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OPEC News Announcement Effect on Volatility in the Crude Oil Market: A Reconsideration*

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Abstract

This paper uses a nonparametric quantile-based methodology to analyse the predictive ability of OPEC meeting dates and production announcements on (Brent Crude and West Texas Intermediate) oil a measure of futures market volatility that is robust to jumps. We found a nonlinear relationship between oil futures volatility and OPEC-based predictors; hence, linear Granger-causality tests are misspecified and the linear model results of non-predictability are unreliable. Results of the quantile-causality test show that OPEC variables' impact on oil futures markets is restricted to Brent Crude futures, with no effect observed for the WTI market. Specifically, OPEC production announcements and meeting dates predict only lower quantiles of the conditional distribution of Brent futures market volatility – a much weaker result compared to when volatility models used in the literature are not robust to jump and outliers .

Keywords: Oil markets; Volatility; OPEC announcements.

JEL: C22; C58; G14; Q41

1. Introduction

Energy is an essential part of life. Crude oil is the world's leading energy source, accounting for 32.9% of global energy consumption (see, World Energy Council (2016, p. 4) for more details). Thus, the dynamics of crude oil has attracted widespread attention, including researchers. In particular, frequent extreme price changes are very important due to the extremely high risk to oil users and oil market investors. Thus, understanding volatility jumps in oil markets help market participants avoid significant losses and improves their portfolio performance.

It is well known that OPEC (Organization of the Petroleum Exporting Countries) has important effects on the price movements in the crude oil market (Brémond et al., 2012; Cairns and Calfucura, 2012; Gülen, 1996; Kaufmann et al., 2004; Pindyck, 1978; Salant, 1976; Van de Graaf, 2017). This is mainly due to the fact that OPEC produces over 40% of global oil production. OPEC produces 41.4% of global oil production in 2015 (BP, 2016, p. 8). OPEC holds the largest share (71.4%) of global proved reserves of crude oil (BP, 2016, p. 6).

The OPEC Conference is the supreme authority of the organization, and ordinarily meets at least twice a year on prescheduled dates, as well as holding additional extraordinary sessions with short notice on un-scheduled dates when necessary. OPEC news announcements following these conferences can have important effects on the dynamics of the crude oil market. Thus, some researchers have investigated the impacts of OPEC news announcements on the price movement in the crude oil market using regression analysis (Mensi et al., 2014; Schmidbauer and Rösch, 2012; Wirl and Kujundzic, 2004) or event study methodology (Demirer and Kutan, 2010; Guidi et al., 2006; Lin and Tamvakis, 2010; Loutia et al., 2016).

OPEC news announcements can also have significant effects on the volatility dynamics in the crude oil market. However, few studies have investigated this relationship. Horan et al. (2004) examined the implied volatility from options on crude oil futures surrounding OPEC meetings. Empirical results derived from the event study, they found that volatility drifts upward as the meeting approaches and drops by three percent following the first day of the meeting. Schmidbauer and Rösch (2012) investigated the impacts of OPEC announcements on expectation and volatility of daily oil price returns. From the estimation results of the AR

(autoregressive)-GARCH (generalized autoregressive conditional heteroskedasticity) model, they found evidence of a post-announcement effect on return expectation, which is negative in the case of a cut decision and positive in the case of an increase or maintain decision.

In addition, a positive pre-announcement effect on volatility was found, which was strongest in the case of a cut decision. Mensi et al. (2014) examined the impacts of OPEC's different news announcements on the conditional expectations and volatility of crude oil markets in the presence of long memory and structural changes. By applying the ARMA (autoregressive moving-average)-GARCH class models to crude oil return data, they found empirical evidence that OPEC announcements have a significant effect on both returns and volatility of crude oil markets.

Gupta and Yoon (2018) examined the predictive ability of OPEC meeting dates and production announcements for oil futures market returns and GARCH-based volatility using a nonparametric quantile-based methodology. The empirical results show that a nonlinear relationship exists between oil futures returns and OPEC-based predictors, and that OPEC production announcements, and meeting dates predict only lower quantiles of the conditional distribution of Brent futures market return. While, predictability of volatility covers the majority of the quantile distribution, barring extreme ends.

