price volatility plays a vital role in portfolio optimization, derivatives pricing, optimum asset allocation decisions and risk management, the findings of our study thus carry important implications for energy economists, investors and policymakers.

Originality/Value: This paper adds to the existing literature, since it is one of the initial studies to explore whether OVX is informative about the realized variance of the US oil market returns. Our findings recommend that the information content of oil implied volatilities should be taken into account when modeling the US oil market volatility. In addition, range-based measures should be utilized while estimating the realized volatility.

Keywords: Oil price volatility; OVX; range-based RV measures; RV models; WTI oil price futures; Forecast encompassing.

1. Introduction

Oil embodies a prominent role in the international economy as it continues to remain world's leading fuel accounting for 32.9% of global energy consumption[1]. Variations in crude oil price are thus likely to bring uncertainty for the global economic development and growth. Since oil market is reported to be one of the most volatile markets, several researchers have examined how and to what extent oil price volatility affects the overall economy. For example, Bouri (2015a) argues that oil price shocks can spill over into equity markets leading to immediate disturbances in financial markets and distant disruptions of economic activities. Vo (2011) also demonstrates that an increment in oil price leads to higher production costs which affect inflation, consumer confidence and hence economic growth. In addition, Chiou and Lee (2009) contend that if oil price has an impact on real output, an increase in oil price will depress aggregate stock prices suggesting a significant association between oil prices and equity market returns. Besides, Zhang and Tu (2016) report that metal industry is highly oil-intensive and hence oil price volatility certainly affects the metal markets and hence the overall economy. Therefore, crude oil is considered a key commodity for the national and international economies.

Considering the significance of the relationship between oil market and the overall economy, it is essential to minimize the negative impact of oil price fluctuations. To do so, it is very important to accurately predict the oil price direction, although forecasting the crude oil price is a hard task due to its intrinsic difficulty and practical applications (Xie et al., 2006). Nevertheless, researchers are always in search of precise methodologies in order to estimate the prices of this widely used energy commodity with accuracy. Consequently, predictions of oil price volatility have received significant attention in the literature. Important contributions include Morana

[1] This information is sourced from www.bp.com

(2001), Cortazar and Schwartz (2002), Fong and See (2002), Lanza et al. (2005), Coppola (2008), Kang et al. (2009), Vo (2009) and others. Morana (2001), for example, documents how the GARCH properties of oil price changes can be employed to forecast the oil price distribution over short-term horizons. The author employs a semi-parametric method to forecast the volatility of Brent crude oil prices. More recently, Kang et al. (2009) compare a number of GARCH models to predict the volatility of Brent, WTI and Dubai crude oil prices. The results show that for Brent and Dubai, the fractionally integrated GARCH model performs better than the other GARCH models, while the component GARCH model is found to outperform the rest in case of WTI crude oil.

Unlike the studies cited above, the present paper aims to forecast the oil price volatility using the information content of a newly published crude oil volatility index (OVX) from the Chicago Board Options Exchange (CBOE). Although numerous studies argue that the performance of volatility models can be substantially improved with the inclusion of VIX (Taylor, 2008), the crude oil volatility index has not received much attention in forecasting oil price variation. This is surprising, since OVX is a market-determined forecast which is quite similar to the implied volatility index in the stock market (Ji and Fan, 2016). For example, Maghyereh et al. (2016) contend that as volatilities are derived from market option prices, they are forward looking and thus they represent the markets' consensus on the expected future uncertainty. Besides, other researchers such as Liu et al. (2013) suggest that the use of OVX in predicting future realized volatility of crude oil prices will be potentially fruitful[2]. Nonetheless, predictions of oil price

[2] Earlier studies document that the information content of commodity market implied volatility index improves the volatility forecasts based on realized volatilities. Luo and Ye (2015), for example, report that the CBOE Silver ETF Volatility Index (VXSLV) is suitable for predicting the volatility of the Shanghai silver futures market. More

volatility using OVX are almost non-existent. The only exception includes Haugom et al. (2014) who document, using a heterogeneous auto-regressive (HAR) model, that the day-ahead and week-ahead volatility forecasts of oil futures can be significantly improved by including information from the crude oil implied volatility index.

In order to extend this scarce literature, the present study uses the information content of the implied oil volatility (IV) index for modeling and forecasting the realized variance of WTI crude oil futures prices. Our paper differs from Haugom et al. (2014) in that we have used various range-based measures to estimate the realized volatility (RV) of oil market returns, while the former considers the RV measure based on squared returns. This can be considered as an important contribution, since several researchers (Alizadeh et al., 2002; Viteva et al., 2014) argue that range-based volatility estimators are better than squared returns in capturing the underlying volatility process. For instance, Alizadeh et al. (2002) contend that range-based volatility measures are more robust to the microstructure noise caused by the bid/ask bounce. We also extend the study by Haugom et al. (2014) by applying the forecast encompassing test to determine whether the use of OVX is of assistance. That is, the test allows us to examine if the underlying IV index is informative about the variation in crude oil futures market.

