# On the Oil Price Uncertainty

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**ABSTRACT**

This study focuses on oil price volatility and uncertainty over the period January 1986–December 2018, covering episodes of oil price increases and collapses. Accordingly, in line with Poon and Granger (2003), and Teräsvirta and Zhao (2011), we propose three different specifications of stochastic oil volatility: standard stochastic volatility, stochastic volatility moving average, leverage stochastic volatility models. We compute the out-of-sample forecasts for the uncertainty in oil prices using the estimates for these three stochastic oil price volatility models and we discuss its effects. Our findings show that the standard stochastic volatility model outperforms the other two models when focusing on oil price uncertainty. This finding is relevant to better forecast and understand the effects of oil price uncertainty on the real economy.

**Keywords:** Oil volatility, Oil price uncertainty, Stochastic volatility models, Forecasting

https://doi.org/10.5547/01956574.40.SI2.zfti

## 1. INTRODUCTION

Following Hamilton's (1983) seminal paper, it is established that oil shocks may have a significant negative effect on the real economy. Indeed, oil is considered a major input for several industries and manufactories. Moreover, oil still matters to entrepreneurs, investors, consumers, and policymakers (Elder and Serletis, 2010; Hamilton, 2011), even though several national ongoing programs have tried to permanently reduce the dependency of advanced countries on the oil sector and propose new alternative energy resources (e.g., COP21).[1] Furthermore, strong evidence of uncertainty/unpredictability is seen in the oil sector (supply, reserves, pricing, the US shale revolution, demand, market regulation). Considered together, two interesting questions can be raised in the context: (i) Do oil prices matter? and (ii) Does oil price volatility and uncertainty matter?

In the aftermath of the recent global financial crisis (2007–2009), major changes were observed in oil prices. The West Texas Intermediate (WTI) oil increased from US$ 58/barrel in January 2007 to US$ 140/barrel in June 2008, but declined to US$ 41/barrel in January 2009 to reach US$ 133/barrel in April 2011 before hitting US$ 48/barrel in September 2016, indicating evidence of high oil price volatility. Thus, high oil price volatility and abrupt changes in oil prices may impact the overall economy and emerge as a source of economic uncertainty,[2] which requires more attention

1. In order to limit the effect of oil price changes on its economy, China, the world's second largest oil consumer since 2009, is negotiating with the main oil-producing countries (i.e., Saudi Arabia) to develop bilateral collaborations and define a suitable floor for oil prices.

2. Uncertainty may have an important microeconomic effect (firms and investors) and macroeconomic effect (economic activity, macroeconomic environment, stock markets), as it could imply a cut in investment, consumption, employment and,

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from consumers, investors, and policymakers. Indeed, oil effects occur through multiple channels: (i) supply-side shocks (fluctuations in oil prices are indicative of an increase in the marginal cost of production); (ii) wealth-effect transfer (transfer of trade surplus from oil consuming countries to oil producing countries); (iii) inflationary effects; and (iv) unexpected effects (i.e., uncertainty about oil prices). Hereafter, we focus on uncertainty in oil prices, which is a crucial issue because, to the best of our knowledge, relatively few previous studies have investigated the effects of oil uncertainty (Elder and Serletis, 2010).

Oil prices exhibit uncertainty for many reasons. First, oil-producing countries do not reveal or communicate their data on oil reserves, real oil extraction costs, and oil reserve management. Saudi Arabia was earlier considered to have the largest proven oil reserves (267 billion barrels accounting for 24.4% of proven world oil reserves in 2000); however, since 2011, Venezuela has surpassed with higher oil reserves. However, these reserves may be subject to measurement errors. Accordingly, the announcement of new oil reserves could affect oil supply and reduce oil prices, while the inverse effect is expected for a pessimistic analysis of oil reserves. Second, oil supply is time-varying, as it depends on the geopolitical environment and agreement among oil producers. For example, Saudi Arabia is a major oil producer worldwide, but its production is variable, with a volume of 10.3 million barrels a day in 1980, 10.6 million barrels a day in 2006, 9.2 million barrels a day in 2008, and 9.76 million barrels a day in 2009. Furthermore, with the recent Saudi Arabia-led military conflict against Yemen and the US sanctions on Iran's oil could destabilize oil production. Third, oil demand is always cyclical and changes with the economic business-cycle fluctuations, increasing when the economy is booming and declining during economic downturns, thus affecting oil demand elasticity and price. For example, the slowdown in global economic growth and China's oil demand (i.e., China's economy grew 7.4% in 2014, its lowest since 1990, and decreased further to 6.9% in 2015) led to the sharp drop in oil prices. Finally, the US shale revolution, (Jawadi, 2018) could induce further uncertainty and volatility in oil prices in the future. Indeed, shale revolution has had an adverse impact, as it opposes technology and traditional oil production, thereby yielding oil production at a lower price and leading to a ceiling on oil prices.

In the existing literature, a strand investigated the impact of oil price uncertainty (OPU) on the real economy. For example, Elder and Serletis (2010) measured OPU using the conditional standard deviation of the forecast error for the change in real oil prices. Using a structural vector autoregressive (VAR) generalized autoregressive conditional heteroskedasticity (GARCH) as the mean, the authors studied the effect of OPU on real economic activity and showed that OPU has a significant negative effect on gross domestic product (GDP), durable consumption, and investment. This effect occurs through two main channels: i) real balances and monetary policy,[3] and ii) income transfer. Rahman and Serletis (2012) also present evidence showing a significant relationship between OPU and Canada's real GDP growth rate. The authors suggested that oil price crashes witnessed in January 1986 and November 2008 involved similar levels of OPU, even if the causes were different.[4] Jo (2014) extended the study of Elder and Serletis (2010), measuring OPU through a stochastic volatility model and showing its negative effect on global industrial production and manufacturing activities. In fact, if oil prices double, quarterly activity growth decreases by 0.1%. Furthermore, Jo (2014) proxies OPU by a time-varying standard deviation as the one-quarter ahead oil price forecast

therefore, output growth (Bernanke, 1983; Pindyck, 1991).

3. The first channel highlighting the effect of OPU on the real economy, based on the real balance effect, stipulates that an increase in oil prices causes a sharp rise in the overall level of prices, leading to a decrease in the real money balance held by both households and firms, thereby affecting economic growth.

4. Indeed, while the 1986 oil shock was driven by supply shocks and induced by a collapse of OPEC oil production, the 2008 oil shock is considered a demand shock following the global recession and financial crisis.

error, for which the time-varying volatility evolves through a stochastic volatility process. Aye et al. (2014) also captured OPU by the conditional standard deviation of the one period-ahead forecast error for the change in oil prices and showed that OPU significantly and negatively affects South Africa's manufacturing production. Bashar, Wadud, and Ahmed (2013) found evidence indicating OPU's importance and showed its significant impact on the Canadian economy, which is in line with Hamilton's (1983, 1996, 2003, 2011) conclusion that oil price shocks are sources of uncertainty, as oil price increases are often followed by declines in the US GDP growth.

Other studies investigated the investment channel hypothesis to characterize the impact of OPU on the real economy (Henriques and Sadorsky, 2011; Aye et al., 2014; Wang et al., 2017). This literature is disaggregated between studies analyzing the effect of OPU on economic activity based on the macroeconomic and microeconomic perspectives. For the first group (Kuper and Soest, 2006; Elder and Serletis, 2010; Rahman and Serletis, 2011), analysis is oriented on the impact of macroeconomic aggregates (inflation, exchange rate, GDP growth, and energy use), while the second group investigated the OPU effect based on the investment decisions of firms (Henriques and Sadorsky, 2011; Wang et al., 2017) and manufacturing production (Aye et al., 2014).

The second strand of literature shows the impact of OPU on expected cash flows, discount rate (Ciner, 2013), and uncertainty related to equity prices (Bernanke, 1983; Pindyck, 1991). Recently, Bams et al. (2017) stipulate that OPU may be an important factor for stock valuation. Wang et al. (2017) also showed the negative effect of OPU on corporate investment expenditure in China, while Joo and Park (2017) showed that OPU negatively affects stock returns. Other studies investigated the impact of OPU on clean energy stock returns, (Dutta, Nikkinen, and Rothovius 2017; Henriques and Sadorsky, 2008). This literature postulates that oil price shocks significantly affect the financial market performance of renewable energy firms. Consequently, OPU plays an important role in the global renewable energy policy planning and the overall economy.

Broadly, while several studies investigated the impact of OPU on the real economy and provided interesting results, we note two remarks. On the one hand, in most previous studies, the proxies for OPU are selected in an ad hoc manner. While on the other hand, previous studies refer to simple and less flexible measures of OPU, implying limited analysis of its impact on the real economy. Overall, four main approaches are used in the related literature to measure OPU. The first approach refers to the monthly standard deviation, as in Federer (1996), while the second approach stipulates the use of squares of log differences in oil price series. A third approach approximates OPU through a 13-month rolling standard deviation of the monthly oil price as a logarithm. Finally, a fourth approach approximates OPU with the conditional standard deviation computed from a GARCH model specifying the log difference in oil price series. Additionally, to the best of our knowledge, no previous study has investigated the issue of OPU forecasting.