This paper re-investigates the impact of OPEC news announcements on the volatility in the crude oil market. The decision to reconsider the causal effect of OPEC news announcements on volatility emanates from the fact that movements in volatility are often characterized by jumps, which in turn are associated with bad volatility (Gkillas et al., 2018). In other words, good volatility can be associated with the continuous and persistent part, while bad volatility captures the discontinuous and jump component (Caporin et al., 2016). Given the importance of accurately measuring volatility, as it is an important input in investment decisions, we need to develop a measure of the same that removes the jumps, and hence, the so-called non-diversifiable risks (Li et al., 2015).

However, the GARCH-type models used in the literature relating OPEC news announcements to oil market volatility are not immuned to jumps (Harvey and Sucarrat, 2014). For this purpose, we first apply the volatility model developed by Harvey and Sucarrat (2014) to obtain a

measure of the continuous and persistent part of volatility for the Brent Crude and West Texas Intermediate (WTI) oil futures over the daily period from January 3, 1991 to December 30, 2016. Next, we analyse whether OPEC news announcements can predict volatility, using a quantiles-based causality test developed in Jeong et al., (2012).

Unlike traditional conditional mean-based tests of causality, the causality-in-quantiles test applied in this paper has two main novelties: First, it is robust to misspecification errors as it detects the underlying dependence structure between the examined time series. This is particularly important as it is well known that oil market movements is nonlinearly associated with its predictors (Balcilar et al., 2016) - a fact we show to hold in our data as well. Secondly, via this methodology, we are able to test not only for causality-in-mean (first moment), but also for causality that may exist in the tails of the joint distribution of the variables. This is particularly important if the dependent variable has fat-tails – something we show in our empirical analysis to exist for oil futures volatility.

This paper can be viewed as an extension and follow-up of the above discussed work of Gupta and Yoon (2018). Since, our measure of volatility excludes possible jumps in oil futures, we are able to analyze the role played by OPEC news announcements on the continuous and persistent part of volatility, which in turn is more important than sudden volatility spikes (i.e., jumps) in determining investment decisions in the oil market.

The rest of the paper is organized as follows: Section 2 briefly describes our methodology; in particular the volatility model and the causality-in-quantiles test. Section 3 discusses the data, while Section 4 presents our results, and finally Section 5 concludes the paper.

2. Methodology

For our first step, we use the Beta-Skew- t -EGARCH model developed in Harvey and Sucarrat (2014) to obtain our measure of volatility for the crude oil market futures. The proposed approach has a number of benefits: First, as argued by Harvey and Sucarrat (2014), the model is superior in comparison to other GARCH-class models, since the Beta-Skew- t -EGARCH model is robust to jumps or outliers. Second, the model incorporates the characteristics of leverage, conditional fat-tails, and conditional skewness, while it divides volatility into a short-

term and a long-term component, which are the most common characteristics associated with time-varying volatility.

At this stage, it is important to point out few technical concerns with the basic EGARCH model. As EGARCH can be derived from a random coefficient complex nonlinear moving average process, it follows that there is no invertibility condition to transform the returns shocks to the standardized residuals. Therefore, there are as yet no asymptotic properties of the Quasi-Maximum Likelihood Estimators (QMLE) of the parameters of EGARCH. Recently, Martinet and McAleer (2017) showed that the EGARCH(p, q) model could be derived from a stochastic process, for which the invertibility conditions can be stated simply and explicitly. This theoretical result is likely to lead to the development of asymptotic properties for the QMLE of EGARCH. Further, Chang and McAleer (2017) showed that, in practice, while EGARCH always displays asymmetry, leverage is not possible.