In order to estimate the oil price risk, we have applied three different range-based RV measures proposed by Parkinson (1980), Rogers and Satchell (1991) and Alizadeh et al. (2002). We then consider these measures in three different RV models. The first one is simply the base-line RV

recently, Luo et al. (2016) show that the information content of the CBOE Gold ETF Volatility Index (GVZ) plays a major role in forecasting realized volatility of the Shanghai gold futures market.

specification which includes only the lagged RV as an independent variable, while the second one examines if OVX alone is sufficient to explain the volatility crude oil futures returns. The third and final model includes both lagged RV along with the lagged OVX as the independent variables. Our findings, in short, suggest that the oil volatility index contains additional information to that provided by the base-line RV model and the economic value of that further evidence appears to be phenomenal. The results thus recommend the application of OVX when modeling and forecasting volatility of the US oil market.

The rest of the paper will proceed as follows. Section 2 briefly reviews the related literature. Section 3 outlines the various realized volatility specifications. Section 4 describes the data we have considered in our empirical analysis. The results are discussed in Section 5. Section 6 concludes.

2. Related Literature

A growing body of literature pays a special attention to modeling and forecasting the oil price volatility considering its huge importance on the global and regional economies. Cortazar and Schwartz (2002), for instance, propose a parsimonious three-factor approach of the term structure of oil futures prices that can be easily estimated from available futures price data. The model is executed using daily prices of all futures contracts traded at the New York Mercantile Exchange between 1991 and 2001. The findings of the in-sample and out-of-sample tests show that the model fits the data extremely well. Fong and See (2002) forecast the volatility of crude oil futures prices using a Markov regime switching model over the period 1992-1997. The regime switching approach is based on the ARCH/GARCH model allowing for jumps in the conditional variance between regimes. The Out-of-sample tests document that the regime switching model performs remarkably better than the non-switching models regardless of evaluation criteria. While exploring the association among ten prices series of heavy crude oils and fourteen price series of petroleum products in Europe and Americas during the period 1994–2002, Lanza et al. (2005) analyze the crude oil and product price dynamics using cointegration and error correction models (ECM). They also consider the ECM specification to predict crude oil prices over the horizon January 2002–June 2002. The study further compares the forecasting performance of ECM with a naïve model in first differences which does not exploit any cointegrating relation.

Xie et al. (2006) suggest a new method for crude oil price forecasting based on support vector machine (SVM). To evaluate the forecasting ability of SVM, the study compares its performance with those of ARIMA and BPNN. The findings reveal that SVM outperforms the other two methods and is a fairly good candidate for the crude oil price prediction. Sadorsky (2006) applies several different univariate and multivariate statistical models to estimate the forecasts of daily volatility in petroleum futures price returns. The out-of-sample forecast results show that the TGARCH model fits well for heating oil and natural gas volatility, while the GARCH model fits well for crude oil and unleaded gasoline volatility. The author also documents that models like state space, vector autoregression and bivariate GARCH do not outperform the single equation GARCH models. Coppola (2008) examines the long-run relationship between spot and futures oil prices using the cointegration tests and the vector error correction model (VECM). In addition, the author considers the random walk model (RWM) as a benchmark. The study finds that the futures market information can explain a sizable portion of oil price movements and that the VECM outperforms the RWM in forecasting price movements of 1-month futures contracts. Alizadeh et al. (2008) estimate the constant and dynamic hedge ratios in the New York

Mercantile Exchange oil futures markets and assessing their hedging performance. In doing so, the authors introduce a Markov regime switching vector error correction model with GARCH error structure. The in and out-of-sample tests show that state dependent hedge ratios are able to provide significant reduction in portfolio risk.

Cheong (2009) aims to investigate the time-varying volatility of two major crude oil markets, the West Texas Intermediate (WTI) and Europe Brent, using a flexible ARCH model which takes into account the stylized volatility facts such as clustering volatility, asymmetric news impact and long memory volatility among others. The empirical results suggest that although both the estimation and diagnostic evaluations are in favor of an asymmetric long memory ARCH model, only the WTI models provide superior in the out-of-sample forecasts. On the other hand, from the empirical out-of-sample forecasts, the study shows that the simplest parsimonious generalized ARCH provides the best forecasted evaluations for the Brent crude oil data. While incorporating regime-switching into the stochastic volatility (SV) framework in order to forecast oil price volatility, Vo (2009) finds a clear evidence of regime-switching in the oil market. In addition, incorporating regime-switching into the SV framework significantly enhances the forecasting power of the SV model. The author also reports that the regime-switching stochastic volatility model is capable of capturing major events affecting the oil market. Moreover, Agnolucci (2009) compares the predictive ability of two approaches which can be used to forecast volatility: GARCH-type models where forecasts are obtained after estimating time series models and an implied volatility model where forecasts are obtained by inverting one of the models used to price options. Besides, the study also investigates whether volatility of the oil futures is affected by asymmetric effects, whether parameters of the GARCH models are influenced by the distribution of the errors and whether allowing for a time-varying long-run mean in the volatility produces any improvement on the forecast obtained from GARCH models.