Our study addresses this gap and contributes to the literature in several ways. First, we propose three different measures of OPU based on the stochastic volatility models (standard stochastic volatility, stochastic volatility moving average, and leverage stochastic volatility models). The use of stochastic volatility models has several advantages. The stochastic volatility model proposes a more flexible framework than classical measures, as it embodies two separate disturbance terms (Carnero et al., 2004). In fact, unlike the GARCH family models, unexpected OPU shocks may be regarded as independent changes in oil prices because the model has its own innovation in addition to innovations in the mean equation. Furthermore, the latent specification in these models rejects any ad hoc assumptions about the specification of conditional volatility. Moreover, since volatility is typically unobservable, the stochastic volatility model embodies a main characteristic of volatility as it is formulated based on latent variables. Second, we compare OPU measures through a forecasting analysis. To the best of our knowledge, this is the first study that provides a forecasting essay of

OPU. Accordingly, we show that the standard stochastic volatility model outperforms the other two models in forecasting OPU.

The remainder of this study is organized as follows. Section 2 presents the theoretical framework and the econometric modeling. Section 3 discusses the empirical results. Section 4 concludes the study.

## 2. ECONOMETRIC METHODOLOGY

### 2.1 Hypothesis of Uncertainty Measure

Uncertainty is defined according to the studied economic and/or financial time-series (e.g., inflation, economic, and financial uncertainties). Formally, three main approaches are used to measure uncertainty. During the 1980s, the standard deviation or the variance of a time series was considered as the most popular proxy of uncertainty. Second, the conditional volatility measure based on the ARCH family models was considered in the 1990s. Finally, since the 1990s, the stochastic volatility measure is deemed as the most appropriate approach for uncertainty modeling, given its flexibility and the consideration of volatility as a latent variable.

In the existing literature, different measures of uncertainty have been adopted for oil prices. For instance, Wang et al. (2017) argued that the two most popular OPU proxies are the standard deviation of daily returns of international oil prices (in line with Sadorsky, 2008; Henriques and Sadorsky, 2011) and the conditional volatility based on the GARCH (1,1) model. Bashar, Wadud, and Ali Ahmed (2013) used four OPU proxies: i) monthly standard deviation;[5] ii) squares of the log-differences in oil price series; iii) 13-month rolling standard deviations of the monthly oil price data in log form; and iv) conditional volatility obtained from a GARCH (1,1) model. Aye et al. (2014) adopted the definition of Elder and Serletis (2010), considering the conditional standard deviation of the one-step-ahead forecast error for the change in real oil prices as a proxy for OPU. More recently, Bams et al. (2017) used the oil variance of risk premiums as a measure of uncertainty. Dutta, Nikkinen, and Rothovius (2017) used the significant effect of the implied crude oil volatility index (VOX) developed by the Chicago Board Options Exchange (CBOE) based on model-free implied volatility. The advantage of this measure is that it contains historical volatility information and investors' expectations about future market conditions.[6] Overall, various approaches have been adopted to measure OPU, but they always refer to fewer flexible measures and provide contrasting results.

This study differs from previous studies in several ways. First, we propose a new OPU measure, based on stochastic volatility models and characterized by a more flexible framework, as it allows oil price uncertainty to be the source of innovations, whether related or not to the oil market. Second, our measure considers oil price uncertainty as a latent variable following low-order Markov chains and is estimated through Bayesian approaches, thus allowing for dynamic parameters as opposed to the classical measures of uncertainty based on unconditional or conditional volatility measures. More specifically, we define OPU as the error of forecasting or innovations in volatility, contrary to most previous studies that proxied oil price uncertainty as a volatility measure.

5. Daily crude oil price data (in log form) are used to compute the standard deviations of oil prices for each month. Data in this standard deviation series are expected to reflect oil price volatility or uncertainty in the respective months.

6. Dutta, Nikkinen, and Rothovius (2017) note that "*The VOX 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,*" (Liu, Ji, and Fan, 2013).

### 2.2 Oil Price Uncertainty Measure Using Stochastic Volatility Model

We propose a new measure based on the definition of OPU proposed by Sadorsky, (2008), Elder and Serletis (2010), and Henriques and Sadorsky (2011). Uncertainty is defined as unexpected volatility, based on the rational expectation hypothesis. The motivation for this choice is explained as follows:

- At the beginning of period ($t_0$), volatility is equal to $V_{t_0}$ and the expected volatility for the next period ($t_1$), realized at time ($t_0$) corresponds to:

$$E_{t_0}[V_{t_1} \mid I_{t_0}] = V^e_{t_1|t_0} \tag{1}$$

- If there is no uncertainty in the market at ($t_1$), the volatility at ($t_1$) will be equal to the expected volatility realized at ($t_0$) for time ($t_1$). Then, volatility is equal to:

$$V_{t_1} = E_{t_0}[V_{t_1} \mid I_{t_0}] = V^e_{t_1|t_0} \tag{2}$$

In such a case, we have only expected volatility, and the unexpected component is equal to zero. In other words, there are no innovations in volatility at time ($t_1$).

- If there is uncertainty in the oil market, volatility at ($t_1$) will be different from the expected volatility at ($t_0$) for time ($t_1$). Therefore, at ($t_1$), $V_{t_1} \neq V^e_{t_1|t_0}$. Accordingly, uncertainty is defined as unexpected volatility $\left(U_{t_1}\right)$, as:

$$E_t\left[U_{t_1}\right] = \left|V_{t_1} - V^e_{t_1|t_0}\right| \tag{3}$$

Accordingly, the oil uncertainty measure at time ($t$), is defined as:

$$E_t\left[U_{t_{+1}}\right] = | V_{t_{+1}} - E_t[V_{t_{+1}} \mid I_t]| \tag{4}$$

(Eq. 4) presents our expected OPU measure.[7] Our strategy to measure OPU comprises four steps. First, we model oil price volatility based on various specifications in the stochastic volatility models, consistent with the main characteristics of time series data for oil prices. Second, we forecast volatility to determine $E_t[V_{t_{+1}} \mid I_t]$. Third, we compare our specifications on oil forecasting volatility measures with a benchmark volatility. However, since volatility is typically an unobserved series, choice of the benchmark model is a sensitive point. From a theoretical perspective, an efficient market (i.e., weak form of efficiency) implies that, at any given time, oil prices fully reflect the available information about the oil market and it follows random walk, we consider our benchmark model of oil volatility as the standard deviation of the random walk process. Therefore, we compare forecasting accuracy for all the models to determine the best model fit for the benchmark series. Finally, we measure OPU based on (Eq. 4).

### 2.3 Volatility modelling

To model the volatility in crude oil prices, we use several specifications of stochastic volatility for satisfying the main stylized facts of time series volatility, as highlighted by Teräsvirta and

7. Our conceptualization of the proposed measure of OPU is inspired by the definition of Elder and Serletis (2010), who consider OPU as the standard deviation of the one-step-ahead forecast error, conditional on the contemporaneous information set. Therefore, we choose to take the absolute value for both equations 3 and 4, in line with the definition of Elder and Serletis (2010). The term volatility denotes the standard deviation.

Zhao (2011), such as the Taylor effect,[8] persistence, and asymmetry. We consider three stochastic volatility models. The first model is the standard stochastic volatility (SSV) model, considering an AR (1) process for volatility. The first model aims to control the main feature of volatility, namely persistence. Next, we determine if the volatility is generated by a short-run dynamic behavior by allowing more correlations between oil shocks through a moving average (MA) component. Specifically, to consider this potential behavior, we propose a stochastic volatility model augmented by a moving average process for oil shocks, denoted by SV-MA. The SV-MA specification allows the data series to be more correlated, and this is one of the main characteristics of the volatility of financial or energy variables. Finally, we propose a third model to check if oil price volatility is characterized by the leverage effect, denoted by SV-L. This model considers a potential additional feature of volatility: the asymmetric effect.

**1** Model 1: Standard stochastic volatility (SSV)

$$Oil_t = \mu + \varepsilon_t^{Oil} \tag{5}$$

$$\varepsilon_t^{Oil} \sim N\left(0, \exp(h_t)\right)$$

where $\exp(h_t)$ defines the volatility of oil prices.
Next, we present the dynamics of the log volatility $\left(h_t\right)$. For the standard SV model, $\left(h_t\right)$ follows an AR(1) process, defined as:

$$h_t = \mu_h + \varphi_h\left(h_{t-1} - \mu_h\right) + \varepsilon_t^h \tag{6}$$

where, $\varepsilon_t^h \sim N\left(0, \sigma_h^2\right)$. From (Eq. 7), we infer that $\left(\varphi_h \prec 1\right)$ is the stationary condition for an AR(1) process. $\mu_h$ defines the unconditional mean. The process (Eq. 7) is initialized with $h_1 \sim N\ (0, \dfrac{\sigma_h^2}{1-\varphi_h^2})$

**2** Model 2: SV-MA model
Compared to the previous model, the SV-MA model imposes a constraint on the dynamics of oil shocks $\varepsilon_t^{Oil}$ to follow a short dynamic behavior based on an MA(1) process, as follows:

$$\varepsilon_t^{Oil} = \xi_t + \omega\xi_{t-1} \tag{7}$$

where, $\xi_t \sim N\left(0, \exp(h_t)\right)$, and $\left(h_t\right)$ have a similar dynamic as in model 1.