Following Harvey and Sucarrat (2014), the martingale difference model of the first-order two-component Beta-Skew- t -EGARCH model can be specified as:

$$z_t = \exp(\lambda_t) \varepsilon_t = \sigma_t \varepsilon_t, \quad \varepsilon_t \sim st(0, \sigma_\varepsilon^2, \nu, \gamma), \quad \nu, \gamma \in (0, \infty), \quad (1)$$

$$\lambda_t = \omega + \lambda_{1,t}^+ + \lambda_{2,t}^+, \quad (2)$$

$$\lambda_{1,t}^+ = \phi_1 \lambda_{1,t-1}^+ + \kappa_1 \mu_{t-1}, \quad |\phi_1| < 1, \quad (3)$$

$$\lambda_{2,t}^+ = \phi_2 \lambda_{2,t-1}^+ + \kappa_2 \mu_{t-1} + \kappa^* \text{sgn}(-z_{t-1})(\mu_{t-1} + 1), \quad |\phi_2| < 1, \quad \phi_1 \neq \phi_2 \quad (4)$$

where z_t is the return series for Brent Crude or WTI oil futures. σ_t is the conditional volatility, σ_ε^2 is the variance of ε_t , and ε_t is the conditional error distributed as a skewed- t with zero mean, scale σ_ε^2 , degree of freedom, ν , and skewness parameter γ . We have a centred and symmetric t -distributed variable with zero mean when $\gamma = 1$, and left-skewed (right-skewed) t -variable is obtained when $\gamma < 1$ ($\gamma > 1$). The long-term log-volatility is denoted by the log-scale intercept, ω . The persistence parameter ϕ_1 represents the degree of clustering. κ_1 is the long-term ARCH parameter that represent the magnitude of response to shocks. κ^* is the leverage parameter. μ_t is the conditional score. Note that $\lambda_{1,t}$ and $\lambda_{2,t}$ can be viewed as the time-varying long-term and short-term components of log-volatility, respectively. Leverage, κ^* , appears only in equation (4) as Engle and Lee (1999) argued that shocks only matter for short term volatility.

We also estimated the one-component Beta-Skew-t-EGARCH model of Harvey and Sucarrat (2014), however we decided to choose the two-component version, because the log-likelihood was higher in the latter case, indicating a better fit of the data. Complete details of the one-component model is available upon request from the authors.

Having discussed the volatility model used in this paper, we now provide a brief description of the quantile-based methodology in Jeong et al. (2012). Let y_t denote oil (Brent Crude or WTI) futures volatility and x_t denote the predictor variable. In our case, the dummies used correspond to OPEC meeting dates and production decisions made on those dates involving a cut, maintain, or increase (as described in detail in the next section of the paper) decision.

Let $Y_{t-1} \equiv (y_{t-1}, \dots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \dots, x_{t-p})$, $Z_t \equiv (X_t, Y_t)$, $F_{y_t|Z_{t-1}}(y_t, Z_{t-1})$, and $F_{y_t|Y_{t-1}}(y_t, Y_{t-1})$ denote the conditional distribution functions of y_t given Z_{t-1} and Y_{t-1} , respectively. If we denote $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$, we have $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$ with probability of one. Consequently, the (non) causality in the θ^{th} quantile hypotheses to be tested are:

$$H_0: P[F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta] = 1, \quad (5)$$

$$H_1: P[F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta] < 1. \quad (6)$$

Jeong et al. (2012) employ the distance measure $J = \{\varepsilon_t E(\varepsilon_t|Z_{t-1})f_Z(Z_{t-1})\}$, where ε_t is the regression error term and $f_Z(Z_{t-1})$ is the marginal density function of Z_{t-1} . The regression error ε_t emerges based on the null hypothesis in (1), which can only be true if and only if $E[\mathbf{1}\{y_t \leq Q_\theta(Y_{t-1})|Z_{t-1}\}] = \theta$ or, equivalently, $\mathbf{1}\{y_t \leq Q_\theta(Y_{t-1})\} = \theta + \varepsilon_t$, where $\mathbf{1}\{\cdot\}$ is an indicator function. Jeong et al. (2012) show that the feasible kernel-based sample analogue of J has the following form:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^T \sum_{s=p+1, s \neq t}^T K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s, \quad (7)$$

where $K(\cdot)$ is the kernel function with bandwidth h , T is the sample size, p is the lag order, and $\hat{\varepsilon}_t$ is the estimate of the unknown regression error, which is estimated as follows:

$$\hat{\varepsilon}_t = \mathbf{1}\{y_t \leq Q_\theta(Y_{t-1})\} - \theta. \quad (8)$$