A recent work by Hou and Suardi (2012) considers a nonparametric method to model and forecast oil price return volatility. Focusing on two crude oil markets, Brent and West Texas Intermediate (WTI), the study reports that the out-of-sample volatility forecast of the nonparametric GARCH model offers superior performance relative to an extensive class of parametric GARCH models. More recently, Haugom et al. (2014) utilize the information content of the CBOE crude oil volatility index when forecasting realized volatility in the WTI futures market. The study also considers other market variables, such as volume, open interest, daily returns and bid-ask spread among others. The in and out-of-sample forecasting tests reveal that econometric models based on realized volatility can be improved by including OVX and other variables.

3. Methodology

3.1. Measuring realized volatility

One of the key purposes of the present study is to investigate how the variation in range-based realized volatility measures affects the relationship between the RV of oil returns and OVX. To this end, we employ three different range-based estimators proposed by Parkinson (1980) (henceforth RVP), Rogers and Satchell (1991) (henceforth RVRS) and Alizadeh, Brandt and Diebold (2002) (henceforth RVABD).

The major benefit of using ranged-based RV measures is that they are superior in computing volatility than simply squaring daily returns. For example, Parkinson (1980) and Alizadeh et al. (2002) argue that that range-based volatility is superior to the usual log absolute returns or squared-returns-based volatility measures as it is more efficient, less noisy and more robust to bid–ask spreads. Besides, the RVRS estimator considers opening and closing prices in addition to high and low prices to capture any jumps during the non-trading times (Viteva et al., 2014).

Following Parkinson (1980), our first RV measure is given by:

$$RVP_t = \frac{1}{4\ln 2}[\ln(high)_t - \ln(low)_t]^2 \qquad (1)$$

where $high_t$ and low_t refer to the highest and lowest prices on a trading day t.

Rogers and Satchell (1991) suggest the following one:

$$RVRS_t = \ln\left(\frac{high_t}{open_t}\right)\ln\left(\frac{high_t}{close_t}\right) + \ln\left(\frac{low_t}{open_t}\right)\ln\left(\frac{low_t}{close_t}\right) \qquad (2)$$

where $open_t$ and $close_t$ denote the opening and closing prices on a trading day t.

Our third and final measure, RVABD, is defined as:

$$RVABD_t = \frac{high_t - low_t}{close_t} \qquad (3)$$

In total, we consider three different volatility estimators to measure the realized variance of the underlying oil market.

3.2. RV models

In this study, we run a series of predictive regressions for assessing the impact of the information content of OVX on the realized volatility of the crude oil futures market. We begin with defining the base line RV model which assumes the following form:

$$RV_{t+1} = \beta_0 + \beta_1 RV_t + \varepsilon_{t+1} \qquad (4)$$

where, RV_{t+1} signifies the realized volatility of the crude oil futures price on day *t*+1.

In order to examine the predictive power of the crude oil implied volatility index in explaining the realized variance of oil futures returns, we aim to estimate the following specification:

$$RV_{t+1} = \beta_0 + \beta_1 OVX_t + \varepsilon_{t+1} \qquad (5)$$

We shall call specification (5) as OVX alone approach in our analysis. Now, in order to assess whether OVX contains information for future oil market volatility, it is sufficient to test $H_0\colon \beta_1 = 0$. That is, if β_1 is statistically different from zero, we conclude that the implied volatility index has significant influence over the oil price uncertainty.

We further investigate whether we should consider the inclusion of oil volatility index in the conventional RV model. To be specific, we make an attempt to assess if OVX carries any additional information to that provided by the historical volatilities of oil returns. To do so, we estimate the following extended RV model which contains both lagged RV and OVX:

$$RV_{t+1} = \beta_0 + \beta_1 RV_t + \beta_2 OVX_t + \varepsilon_{t+1} \qquad (6)$$

We continue to repetitively estimate the above models using different range-based measures of realized volatility.

4. Data

The crude oil volatility index, an important tool for trading oil price volatility, is published by the Chicago Board Options Exchange (CBOE) from the middle of 2007. The OVX considers real-time bid/ask quotes of nearby and second nearby options with at least 8 days to expiration, and weights these options to derive a constant, a 30-day estimate of the expected volatility of crude oil prices (Liu et al., 2013).