**3** Model 3: SV-L model
In Model 3, we consider the additional potential stylized impact of volatility in energy time series, that is, the leverage effect. Specifically, the innovations in the observed and stated equation may be correlated. This phenomenon is modeled based on the joint distribution of $\varepsilon_t^{Oil}$ and $\varepsilon_t^h$, as follows:

$$\begin{pmatrix} \varepsilon_t^{Oil} \\ \varepsilon_t^h \end{pmatrix} \sim \begin{pmatrix} \exp(h_t) & \rho\exp(0.5h_t\sigma_h) \\ \rho\exp(0.5h_t\sigma_h) & \sigma_h^2 \end{pmatrix} \tag{8}$$

8. The Taylor effect refers to the Taylor property (1986, p. 52–55), defined when the sample autocorrelations of absolute returns seem to be larger than the sample autocorrelations of squares. Ding et al. (1993), though interested in the S&P500 index, show that the autocorrelations for absolute S&P500 returns raised to the power are maximized when is around 1, that is, the largest autocorrelations are found in absolute returns. Granger and Ding (1995) called this property the Taylor effect.

The above joint distribution between innovations in oil markets and innovations in the volatility present in oil markets highlight the leverage effects. In fact, the negative shocks in the oil market at time ($t$) ($\rho<0$) generate a larger volatility at time ($t+1$), and vice versa. Interestingly, for case ($\rho=0$), we use the standard stochastic volatility model (Model 1).

All the stochastic volatility models are estimated based on Bayesian techniques, in line with Chan (2017), and Chan and Grant (2016). We use the acceptance-rejection feature of the Metropolis-Hastings algorithm described in Chan (2017), which is based on the precision sampler of Chan and Jeliazkov (2009) for the joint sampling of the log volatilities. Interestingly, this algorithm uses fast band matrix routines rather than the Kalman filter.[9]

## 2.4. Forecasting Strategy

To forecast the stochastic volatility for oil prices based on the above three models, we employ a rolling out-of-sample strategy. The *h-step* forecasts are calculated for $t=k,...,T$, where $k$ is the forecasting start date and ($t$) is the end date for the oil price series. As our data start from January 1986, we fix ($k$) to January 2009. Therefore, the excepted stochastic volatility will be available from this date, providing us 120 observations.

The forecasting accuracy is evaluated based on the mean error (ME), mean absolute error (MAE), root mean square error (RMSE), and Theil's U indicator (TU), defined as follows:

$$TU=\sqrt{\frac{\sum\left(\frac{\hat{Y}_{i,t+1}-Y_{i,t+1}}{Y_{i,t}}\right)^2}{\sum\left(\frac{Y_{i,t+1}-Y_{i,t}}{Y_{i,t}}\right)^2}} \tag{9}$$

where, ($\hat{Y}_{i,t+1}$) is the volatility forecast at point ($t+1$) based on the specification ($i$), with $i=Model1,Model2,Model3$. ($Y_{i,t+1}$) and ($Y_{i,t}$) are the observed values at times ($t+1$) and ($t$), respectively, based on the specification ($i$). ($N_i$) denotes the number of data points in our study, which are equal to 120 observations.

The evaluation of the forecasted series is based on these four criteria. Specifically, the best forecasting model should minimize these criteria.

For additional accuracy, we employ a test to evaluate the significance of the difference between two competing models, the Harvey, Leybourne, and Newbold (1997) test (hereafter MDM). This test is a modified version of the Diebold-Mariano (1995) test (DM). The latter suffers from a correlation bias when the forecast horizon is above 1, as in our case, and it assumes that the statistical test follows a standard normal distribution.[10]

The pairwise methods, such as the MDM test, have been criticized, as the retained model may be a chancy result (White, 2000). More specifically, White (2000) highlighted the problem of data snooping, which may be a source of bias in the pairwise methods. To overcome this problem, the author proposed a new method known as the reality check (RC). This method tests the null hypothesis that the best model has no superior predictive ability over a benchmark model. However,

9. For more details regarding used priors and Bayesian estimation, please see Appendix A in Chan and Grant (2016), as we have used the same prior, developed in line with Chan (2017)

10. For more details on the MDM test, see Harvey, Leybourne, and Newbold (1997); for a summary, see Ftiti and Jawadi (2018).

Hansen (2005) has criticized this method for its instability against poor and irrelevant candidate models. Hansen (2005) proposed a new test known as the superior predictive ability (SPA) test, which is a modified version of RC to ensure stability against irrelevant and poor candidate models.

The SPA test compares M forecasts series and aims to analyze the significance of the differences between the forecasting error measures. More specifically, it compares the relative performance of a benchmark model with its competitors based on a defined loss function. The null hypothesis of the SPA test considers that the benchmark model is not outperformed by any other candidate model. The p-values of the SPA are obtained based on the stationary bootstrap procedure.[11]

The main limitation of the SPA is its inability to discriminate between the selected best models. Hansen, Lunde, and Nason (2011) overcome this limit through developing a new method known as the model confidence set (MCS). This method selects a smaller set of models, called as model confidence sets, containing the best forecasting competitors at a given level of confidence. The selected models (model confidence set) have an equal predictive ability.[12] Therefore, in our analysis we draw both approaches, namely the SPA test and the MCS method to validate the sensitivity of our best model.

## 3. EMPIRICAL ANALYSIS

### 3.1 Data

Our data include the monthly WTI oil price data from January 1986 to December 2018. We use the US consumer price index (CPI) to deflate oil prices and use the real oil price. The WTI and US CPI data are collected from the database of the Federal Reserve Bank of Saint-Louis.

Table 1 presents the descriptive statistics for real oil prices. On average, real oil price is equal to US$ 52.828/barrel. During our study period, real oil prices ranged from US$ 16.950/barrel to US$ 136.384/barrel. This spread shows the high variability in real oil prices during the study period, which is indicative of high uncertainty in the market. Specifically, the standard deviation exhibits a high value (26.706), which confirms the high volatility in real oil prices. Furthermore, the kurtosis value is less than 3, presenting evidence of a platykurtic distribution of real oil prices (Figure 1). Moreover, the data are skewed to the right. This result is in line with the Jarque-Bera test, rejecting the normal distribution of real oil prices.

**Table 1: Descriptive statistics of the real oil price**

| Variable | Mean | Min | Max | Med | S.D | Skw | Kr | J-B |
|---|---|---|---|---|---|---|---|---|
| Real oil price | 52.828 | 16.950 | 136.384 | 41.460 | 26.706 | 0.984 | 2.857 | 64.284*** |

Note: Med, S.D, Skw, Kr, and J-B denote the median, Standard deviation, Skewness, Kurtosis, and the Jarque-Bera statistic. *** denotes the significance level of 1%.

### 3.2. Empirical Results

#### *3.2.1. Oil volatility modeling (step 1)*

The first step in our analysis is to model the oil price volatility. In this study, three specifications of stochastic volatility are chosen, as described in subsection 2.3.

11. See Hansen (2005) for more details on the SPA test.

12. The MCS procedure is a model selection algorithm, filtering out a set of competitors from a given large set of models. Contrary to the SPA test, we did not define any model as a benchmark under the MCS method. We did not report the details of the MCS procedure to save space. For more details, please see Hansen, Lunde, and Nason (2011).