$\hat{Q}_\theta(Y_{t-1})$ is an estimate of the θ^{th} conditional quantile of y_t given Y_{t-1} , and we estimate $\hat{Q}_\theta(Y_{t-1})$ using the nonparametric kernel method as:

$$\hat{Q}_\theta(Y_{t-1}) = \hat{F}_{y_t|Y_{t-1}}^{-1}(\theta|Y_{t-1}), \quad (9)$$

where $\hat{F}_{y_t|Y_{t-1}}(y_t|Y_{t-1})$ is the Nadarya-Watson kernel estimator given by:

$$\hat{F}_{y_t|Y_{t-1}}(y_t|Y_{t-1}) = \frac{\sum_{s=p+1, s \neq t}^T L\left(\frac{Y_{t-1} - Y_{s-1}}{h}\right) \mathbf{1}(y_s \leq y_t)}{\sum_{s=p+1, s \neq t}^T L\left(\frac{Y_{t-1} - Y_{s-1}}{h}\right)}, \quad (10)$$

with $L(\cdot)$ denoting the kernel function and h the bandwidth.

The empirical implementation of causality testing via quantiles entails specifying three important choices: the bandwidth h , the lag order p , and kernel type for $K(\cdot)$ and $L(\cdot)$. In this study, a lag order of one is used on the basis of the Schwarz information criterion (SIC). Note that, with respect to choosing lags, the SIC is considered parsimonious compared with other lag-length selection criteria. The SIC helps overcome the issue of the over-parameterization that typically arises with nonparametric frameworks. Hurvich and Tsai (1989) examine the Akaike information criterion (AIC) and show that it is biased towards selecting an over-parameterized model, whereas the SIC is asymptotically consistent.

However, in our case, the AIC also chose a lag-length of one. Complete details on the lag-length tests are available on request from the authors. The bandwidth value is chosen by employing least squares cross-validation techniques. For each quantile, we determine the bandwidth h using the leave-one-out least-squares cross validation method of Racine and Li (2004) and Li and Racine (2004). Finally, for $K(\cdot)$ and $L(\cdot)$, Gaussian-type kernels are employed.

3. Data and Volatility Estimation

Our sample data consists of four OPEC-related variables used in predicting the volatility jumps of Brent Crude and WTI futures. Daily data of these oil futures were obtained from Datastream, with returns computed as the daily logarithmic change of oil futures settlement prices multiplied by 100 to convert the returns into percentages. Driven by liquidity considerations and to obtain representative futures returns series (from which the volatility is derived), we collected data on the nearest and second nearest contracts. We suppose that traders hold futures contracts until the last day of the month prior to contract expiration. On that date, the trader rolls his/her position to the second nearest contract and holds it until the last day of the month before the delivery month. This procedure is then rolled forward to the next set of nearest and second nearest contracts.

OPEC news announcements on production decisions are made during OPEC conferences, which occur at least twice a year. The decisions may take the form of quota reductions, increases, or maintenance of the status quo. Three dummy variables are constructed in terms of the type of production decisions undertaken, and are included in the analysis. The data for conference decisions are obtained from the OPEC website (<http://www.opec.org>). There were 92 announcements during our study period (January, 1991- December, 2016): 19 cut, 17 increase, and 57 maintain decisions were made.

Sample data covers January 3, 1991- December 30, 2016, yielding 6,620 and 6,530 observations for Brent Crude and WTI futures returns, respectively. Table 1 provides the parameter estimates of the Beta-Skew- t -EGARCH model fitted to Brent Crude and WTI returns, with all parameters being found to be statistically significant at the 1 percent level.