Moreover, the data on crude oil futures come from NYMEX. To be specific, price for the crude oil futures is for the nearest expiration contract on NYMEX. Our sample period starts in 10 May 2007 and ends in 30 June 2016, providing a total of 2303 data points. All the information is extracted from the Thomson Reuters DataStream database.

Fig.1 demonstrates the crude oil volatility index for the whole sample period. The figure exhibits several major spikes in OVX during the sample period considered. The first one occurs in the second half year of 2008, during the global financial crisis, when WTI oil prices drop drastically, and OVX reaches its historical high (Ji and Fan, 2016). It is noteworthy that these hikes are the consequences of either economic or political events. For instance, the spike arising in OVX during the beginning of 2011 can be accredited to the Libyan war for which the oil price uncertainty increases evidently (Liu et al., 2013).

Now Table 1 displays the descriptive statistics for both series. The findings reveal that crude oil futures prices show negative skewness, while OVX is negatively skewed. Besides, we find that both indices have kurtosis higher than 3, implying that each series has a leptokurtic distribution with asymmetric tails. Furthermore, the Jarque-Bera test rejects the null hypothesis of normality on every occasion.

Moreover, Table 2 reports the summary statistics for various RV measures. The application of Dickey-Fuller along with the Phillips-Perron unit root tests indicates that the all RV time series are stationary during the sample period. In addition, the autocorrelation over 10 lags suggests that none of these RV indices reveals long memory.

[Fig. 1 about here]

[Table 1 about here]

[Table 2 about here]

5. Empirical results

5.1. In-sample fitting

5.1.1. Full period analysis

Table 3 reports the estimation results of our volatility models which are specified in Equations 4-6. Panel A shows the findings for the base-line RV approach, Panel B contains the same when only OVX is used as the independent variable, and the outcomes of Panel C are based on the extended RV model that comprises both historical as well as implied oil volatilities as the explanatory variables.

The findings of Panel A show that the lagged RV in each case is statistically significant at 1% level suggesting strong persistence in the realized volatility dynamics. While adding the implied volatility index (see the results shown in Panel C), it is also found to be highly significant at 1% level, albeit the coefficient size is generally smaller compared to that of RV. Thus the lagged RV remains the main variable when both the historical along with the implied oil volatilities are considered in the realized variance model. Moreover, the outcomes of Panel B also confirm that OVX is highly significant for all the measures estimating the realized variance of oil market returns. The impact is positive implying that a rise in oil price uncertainty makes the crude oil futures market more volatile. Our results further reveal that the RV measure suggested by Alizadeh et al. (2002) produces higher R^2 value than the rest.

One important and interesting finding is that OVX demonstrates better predictive power compared to the historical volatility of oil returns. For example, when the variance of oil market is proxied by RVABD, the R^2 values provided by the base line as well as the OVX alone models amount to 0.410 and 0.553 respectively. The R^2 values shown in Panel C also verdict that OVX provides further evidence beyond what is contained in the historical volatilities. Hence the introduction of OVX improves the explanatory power of the RV model. We thus conclude that the information content of OVX could be extremely beneficial for modeling the realized variance of crude oil futures market.

[Table 3 about here]

5.1.2. Subsample analysis

We present the results of our subsample analyses in Tables 4 and 5. Table 4 reports the findings for Subsample I, while the numbers displayed in Table 5 are based on Subsample II. Now

Subsample I refers to the crisis period (2 January, 2008 to 30 June, 2009), while subsample II indicates the post crisis period (1 July, 2009 to 30 June, 2016). Such sub-period investigations will help us to assess the effect of the global financial crisis on the relationship between realized and implied oil volatilities. It is noteworthy that we define the period of the global financial crisis following the NBER (National Bureau of Economic Research) guidance[3].

While observing the estimates exhibited in Tables 4 and 5, we document several exciting findings. First, during the crisis period, the magnitudes of all the OVX-coefficients have increased, while for the post crisis period, on the other hand, the corresponding coefficient sizes are lower than when fitting the RV model to the whole or crisis period sample. For example, if the realized variance is computed using the measure suggested by Alizadeh et al. (2002), the estimated coefficients of OVX are equal to 0.00098, 0.00099 and 0.00097 for the full period, crisis period as well as post crisis period respectively. The results displayed in Panel C of all the three tables also conclude the same. These findings simply indicate that the association between oil price uncertainty and the realized volatility of crude oil futures returns appears to have strengthened during the global financial crisis era.

Second, the findings of Table 4 reveal that when both historical and implied volatilities are used to model the future oil market volatility, the lagged RV is found to be statistically insignificant in each case, while OVS is still highly significant at 1% level. Thus during the crisis period, the implied volatility index seems to be a more important variable than the oil market's own past volatility shock in explaining the variations in crude oil futures prices.