**Figure 1: The dynamic of the real oil price**

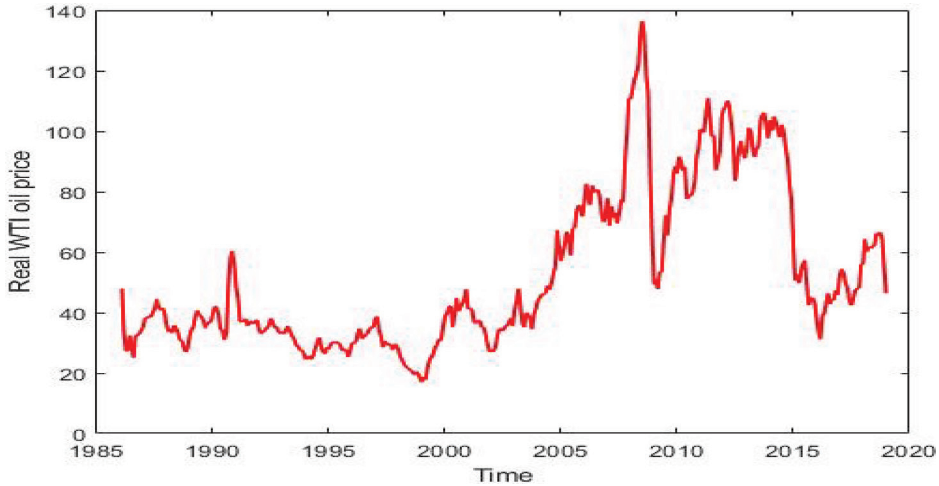
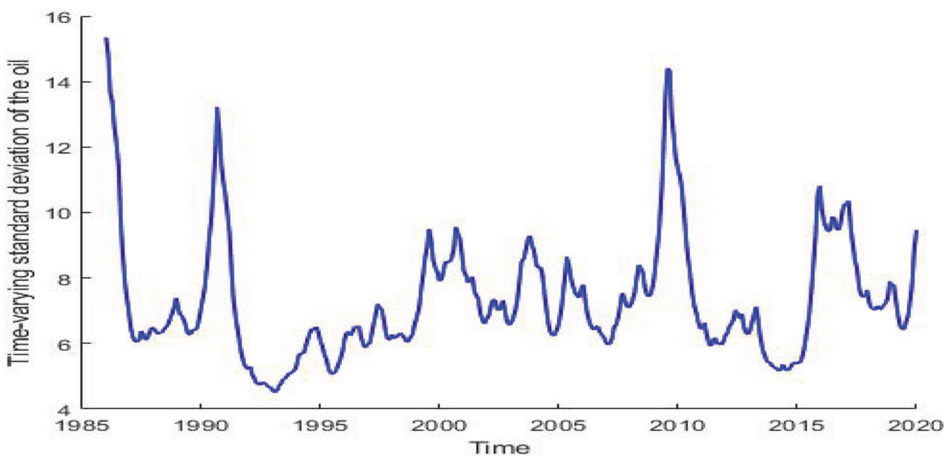



**Figure 2: The oil volatility modeling based on Model 1**




Figures 2–4 present the oil price volatility during the period 1986–2018, based on the standard and moving average, and leverage stochastic volatility models, respectively. These graphs show some interesting aspects. First, the general pattern in oil price volatility measures is consistent with the real oil price dynamics (Fig. 1). More interestingly, based on the dynamics of real oil prices (calm periods, as well as peaks and troughs, as given in Figure 1), our volatility measures also exhibit some noteworthy aspects. The calm periods spanning 1993–2005 and after 2015 translate into low volatility levels in the three models (Figs. 2–4). The average oil volatility during the analysis period is around 6.892, 6.907, and 6.943 in Models 1, 2, and 3, respectively (Table 2).

Model 1 (standard stochastic volatility) considers the persistence behavior, based on only one channel, namely through the AR(1) process of the oil volatility equation (Eq. 4). This model gives us the average oil volatility that is equal to 6.892 with standard deviation at 1.917. Model 2 controls for higher levels of volatility persistence through a second channel, where the moving average of oil shocks is used to increase the correlation between oil innovations. In other words, this model checks if oil volatility is characterized by the short-term dynamic behavior. Model 3 consid-

**Figure 3: The oil volatility modeling based on Model 2**

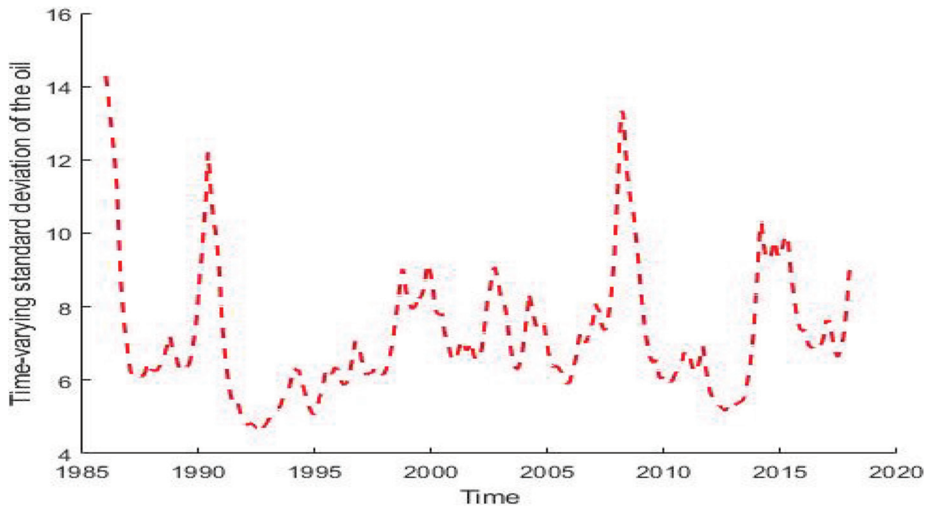
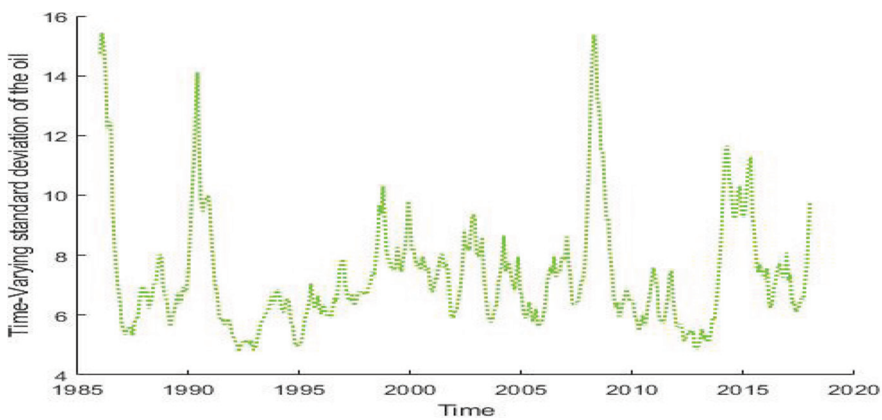



**Figure 4: The oil volatility modeling based on Model 3**




ers a potential asymmetry (i.e., leverage effects) in oil volatility modelling and shows the highest level of oil volatility on average.

Table 2 displays the results of the standardized errors across the three models. The average error is lowest for the model with the lowest standard deviation. More importantly, the errors follow a normal distribution for all the models. Based on this preliminary analysis, it seems that Model 1 may be the best fit model for oil volatility.

During the turmoil period (2007–2009), the results for volatility modeling highlight some noteworthy aspects. As observed in Figure 1, real oil prices exhibit peaks and troughs in 1985, at the beginning of 1990s, and during the period 2005–2015, in line with the pattern of the three volatility measures. We note that the average volatility levels in oil prices decreased from 16, 14, and 15 to 6.5, 6, and 5, based on Models 1, 2, and 3, respectively. The decline in oil prices during the period 1981–1986 is known as the period of great plunge in oil prices: For instance, 1981 is marked by the protracted war between Iraq and Iran leading to the decline in their respective oil production and the consequent increase in oil prices, especially after Saudi Arabia voluntarily curtailed its production by 75%. Similarly, 1986 is marked by the collapse in oil prices, as Saudi Arabia started to ramp up

**Table 2: Descriptive statistics of oil volatility measures**

| Variable | Mean | Min | Max | Med | S.D | Skw | Kr | J-B |
|---|---|---|---|---|---|---|---|---|
| The oil volatility measures across the three models | | | | | | | | |
| Model 1 | 6.892 | 4.093 | 15.171 | 6.423 | 1.917 | 1.482 | 5.663 | 260.685*** |
| Model 2 | 6.907 | 4.878 | 13.523 | 6.481 | 1.518 | 1.666 | 6.300 | 361.313*** |
| Model 3 | 6.943 | 4.252 | 14.986 | 6.554 | 1.877 | 1.674 | 6.604 | 397.518*** |
| The standardized errors for the three oil volatility models | | | | | | | | |
| Model 1 | 0.011 | –0.653 | 0.833 | 0.009 | 0.248 | 0.141 | 2.947 | 1.366 |
| Model 2 | –0.028 | –0.889 | 0.933 | –0.031 | 0.329 | –0.043 | 2.867 | 0.412 |
| Model 3 | –0.014 | –0.786 | 0.837 | –0.017 | 0.277 | 0.062 | 2.860 | 0.749 |

Note: Med, S.D, Skw, Kr, and J-B denote the median, Standard deviation, Skewness, Kurtosis, and the Jarque-Bera statistic. *** denotes the significance level of 1%.

its production back up, which led to a sharp decrease in real oil prices from US$ 50 /barrel in 1985 to US$ 20/barrel in 1986.

The early 1990s is marked by Iraq's invasion of neighboring Kuwait. Since these two countries together account for an estimated 9% of global oil production, real oil prices (Fig. 1) rose above US$ 60/barrel accompanied by a sharp rise in OPU to 13, 12, and 14, for Models 1, 2, and 3, respectively (Figs. 2–4). During the periods 1997–1998, 2000–2001, and 2003, although real oil prices increased, the rise was relatively lower than the previous growth. These movements were accompanied by similar movements in our measure of oil price volatility and were lower compared to the previous movement (Figs. 2–4). Interestingly, the subprime mortgage crisis period, occurring between 2007 and 2008, is marked by an acceleration in real oil prices from around US$ 60/barrel to more than USD 135/barrel. This extreme movement is also observed in our three volatility measures (Figs. 2–4). A similar behavior is observed in 2015.