Table 2 presents the summary statistics of the conditional volatility jumps obtained from the Beta-Skew- t -EGARCH model. Both volatility series are found to be skewed to the right, with excess kurtosis, resulting in non-normal distributions as indicated by the strong rejection of the Jarque-Bera statistic at the 1 per cent significance level. The heavy tails of the distributions of volatility provide preliminary justification for the causality-in-quantiles test used in the empirical analysis. Fig. 1 plots the conditional volatility recovered from the Beta-Skew- t -EGARCH model.

[Tables 1 and 2 here]

[Figure 1 here]

4. Empirical Results

Before we discuss findings from the causality-in-quantiles tests, for the sake of completeness and comparability, we first provide the findings from the standard linear Granger-causality test using a lag-length of one as determined by the SIC. As shown in Table 3, the standard linear Granger-causality tests yield no evidence of causality from any of the OPEC-based variables to either Brent Crude or WTI futures volatility, even at the 10 per cent level of significance. Therefore, standard linear tests support the conclusion that no significant OPEC-related effects are evident with the oil futures volatility.

[Table 3 here]

Given the linear causality tests results, we statistically examine the presence of nonlinearity in the relationship between oil futures volatility and the OPEC variables. For this purpose, we apply the Brock et al. (1996, BDS) test on the residuals from the volatility jumps equation involving one lag of volatility and one lag of the OPEC variables (considered in turn). Table 4 presents the results of the BDS test of nonlinearity, which show strong evidence – at the highest significance level – for the rejection of the null hypothesis of iid residuals at various embedded dimensions (m). Thus, strong evidence exists of the nonlinearity in the relationship between oil futures volatility and the various OPEC variables.

This evidence indicates that the findings based on the linear Granger-causality test presented in Table 3 cannot be deemed robust and reliable. Given the strong evidence of nonlinearity in the relationship between volatility and OPEC meeting dates and announcements, we now consider the causality-in-quantiles test, which is robust to misspecification given its nonparametric (i.e., data-driven) approach.

[Table 4 here]

Figure 2 presents the findings from the causality-in-quantiles tests for oil futures volatility for the Brent Crude and WTI markets that derives from the OPEC meeting dates and production decisions for the quantile range of 0.05- 0.95. As Fig. 2(b) shows, irrespective of the OPEC variable used as the predictor, no evidence exists for the predictability of WTI volatility. Therefore, the results of the linear causality test for WTI volatility jumps apply to the causality-in-quantiles even after controlling for misspecifications in the linear model attributable to the existence of nonlinearity. However, in Fig. 2(a), we observe that all OPEC variables behave similarly in affecting the Brent Crude futures volatility over the quantile range of 0.05-0.30, i.e., predictability is observed in the lower quantiles which represent the lower volatility.

So when we compare our results with those obtained for volatility by Gupta and Yoon (2018), we find that while excluding jumps does not matter for the WTI futures market, it indeed does make the effect weaker for the Brent Crude volatility, as now the effect is only restricted to the lower quantiles of its conditional distribution, instead the most of it as observed by Gupta and Yoon (2018). To put it alternatively, much of the effect on aggregate Brent Crude volatility due OPEC news announcements seems to come through the jump component.

The results suggest that WTI futures are effective hedges against risks associated with OPEC announcements, but this only applies in the case of Brent Crude when the persistent and continuous component of volatility are large in magnitude (i.e., barring the lower quantiles of its conditional distribution). From the perspective of policy makers concerned with the persistent impact of oil price volatility on the real economy, they should be ready to undertake appropriate measures to circumvent the negative impacts from a Brent Crude market that is not performing at its peak following OPEC meetings and announcements.

However, it must be noted that investors and policy makers should be using nonlinear/nonparametric models to correctly identify the effect of OPEC announcements on oil futures because linear models are likely to lead to incorrect inferences, especially with respect to Brent Crude futures. Finally, from an academic viewpoint, WTI futures market can be categorized as an efficient market, whereas Brent Crude futures market is efficient only when the volatility are large in magnitude.