[3] Bouri (2015b) also uses the same reference from NBER.

Third, like the full sample analysis, the sub-period investigations also show that OVX generally reveals better predictive power compared to the historical volatility of oil returns. The only exception is observed when the RV measure, proposed by Parkinson (1980), is employed during the post-crisis period. In this case, the R^2 value provided by the OVX alone model (0.337) is slightly lower than that obtained from the conventional RV model (0.360). All these results confirm our previous inference that OVX is remarkably informative about the realized variance of crude oil futures market.

On the whole, the empirical analysis reveals that the regression coefficients differ as the sample period changes. In addition, we document that the parameter estimates are sensitive to various changes in the RV measure. That is, applying several measures leads to different properties of the underlying regression process. Therefore, one could expect that the predictive content of realized volatility is affected by the alterations in both the model specification as well as the sample period. Nevertheless, our results are consistent in that OVX is a highly significant variable when modeling the volatility of crude oil futures returns and hence the information content of this IV index could be extremely useful for explaining the variation in oil market prices.

[Table 4 about here]

[Table 5 about here]

5.2. Out-of-sample forecast

In order to assess the prediction performance of various approaches considered in our empirical analysis, we use two popular loss functions: Root Mean Square Error and Mean Absolute Error. Our objective is to verify if the use of information content of crude oil volatility index improves the volatility forecasts. In doing so, we choose the in-sample estimation period from May 10, 2007 to December 31, 2014 and the out-of-sample forecast period from January 1, 2015 to June 30, 2016. It should be mentioned that the one-step-ahead forecasts for volatility are obtained in our analysis.

Now the loss functions are defined as:

$$\text{Root Mean Square Error: } RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(RV_{a,t} - RV_{f,t}\right)^2}$$

$$\text{Mean Absolute Error: } MAE = \frac{1}{n}\sum_{i=1}^{n}\left|RV_{a,t} - RV_{f,t}\right|$$

Within this framework, *n* denotes the number of forecast data points, $RV_{a,t}$ refers to the actual volatility on day *t* computed from different ranged-based RV measures and $RV_{f,t}$ stands for the volatility forecast for day *t* estimated using the RV models.

Table 6 exhibits the estimated RMSE and MAE values for different cases. These outcomes confirm that including OVX in the analysis improves the volatility forecasts on a regular basis. For example, in case of RVABD, the MAE statistics obtained from base-line RV model, OVX alone model and extended RV models amount to 0.0118, 0.0107 and 0.0105 respectively. Similar findings are documented in other cases as well. Thus the results confirm that models involving OVX generate more accurate out-of-sample volatility forecasts than does the base-line RV model.

[Table 6 about here]

5.3. Forecast encompassing

The forecast encompassing test, proposed by Chong and Hendry (1986), is used to investigate the relative forecasting performance. That is, the test assists us in gauging whether the forecast obtained from the extended RV model or OVX alone model conveys further evidence over a base-line RV approach. If our modified methodology provides no additional information, then the conventional RV model is said to 'encompass' the former (Kambouroudis and McMillan, 2016). In order to apply this forecast encompassing test, we estimate the following regression model:

$$RV_{t+1} = a + \theta_1 \widehat{RV_{1,t}} + \theta_2 \widehat{RV_{2,t}} + \epsilon_t \qquad (7)$$

where, $\widehat{RV_{1,t}}$ indicates the base-line RV forecast and $\widehat{RV_{2,t}}$ signifies the modified RV forecast. In case, when $\theta_1 = 0$ and $\theta_2 \neq 0$, our refined model forecast encompasses that provided by the conventional RV specification. Similarly, the base-line RV model forecast encompasses its counterpart if $\theta_1 \neq 0$ and $\theta_2 = 0$. If both parameters have non-zero values, then the implied volatility index contains additional information to that delivered by the base-line model.

The results of the encompassing tests are displayed in Table 7. Panel A shows the results when the base-line forecast is compared with the OVX alone model forecast, while Panel B contains the comparison between base-line and extended RV model forecasts. Observing the numbers shown in Panel A, we report that both the base line as well as the modified RV forecast coefficients (θ_1 and θ_2) are found to be statistically significant and θ_1 is smaller than θ_2 in each case.

Next, Panel B provides more interesting outcomes. The findings show that the modified RV forecast encompasses the base line forecast in majority of the cases. That is, we do not even find a statistically significant $\theta_1$in two out of three cases. We obtain significant θ_1 only when the RV measure of Parkinson (1980) is used. These results hence indicate that the conventional RV forecasts are markedly improved when the crude oil implied volatility index is taken into account. The findings also suggest that energy economists, investors and policymakers should consider the information content of OVX when forecasting oil price volatility.