The first interesting result is that our volatility measures reproduced the variability in the oil market. Interestingly, we have a co-movement between our volatility measures and real oil prices.

The second result is related to the comparison between our measures of oil price volatility across the three specifications. Although the general pattern is similar, some differences are observed. Mainly, volatility measures are different among the three specifications around the level of movement in reaction to different oil price shocks. From Figures 2–4, we note that the upward or downward movement in volatility does not occur at the same time: there is a difference in certain number of days. We suggest that it is optimal for investors, hedgers, and policymakers to recognize the accurate model to optimize their portfolio diversification, hedging, and regulations, respectively.

The conclusions discussed above are verified for the entire period. Table 2 presents the main descriptive statistics for the oil volatility series for the three models. We note that the average level is relatively small between the models, but we observe differences in terms of the extreme movement, especially in the standard deviation.

*3.2.2. Oil volatility modeling (step 2)*

The second step in the proposed empirical design is to forecast oil price volatility to determine OPU based on (Eq. 4). We opt for an out-of-sample forecasting for oil volatility based on the three specifications. Our strategy consists of estimating oil price volatility from January 1986 to January 2009. Next, based on the specifications presented in subsection 3.2, we forecast the remaining oil volatility.

Figures 5–7 present the forecast for oil price volatility based on Models 1–3. Figures 5–7 show that the forecast volatility for the three models are convex functions. This convexity is an

**Figure 5: The oil volatility forecast based on Model 1**

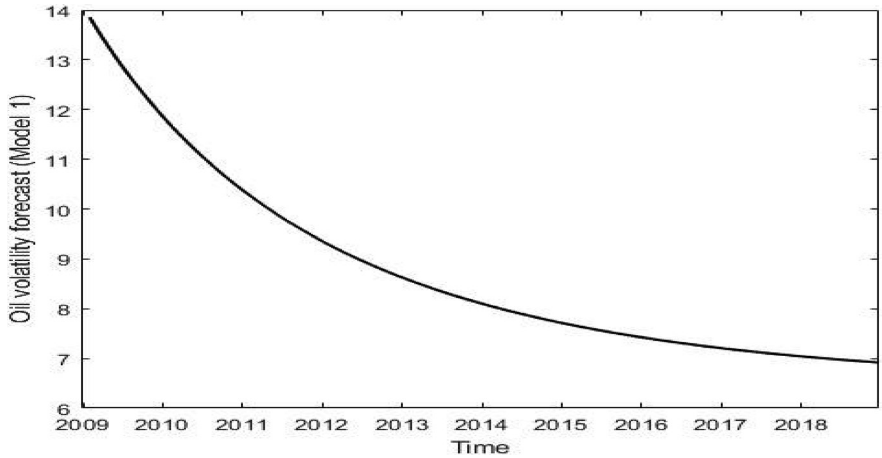
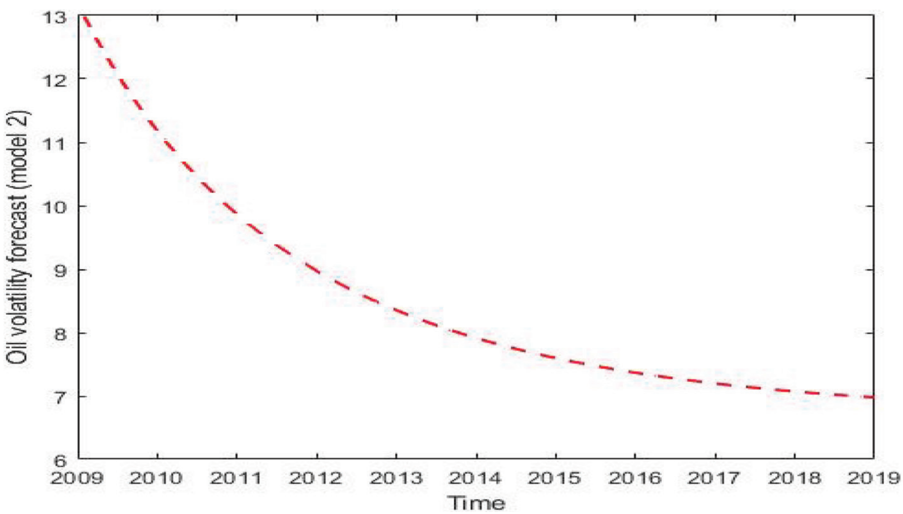


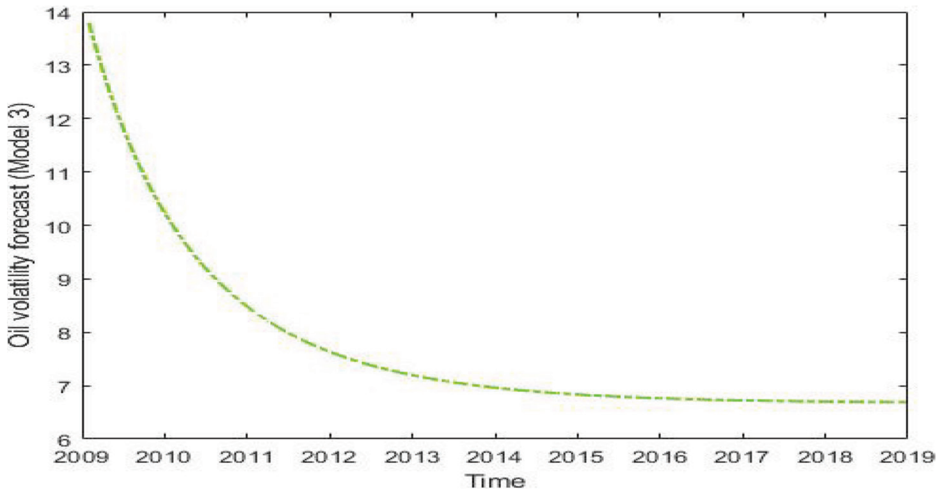

**Figure 6: The oil volatility forecast based on Model 2**




interesting result as it implies that the first derivate is negative and the second one is positive. The negative first difference function implies that economic agents adjust their volatility forecast gradually. More specifically, as the forecast span starts from 2009, oil prices declined sharply after the surge observed in 2007–2008. In other words, after this high level of uncertainty characterized by increased volatility in oil prices, as observed in Figures 2–4, economic agents adjust oil price volatility on the expectation of movement in oil prices, as observed in 2009. The main difference across the three models is the degree of curvature. We observe a quicker adjustment through Model 1, while Model 2 exhibits a tighter curvature compared to Model 1, and the maximum tight curvature behavior is observed for Model 3.

The difference in the degree of curvature leads to a necessary difference in the volatility expectation for each period. For example, Model 1 gives an expected level above 7 during 2018, Model 2 is equal to 7, and Model 3 is below 7. We suggest that investors, policymakers, and hedgers should be informed about the appropriate model for forecasting oil volatility.

**Figure 7: The oil volatility forecast based on Model 3**




*3.2.3. Accuracy of Oil Volatility Measures (step 3)*

The third step compares the three forecasts for the oil volatility series with a benchmark. Since volatility is an unobserved series, the choice of the benchmark model is a sensitive point. Thus, we posit that the benchmark is obtained when the market is efficient. In other words, at any given time, oil prices fully reflect the available information in the oil market in our benchmark model. Empirically, benchmark oil volatility is regarded as the standard deviation for the oil price dynamic generated from a random walk process.[13]

**Table 3: Descriptive statistics of the benchmark volatility**

| Variable | Mean | Min | Max | Med | S.D | Skw | Kr | J-B |
|---|---|---|---|---|---|---|---|---|
| RV | 9.558 | 7.318 | 23.100 | 8.597 | 2.472 | 2.040 | 7.778 | 648.324*** |

Note: Med, S.D, Skw, Kr, and J-B denote the median, Standard deviation, Skewness, Kurtosis, and the Jarque-Bera statistic. *** denotes the significance level of 1%.

Figure 8 presents the dynamics of the benchmark oil volatility, hereafter called realized volatility (RV). In 2009, oil RV was high, in line with our oil volatility measures. Later, it exhibited a similar decrease from 2010 onward. The pattern is similar during the rest of the analysis period. Table 3 presents the main descriptive statistics for the RV series.

First, we compare our forecasted oil volatility with RV, which is defined based on the efficient hypothesis. We aim to investigate the performance of each model with respect to a random walk process. Table 4 present the results for the three forecasted volatility series with the benchmark model in terms of mean error, MAE, RMSE, and TU.