[Figure 2 here]

5. Conclusion

This paper utilizes a nonparametric quantile-based methodology in analysing the predictive ability of OPEC announcements concerning production decisions and meeting dates for the volatility of the oil futures market. Standard linear causality tests yield insignificant results for both Brent Crude and WTI future markets during the period January 3, 1991- December 30, 2016. However, we find that linear Granger-causality test results cannot be relied upon because formal tests reveal strong evidence of nonlinearity between oil futures volatility and the OPEC-based predictor variables. Hence, linear Granger-causality tests are misspecified.

When we employ the quantile-causality test, we observe that the OPEC variables only affect the Brent Crude futures market, and no effect is observed for the WTI market – the latter result is similar to that of the linear misspecified model. Specifically, OPEC production cut, maintain, and increase announcements, as well as the meeting dates predict only the lower quantiles of the conditional distribution of Brent futures market volatility. Therefore, the OPEC-related variables can predict only the small-sized volatility associated with Brent futures market.

Few studies have investigated the price jumps of crude oil markets (see for example, Lee et al., 2010; Bjursell et al., 2015; Baum and Zerilli, 2016). However, we were not able to identify studies focusing on the impact of OPEC news announcements on the volatility jumps of the crude oil market. Crude oil markets are known to be very volatile, hence, our aim in the future would be to analyse whether volatility jumps (based on intraday data), are caused due to unexpected news from the OPEC conference, since these would have important implications for both investors and policymakers. This way, we would be able to supplement our existing analysis which deals with the continuous and persistent part of oil market volatility.

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Table 1
Volatility Estimation of Oil Futures Returns

ω	ϕ	κ_1	κ_2	κ^*	ν	γ
Brent Crude						
0.6970*	0.9982*	0.0159*	0.0166*	0.0118*	6.3864*	0.9415*
(0.2243)	(0.0015)	(0.0062)	(0.0069)	(0.0023)	(0.4719)	(0.0152)
Log-likelihood	-13535.8442					
SIC	4.100011					
WTI						
0.7126*	0.9927*	1.1067*	-1.0752*	0.0142*	7.2845*	0.9317*
(0.0829)	(0.2088)	(0.9050)	(0.0878)	(0.0022)	(0.2955)	(0.0159)
Log-likelihood	-13846.5595					
SIC	4.251668					

Notes: * indicates significance at 1% level. Standard errors of parameter estimates are in parentheses. Estimation follows Harvey and Sucarrat (2014).

Table 2
Summary Statistics

Statistic	Variable	
	Brent Crude volatility	WTI volatility
Mean	2.0714	2.2099
Median	1.9937	2.0981
Maximum	6.1413	7.2974
Minimum	0.7037	0.8229
Std. Dev.	0.7539	0.8242
Skewness	1.4049	1.8834
Kurtosis	6.9250	9.1168
Jarque-Bera	6427.0100	14040.2800
<i>p</i> -value	0.0000	0.0000
Observations	6620	6530

Notes: Std. Dev. denotes standard deviation. *p*-value corresponds to the Jarque-Bera test of the null hypothesis of normality.

Table 3
Linear Granger Causality Test

Dependent variable	Independent variable	<i>F</i>-statisric	<i>p</i>-value
Brent Crude volatility	Cut	0.0365	0.8485
	Increase	0.1969	0.6572
	Maintain	0.1754	0.6754
	OPEC meeting	0.0738	0.7859
WTI volatility	Cut	1.3326	0.2484
	Increase	1.1555	0.2824
	Maintain	0.5557	0.4560
	OPEC meeting	0.1328	0.7155

Note: The null hypothesis is that a specific OPEC-related piece of news does not affect Brent Crude or WTI volatility.

Table 4
Brock et al. (1996) (BDS) Test of Nonlinearity

Dependent variable	Independent variable	Dimension				
		2	3	4	5	6
Brent Crude volatility	Cut	9.509*	11.178*	12.325*	13.689*	14.724*
	Increase	9.524*	11.199*	12.346*	13.711*	14.747*
	Maintain	9.523*	11.190*	12.338*	13.708*	14.749*
	OPEC meeting	9.514*	11.178*	12.326*	13.693*	14.732*
WTI volatility	Cut	10.519*	11.998*	12.853*	13.485*	14.082*
	Increase	10.552*	12.018*	12.889*	13.510*	14.093*
	Maintain	10.544*	11.985*	12.837*	13.456*	14.044*
	OPEC meeting	10.548*	12.018*	12.881*	13.504*	14.092*

Notes: Entries correspond to the z-statistic of the BDS test with the null of *iid* residuals, with the test applied to the residuals recovered from the VAR(1) model of oil futures volatility using OPEC-related variables. * indicates rejection of the null hypothesis at the 1 per cent level of significance.