[Table 7 about here]

5.4. Testing Asymmetric impacts of OVX

Until now, we have documented that OVX has a major impact over crude oil futures returns. It would be interesting to assess whether such impact is asymmetric. In order to reach our goal, we estimate the following model:

$$RV_{t+1} = \pi + k_1 \Delta OVX_t^+ + k_2 \Delta OVX_t^- + \epsilon_{t+1} \qquad (8)$$

In Equation 8, $\Delta OVX_t^+ = \max(\Delta OVX_t, 0)$ and $\Delta OVX_t^- = \min(\Delta OVX_t, 0)$, where $\Delta OVX_t = OVX_t - OVX_{t-1}$. Testing $H_0: k_1 = k_2$ will then serve our purpose.

Table 8 exhibits the estimation results for Equation 8. The findings suggest that both ΔOVX_t^+ and ΔOVX_t^- are found to significantly affect the RV of oil returns on every occasion. We further report that null hypothesis of symmetric effect is rejected each time confirming that crude oil volatility index appears to have asymmetric impacts on the returns of crude oil futures market. In other words, the rise and fall in oil volatility index would have heterogeneous effects on the oil market realized volatility.

[Table 8 about here]

It is noteworthy that our findings are consistent with those reported by Haugom et al. (2014) who also show that inclusion of oil volatility index improves the R^2 value of the underlying RV model. That is, OVX contains additional information beyond what is embedded in the realized oil volatility. However, although Haugom et al. are the first to document the significance of using the information content of OVX in explaining oil market volatility, we extend their work in several aspects. First, the earlier study considers intra-day returns to estimate the realized oil volatility, while we use range-based measures to serve our purpose. While it is possible to estimate volatility more precisely using the intraday data, Dacorogna et al. (2001) argue that due to market microstructure effects, the volatility estimation from high frequency intra-day data is rather a complex issue. The range-based volatility proxy, on the other hand, is not only highly efficient, but also approximately Gaussian and robust to microstructure noise (Alizadeh et al., 2002). Second, unlike Haugom et al. (2014), we make use of the forecast encompassing test to assess whether considering OVX is beneficial. Applying this test suggests that the oil volatility forecasts are significantly improved when the base-line RV model is extended by including the oil volatility index, an indicator of oil market uncertainty. Third, we attempt to assess whether the global financial crisis has significant impact on the association between realized and implied oil volatilities. We document that the relationship between oil price uncertainty and the realized volatility of crude oil futures returns tends to be strengthened during the global financial crisis era. Finally, we aim at testing whether there exist any asymmetric associations between implied and realized oil volatilities. Such inspection allows us to determine whether positive OVX shocks affect the realized oil volatility more than the negative shocks. In addition, the existence of asymmetric relations, as evidenced by our empirical work, would shift market analysts from linear modeling to the application of non-linear models. Note that it is a difficult task to compare the results of our paper with those of previously published articles, since they do not consider the application of OVX. Nevertheless, it would be motivating to replicate the analyses of former studies which have been conducted after the introduction of oil volatility index.

6. Conclusion

Since oil is considered one of the most important production inputs in an economy, it is essential to reduce the oil price risk. Doing so requires precise predictions of the oil price direction. Despite the fact that a large number of scholarly works make decent attempts to find appropriate methods to forecast oil price volatility, there is no real consensus on the preferred approach. In this study, unlike the previous research, we investigate whether the variance of oil market returns can be explained using the information content of crude oil volatility index (OVX), a measure of oil price uncertainty. In doing so, we consider applying several range-based measures to frame the realized volatility (RV) of crude oil futures returns. Our main objective is to observe the predictive power of OVX when modeling the realized variance of oil market returns.

The major findings of our empirical research can be summarized as follows. First, OVX has a significant impact on the realized volatility of crude oil futures returns. The impact is positive implying that a rise in market uncertainty makes the oil price more volatile. Second, we find strong evidence that OVX contains extra information to that provided by the historical volatilities of oil returns. Third, the connection between realized and implied oil volatilities becomes firm during the period of global financial crisis. Forth, the impact of OVX on crude oil futures returns appears to be asymmetric. Finally, the forecast encompassing test suggests that the modified RV model (when OVX is introduced in the base-line RV model) forecast encompasses the conventional RV forecast in majority of the cases. To sum up, the inclusion of OVX provides some additional information not contained in the base line RV forecasts and the economic value of that extra evidence seems remarkable.

The precise predictions of oil price volatility play a vital role in portfolio optimization, derivatives pricing, optimum asset allocation decisions and risk management. The findings of our study are thus believed to convey important implications for traders and investors. Since various financial assets are traded on the basis of oil market, investors could use our results for making proper investment decisions and achieving better portfolio diversification benefits. In addition, financial institutions could utilize these outcomes to predict the future oil market trends and improve their hedging performances. To this end, the application of oil market VIX will improve the volatility forecasting and enhance market participants' ability to more accurately measure the price risk in global crude oil market.