The results in Tables 4 and 5 should be discussed with caution, as they depend on the choice of the benchmark, as volatility is unobservable. Table 4 results show that Model 1 is closer to the RV based on two criteria (i.e., the mean error and TU indicator), leading to the superiority of the standard stochastic volatility (SSV) specification, as it is closer to the RV than the other models. However, two other criteria challenge this finding, since Model 2, based on the MAE and RMSE,

13. The dynamic standard deviation of oil volatility from the benchmark model is extracted based on an ARCH process.

**Figure 8: The benchmark of the oil volatility (RV)**

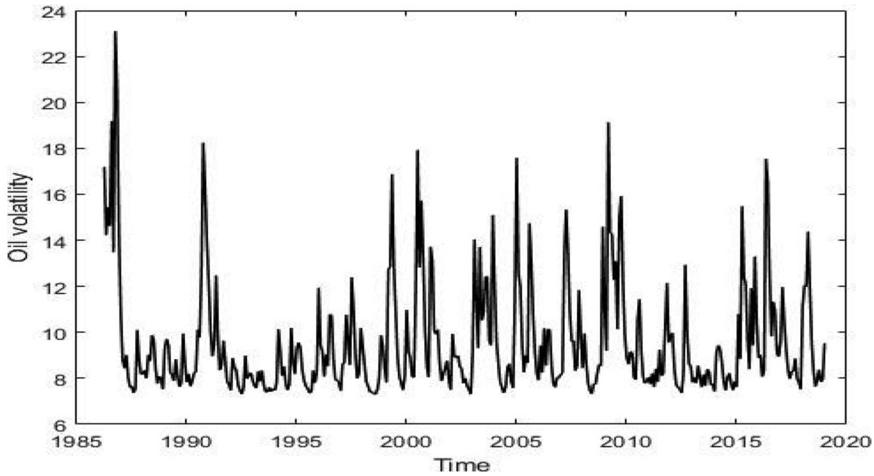



**Table 4: Evaluation of the accuracy of the three oil volatility forecasting measures compared to the RV**

| | Model 1 *V.S.* RV | Model 2 *V.S.* RV | Model 3 *V.S.* RV |
|---|---|---|---|
| ME | 0.858 | 1.114 | 1.908 |
| MAE | 1.994 | 1.935 | 2.202 |
| RMSE | 2.752 | 2.723 | 3.004 |
| Theil's U | 1.245 | 1.277 | 1.410 |

Note: RV denotes the Benchmark of the oil volatility. ME denotes the mean errors.

**Table 5: Forecasting accuracy based on the MDM test**

| | Model 1 *V.S.* Model 2 | Model 1 *V.S.* Model 3 | Model 3 *V.S.* Model 2 |
|---|---|---|---|
| MDM Statistic | 1.0099 | –2.2359 | 5.2350 |
| p-value of MDM | 0.1562 | 0.0126** | 0.0000*** |
| Conclusion | Model 1 = Model 2 | Model 1 > Model 3 | Model 2 > Model 3 |

Note: "=" denotes" Same power of prediction"; ">" denotes "outperforms". ** and *** denote the significance level of 5% and 1%, respectively.

is closer to the RV than the other models. Consistent with these indicators, the pairwise test, in our study the MDM test, is unable to discriminate between the models. Table 5 presents the result of the forecasting accuracy between the pairs of competitors models based on the MDM test. This test shows that Models 1 and 2 have the same power of prediction, as the difference between their loss functions (both MAE and RMSE) is not statistically significant. Next, we show that Model 1 outperforms Model 3, and Model 2 outperforms Model 3. Therefore, the MDM test as well as these indicators are inconclusive.

The results presented in Tables 4 and 5 are mitigated and, as discussed above, the pairwise test may be the source of bias, as the results may be chancy (White, 2000). To overcome this limit, we adopt the SPA test and the MCS procedure and present the results in Table 6. The SPA test shows that both Models 1 and 3 are not performed by Model 2. The MCS procedure confirms this result, but the confidence level is more important (100%) for Model 1.

This finding is important, as it provides additional insights into forecasting oil price volatility and, therefore, uncertainty. Specifically, policymakers and investors should consider the standard

**Table 6: The results of SPA test and MCS method**

| | The p-value of the SPA Test | | The p-values MCS method | |
|---|---|---|---|---|
| The loss function | MAE | RMSE | MAE | RMSE |
| Model 1 | 0.8550 | 0.8550 | [1.000] | [1.000] |
| Model 2 | 0.1009 | 0.1009 | — | — |
| Model 3 | 0.1176 | 0.1152 | [0.1101] | [0.1385] |

Note: Numbers reported in this left side of the table denote the p-values of the SPA test of Hansen (2005) under the null hypothesis that a benchmark model cannot be outperformed by other candidate models. [.] denotes the p-value of MCS of the retained best models. The p-values of the SPA test and MCS p-value are computed based on 10,000 bootstrap samples. The confidence level for MCS is 90.

stochastic volatility (Model 1) and/or leverage model (Model 3). In other words, our findings show that oil volatility does not exhibit a short-term dynamic persistence. In fact, Model 1 must be considered, as it has the highest level of confidence (based on the MCS procedure), without including any other aspects of the previously stylized facts such as leverage effect, asymmetry, and a higher level of correlation. Our results show that investors should not include further constraints in modeling their volatility expectation. Moreover, our findings show that the standard stochastic volatility specification should be used to forecast the oil market volatility.

*3.2.4. Forecasting Oil Price Uncertainty Measures (Step 4)*

Based on (Eq. 1), oil price uncertainty forecasting is computed based on the oil market volatility forecast. Figures 9–11 present the dynamics of oil price uncertainty based on Models 1–3, respectively. Table 7 presents the main descriptive statistics for oil uncertainty for the three models. The results show a clear difference among the three models: the average oil uncertainty is different, as Model 1 exhibits the highest value, followed by Models 2 and 3. A similar finding is shown for the standard deviation, minimum, and maximum values.

Based on our previous results, oil price uncertainty should be modelled based on Model 1. The pattern for oil uncertainty (Fig. 9) reproduces some noteworthy aspects acknowledged in the oil market, as uncertainty reached its maximum in 2009.

Our results make a significant contribution to previous studies (e.g., Henriques and Sadorsky, 2011; Kuper and Soest, 2006; Elder and Serletis, 2010; Rahman and Serletis; 2010; Aye et

**Figure 9: The oil uncertainty based on Model 1**

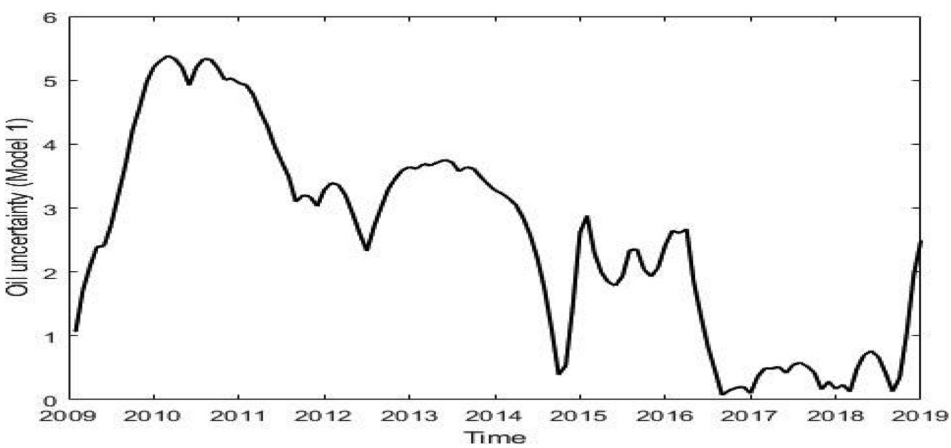


**Figure 10: The oil uncertainty based on Model 2**

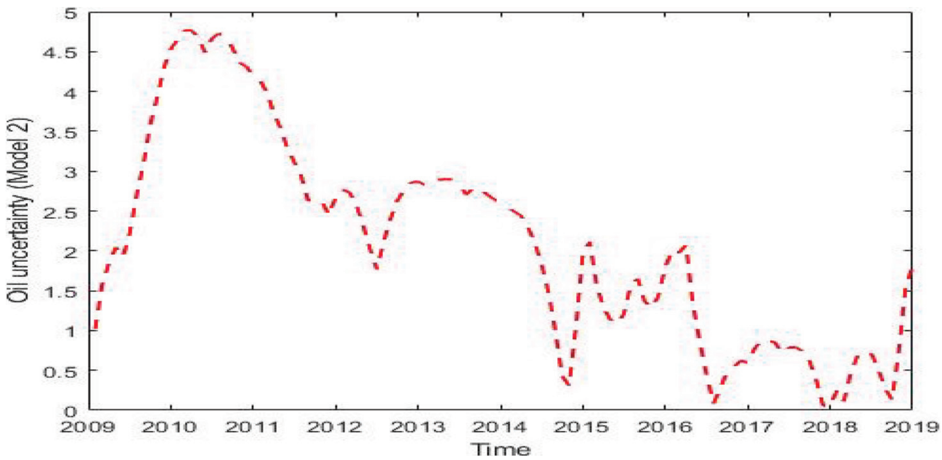
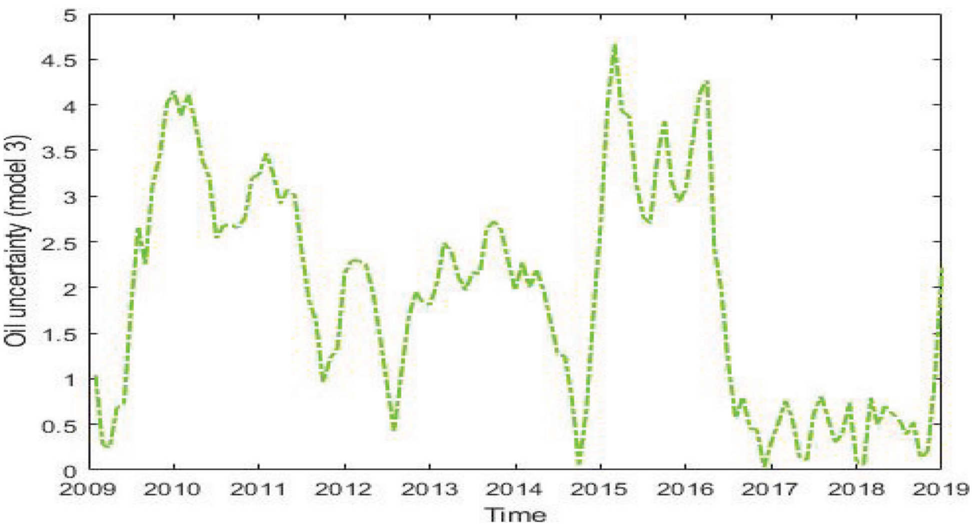



**Figure 11: The oil uncertainty based on Model 3**




al., 2014; Wang et al., 2017) in several aspects. First, previous studies adopted a proxy for oil price uncertainty in an ad hoc manner. More particularly, most studies considered oil price volatility as a conditional volatility (Sadorsky, 2008) while some others as a one-head forecast error for the conditional volatility (Elder and Serletis, 2010). In this study, we propose a new framework for oil price uncertainty based on the forecasting error for the stochastic volatility and by considering innovations in both oil prices and volatility. This specification improves flexibility. These characteristics make our measure proximate to the real oil uncertainty pattern, as demonstrated by our results. Second, we propose different specifications to test some hypotheses about OPU such as persistence, short-term dynamics, and asymmetry. Third, to identify the most accurate measure of OPU, we propose to compare the forecasted candidate models with a proxy for realized volatility. Hence, we believe that this study addresses an important gap in the literature on uncertainty forecasting, especially OPU. Our results present two key findings. First, Models 1 and 3 are both accurate for OPU modeling and forecasting; however, based on the MSC procedure, Model 1 has the highest level of

**Table 7: Descriptive statistics of oil uncertainty measures**

| Variable | Mean | Min | Max | Med | S.D | Skw | Kr | J-B |
|---|---|---|---|---|---|---|---|---|
| Model 1 | 2.539 | 0.072 | 5.380 | 2.631 | 1.598 | 0.033 | 1.958 | 5.450* |
| Model 2 | 2.107 | 0.053 | 4.766 | 2.060 | 1.330 | 0.365 | 2.227 | 5.657* |
| Model 3 | 1.922 | 0.030 | 4.667 | 1.973 | 1.229 | 0.171 | 1.948 | 6.114** |

Note: Med, S.D, Skw, Kr, and J-B denote the median, Standard deviation, Skewness, Kurtosis, and the Jarque-Bera statistic. * and ** denote the significance level of 10% and 5%, respectively.

confidence. Thus, based on these findings, we conclude that economic agents may have used Model 1 to control for the persistence in forecasting OPU.

*3.2.5. Robustness Check*

3.2.5.1 Sensitivity based on the observed oil volatility

Since volatility is an unobserved variable, the choice of observed oil volatility is complex. In our analysis, we have deemed that the benchmark oil volatility is measured under market efficiency. For more robustness, we check our results based on the crude oil (WTI) volatility series as a benchmark series. The main motivations for this choice are: i) this measure considers market information and investor expectations, and ii) it measures the market's expectation of a 30-day volatility for crude oil prices by applying the VIX methodology proposed by the CBOE.

**Figure 12: Standard deviation of the crude oil WTI volatility**

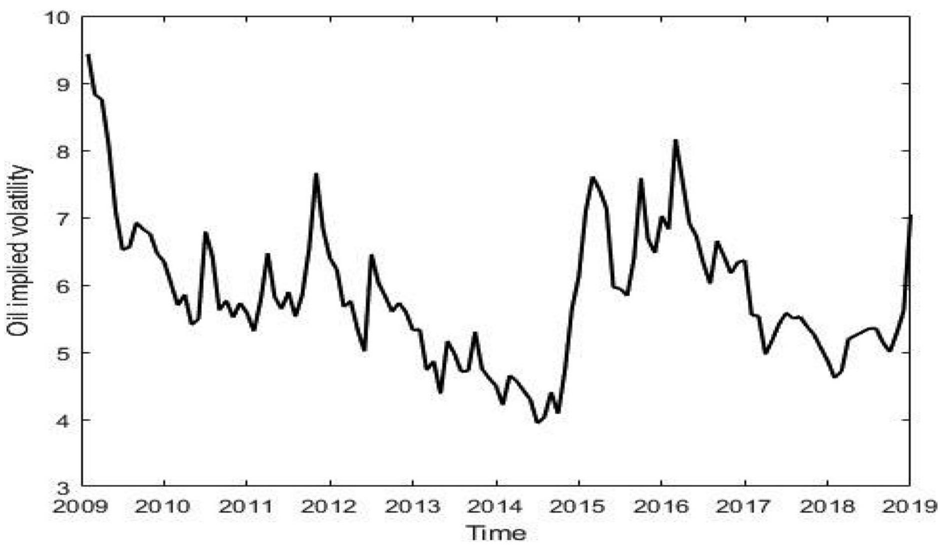



Figure 12 presents the dynamics of the oil volatility and shows a pattern that is similar to our benchmark. The oil volatility was high in 2009, in line with our oil volatility measures. Later, it exhibited a decline from 2010, and the pattern is similar during the remainder of the study period. Table 8 presents the main descriptive statistics for these series.

Table 9 presents the comparison between the three forecasted volatility series with the proxy for the observed oil volatility, and this confirms the superiority of Models 1 and 3 based on the SPA test. The MCS procedure confirms this finding but with the highest confidence level for Model 1, thereby reinforcing our previous findings.

**Table 8: Descriptive statistics of the crude oil (WTI) volatility**

| Variable | Mean | Min | Max | Med | S.D | Skw | Kr | J-B |
|---|---|---|---|---|---|---|---|---|
| Real oil price | 5.860 | 3.939 | 9.430 | 5.684 | 1.030 | 0.766 | 3.785 | 15.585*** |

Note: This table presents the descriptive statistics of the crude oil (WTI) volatility as a benchmark of the oil volatility. Med, S.D, Skw, Kr, and J-B denote the median, Standard deviation, Skewness, Kurtosis, and the Jarque-Bera statistic. *** denotes the significance level of 1%.

**Table 9: The results of SPA test and MCS method**

| | The p-value of the SPA Test | | The p-values MCS method | |
|---|---|---|---|---|
| The loss function | MAE | RMSE | MAE | RMSE |
| Model 1 | 0.8863 | 0.9287 | [1.000] | [1.000] |
| Model 2 | 0.0220 | 0.0972 | — | — |
| Model 3 | 0.1152 | 0.1176 | [0.1101] | [0.1385] |

Note: The loss functions are determined through considering the crude oil volatility as benchmark. Numbers reported in this left side of the table denote the p-values of the SPA test of Hansen (2005) under the null hypothesis that a benchmark model cannot be outperformed by other candidate models. [.] denotes the p-value of MCS of the retained best models. The p-values of the SPA test and MCS p-value are computed based on 10,000 bootstrap samples. The confidence level for MCS is 90.

3.2.5.2. Sensitivity regarding oil price measures

In the financial markets, different types of crude oil prices are offered. The findings of our analysis are based on the WTI oil prices. Therefore, in this subsection we aim to analyze the sensitivity of our results by using other proxy for the oil price such as the Brent crude oil price. This price is considered to be more global, representing both the European markets, and the Northwest Europe sweet crude market; however, since it is used as the benchmark for all West African and Mediterranean crude and for some Southeast Asian crudes, it is directly linked to a larger market. Figure 13 presents the dynamics of the real Brent and the WTI oil prices.