The empirical findings could also assist policymakers to adopt effective strategies to moderate the impact of oil market uncertainty. A large oil-importing nation like the US could benefit from improving their strategic petroleum reserves and thus protect their economies from the adverse effect of oil price fluctuations. Previous studies (e.g., Maghyereh and Awartani, 2016; Zhang and Tu, 2016) also argue that oil reserve is essential for those countries which are highly dependent on imported oil. Moreover, the increased use of renewable energy could also stabilize the global oil market to some extent. In order to promote the environment-friendly biofuels, governments could tax fossil fuel usage (Sadorsky, 2012). Considering such steps would then drive those sectors, which heavily rely on fossil fuel, towards the employment of alternative or clean energies. Since it is quite challenging to develop an appropriate model for forecasting oil market volatility more precisely, taking all these policies into account might help to mitigate the oil price risk.

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Table 1: Descriptive statistics

	WTI futures price	OVX
Mean	81.573	37.606
Standard deviation	22.580	14.565
Skewness	-0.301	1.262
Kurtosis	2.564	5.203
Jarque-Bera	53.197***	1077.265***

Notes: *** indicates statistical significance at 1% level.

Table 2: Summary statistics for different RV measures

	RVABD	RVRS	RVP
Mean	0.0316	0.0001	0.0002
Standard deviation	0.0192	0.0003	0.0010
DF	-3.6952***	-3.7347***	-3.4330***
PP	-40.7778***	-48.0798***	-57.7227***
AC (1)	0.641	0.534	0.412
AC (10)	0.553	0.457	0.402

Notes: DF and PP represent the Dickey-Fuller and the Phillips-Perron unit root tests respectively. *** indicates statistical significance at 1% level.

Table 3: Full period estimation results

	RVABD	RVRS	RVP
Panel A: $RV_{t+1} = \beta_0 + \beta_1 RV_t + \varepsilon_{t+1}$			
Constant	0.01140***	0.00032***	0.00011***
RV	0.64098***	0.41165***	0.53400***
R^2	0.410	0.169	0.285
Panel B: $RV_{t+1} = \beta_0 + \beta_1 OVX_t + \varepsilon_{t+1}$			
Constant	-0.00529***	-0.00100***	-0.00035***
OVX	0.00098***	0.00004***	0.00002***
R^2	0.553	0.339	0.425
Panel C: $RV_{t+1} = \beta_0 + \beta_1 RV_t + \beta_2 OVX_t + \varepsilon_{t+1}$			
Constant	-0.00418***	-0.00090***	-0.00029***
RV	0.16316***	0.100215***	0.16975***
OVX	0.00082***	0.00004***	0.00001***
R^2	0.563	0.345	0.440

Notes: *** indicates statistical significance at 1% level.

Table 4: Crisis period estimation results

	RVABD	RVRS	RVP
Panel A: $RV_{t+1} = \beta_0 + \beta_1 RV_t + \varepsilon_{t+1}$			
Constant	0.02444***	0.00105***	0.00033***
RV	0.50337***	0.25630***	0.36607***
R^2	0.254	0.065	0.134
Panel B: $RV_{t+1} = \beta_0 + \beta_1 OVX_t + \varepsilon_{t+1}$			
Constant	-0.00544*	-0.00185***	-0.00062***
OVX	0.00099***	0.00006***	0.00002***
R^2	0.485	0.264	0.378
Panel C: $RV_{t+1} = \beta_0 + \beta_1 RV_t + \beta_2 OVX_t + \varepsilon_{t+1}$			
Constant	-0.00566*	-0.00016***	-0.00006***
RV	-0.02449	-0.02655	-0.05399
OVX	0.00101***	0.00006***	0.000002***
R^2	0.396	0.127	0.368

Notes: *** and * indicate statistical significance at 1% and 10% levels significantly.

Table 5: Post crisis period estimation results

	RVABD	RVRS	RVP
Panel A: $RV_{t+1} = \beta_0 + \beta_1 RV_t + \varepsilon_{t+1}$			
Constant	0.01079***	0.00017***	0.00007***
RV	0.62191***	0.53927***	0.59983***
R^2	0.387	0.291	0.360
Panel B: $RV_{t+1} = \beta_0 + \beta_1 OVX_t + \varepsilon_{t+1}$			
Constant	-0.00495***	-0.00052***	-0.00024***
OVX	0.00097***	0.00003***	0.00001***
R^2	0.468	0.342	0.337
Panel C: $RV_{t+1} = \beta_0 + \beta_1 RV_t + \beta_2 OVX_t + \varepsilon_{t+1}$			
Constant	-0.00311***	-0.00036***	-0.00013***
RV	0.26794***	0.29361***	0.38944***
OVX	0.00069***	0.00001***	0.000001***
R^2	0.502	0.398	0.431

Notes: *** indicates statistical significance at 1% level.