We observe that there are some differences between the two prices, but they exhibit a similar movement. Table 10 presents these differences. On average, Brent crude oil prices are higher than WTI prices (Figure, 13). Extreme movements are more pronounced in Brent crude than in WTI, as the maximum is US$ 145.25 for Brent and US$ 136.38 for WTI, and the minimum is US$

**Figure 13: The dynamic of the Brent and the WTI real oil prices**

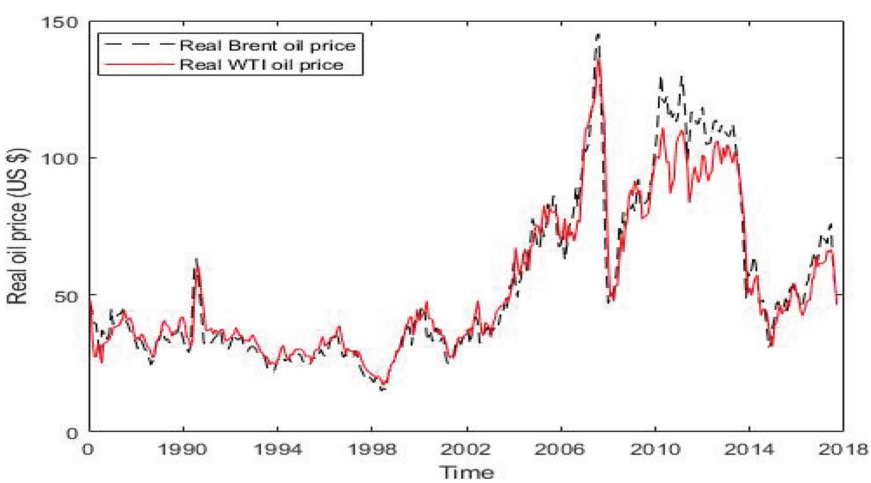


**Table 10: Descriptive statistics of the real oil prices**

| Variable | Mean | Min | Max | Med | S.D | Skw | Kr | J-B |
|---|---|---|---|---|---|---|---|---|
| Real Brent oil price | 53.715 | 14.802 | 145.255 | 39.913 | 30.407 | 1.049 | 2.951 | 72.598*** |
| Real WTI oil price | 52.828 | 16.950 | 136.384 | 41.460 | 26.706 | 0.984 | 2.857 | 64.284*** |

Note: Med, S.D, Skw, Kr, and J-B denote the median, Standard deviation, Skewness, Kurtosis, and the Jarque-Bera statistic. *** denotes the significance level of 1%.

**Figure 14: The dynamic of the Brent oil uncertainty based on Model 1**

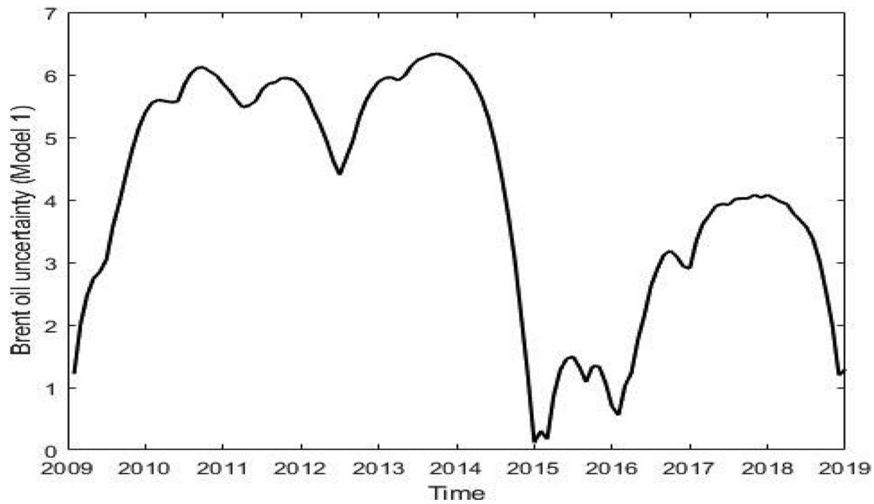
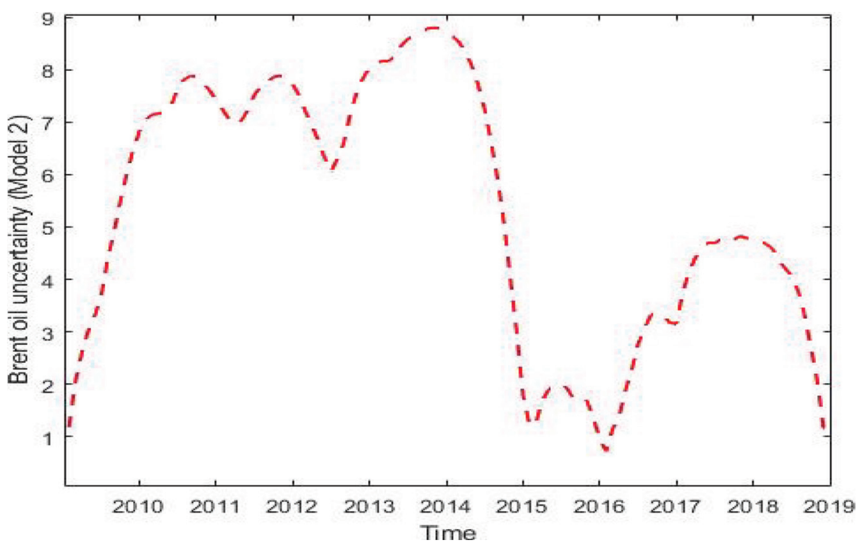



**Figure 15: The dynamic of the Brent oil uncertainty based on Model 2**




14.08 for Brent and US$ 16.95 for WTI. Underlying this difference, Brent oil prices may provide an appropriate sensitivity analysis for our empirical framework. Therefore, our empirical strategy is repeated for Brent.[14] The results are in line with those based on WTI (Table 11).

14. The Brent crude price is collected from the DataStream database for the same sample from September 1986 to December 2018. The real Brent oil price is non-stationary. Similar to WTI, we calculate the first difference in the logarithm of price.

**Figure 16: The dynamic of the Brent oil uncertainty based on Model 3**

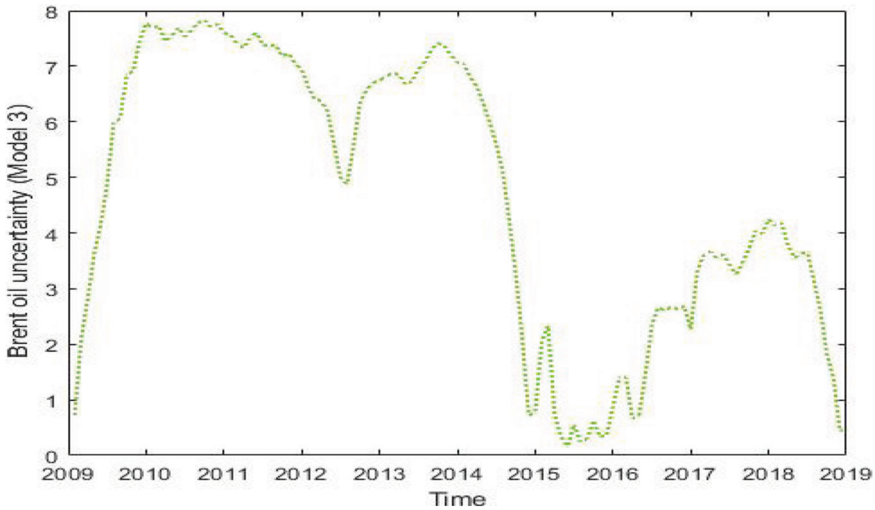



**Table 11: The results of SPA test and MCS method**

| | The p-value of the SPA Test | | The p-values MCS method | |
|---|---|---|---|---|
| The loss function | MAE | RMSE | MAE | RMSE |
| Model 1 | 0.8059 | 0.5177 | [1.000] | [1.000] |
| Model 2 | 0.000 | 0.000 | — | — |
| Model 3 | 0.1941 | 0.0370 | [0.3448] | — |

Note: The loss functions are determined through considering the crude oil volatility as benchmark. Numbers reported in this left side of the table denote the p-values of the SPA test of Hansen (2005) under the null hypothesis that a benchmark model cannot be outperformed by other candidate models. [.] denotes the p-value of MCS of the retained best models. The p-values of the SPA test and MCS p-value are computed based on 10,000 bootstrap samples. The confidence level for MCS is 90.

## 4. CONCLUSION

This study examines OPU for the period January 1986–December 2018 in line with Poon and Granger (2003) and Teräsvirta and Zhao (2011). To this end, we propose three different specifications for stochastic oil volatility modeling to measure oil price volatility, as it ensures a high level of flexibility in modeling OPU and considers the innovation in both oil returns and oil price volatility, thereby providing a time-varying measure for OPU. Next, we estimate OPU and evaluate the forecasting performance of these three models. The analysis of our out-of-sample forecasting results show that the standard stochastic volatility model and the leverage stochastic volatility model outperform the modeling and forecasting for OPU. Our findings suggest that the two relevant characteristics to be considered in oil volatility modelling are the high levels of persistence and the potential asymmetry effect. Our specification remains more performing than the other measures for OPU even when using another proxy for the oil price (Brent). Our results have important policy implications for investors and hedgers in terms of portfolio diversification, investment strategy, and hedging, as forecasting OPU could help them to better select their investments. A future direction for this study would be to extend the modeling to other classes of commodities.

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