Table 6: Out-of-sample forecasts

Models ↓	RVABD		RVRS		RVP	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
$RV_{t+1} = \beta_0 + \beta_1 RV_t + \varepsilon_{t+1}$	0.0158	0.0118	0.0007	0.0004	0.0003	0.0002
$RV_{t+1} = \beta_0 + \beta_1 OVX_t + \varepsilon_{t+1}$	0.0147	0.0107	0.0006	0.0004	0.0002	0.0001
$RV_{t+1} = \beta_0 + \beta_1 RV_t + \beta_2 OVX_t + \varepsilon_{t+1}$	0.0143	0.0105	0.0006	0.0004	0.0002	0.0001

Table 7: Forecasting encompassing test results

RV measures ↓	θ_1			θ_2		
	Estimate	S.E.	p-value	Estimate	S.E.	p-value
Panel B: Base-line vs OVX alone models						
RVABD	0.2294***	0.0874	0.00	0.9937***	0.1120	0.00
RVP	0.4795***	0.1052	0.00	0.9063***	0.1259	0.00
RVRS	0.1106*	0.0601	0.06	0.4122***	0.0451	0.00
Panel B: Base-line vs extended RV models						
RVABD	0.0013	0.1062	0.98	1.1435***	0.1289	0.00
RVP	0.2589**	0.1261	0.04	1.0235***	0.1421	0.00
RVRS	0.0250	0.0656	0.70	0.4511***	0.0489	0.00

Notes: ***, ** and * indicate statistical significance at 1%, 5% and 10% levels respectively.

Table 8: Testing the asymmetric impacts of OVX

	RVABD	RVRS	RVP
Constant	0.02609***	0.00030***	0.00014***
ΔOVX_t^+	0.00543***	0.00020***	0.00008***
ΔOVX_t^-	-0.00309***	-0.000167***	-0.00005***
$H_0: k_1 = k_2$	34.98***	3.02***	4.90***

Notes: These results are obtained by estimating the following equation $RV_{t+1} = \pi + k_1 \Delta OVX_t^+ + k_2 \Delta OVX_t^- + \epsilon_{t+1}$. The last row reports the value of *t*-statistic for testing $H_0: k_1 = k_2$. *** indicates statistical significance at 1% level.

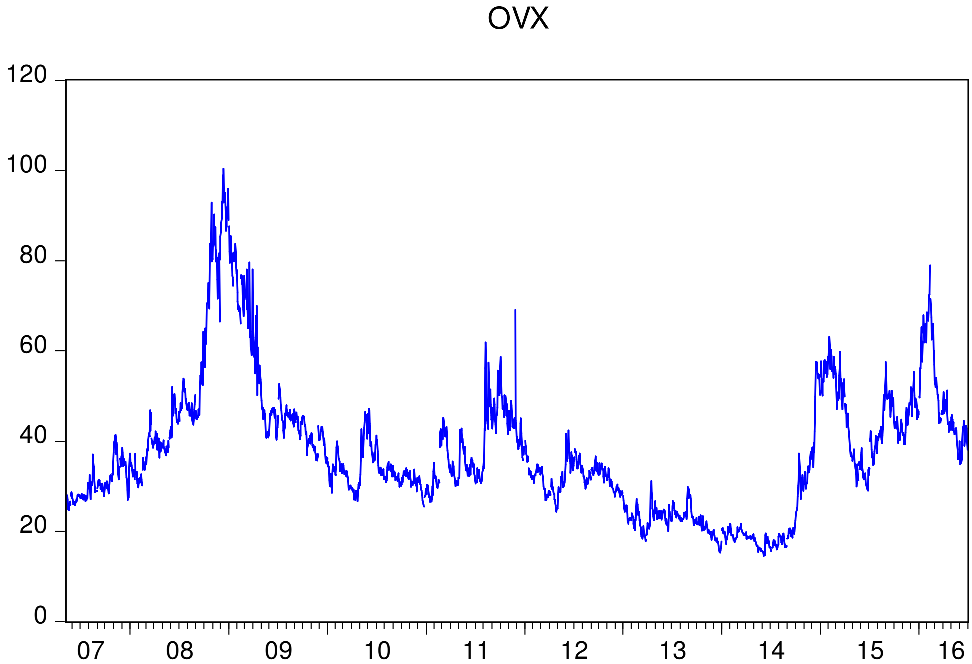

Fig. 1: Crude oil volatility index from 10/05/2007-30/06/2016