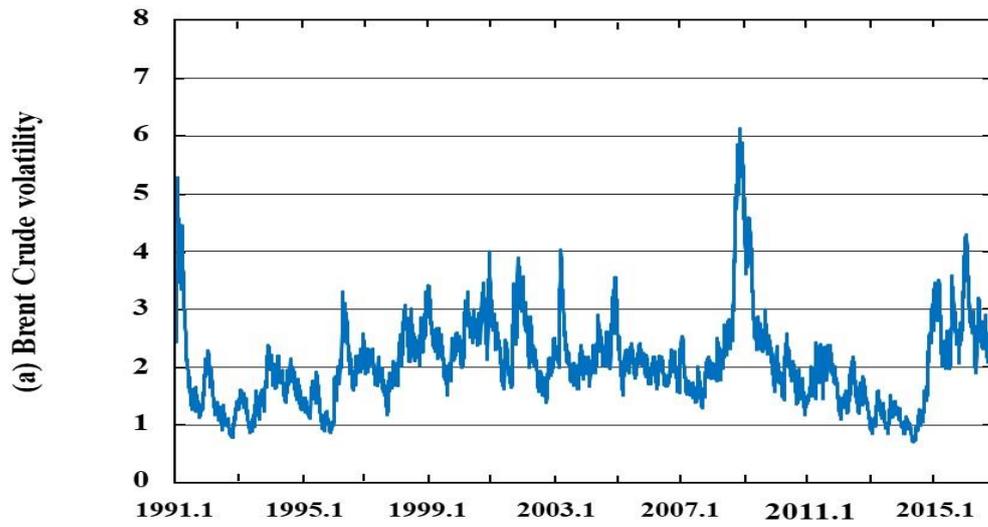


Figure 1(a)
Brent Crude volatility

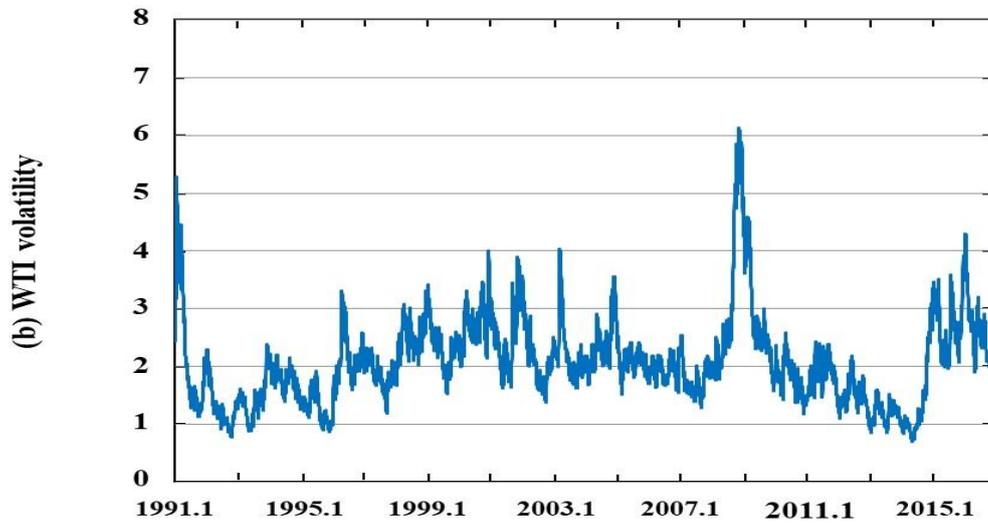


Figure 1(b)
WTI volatility

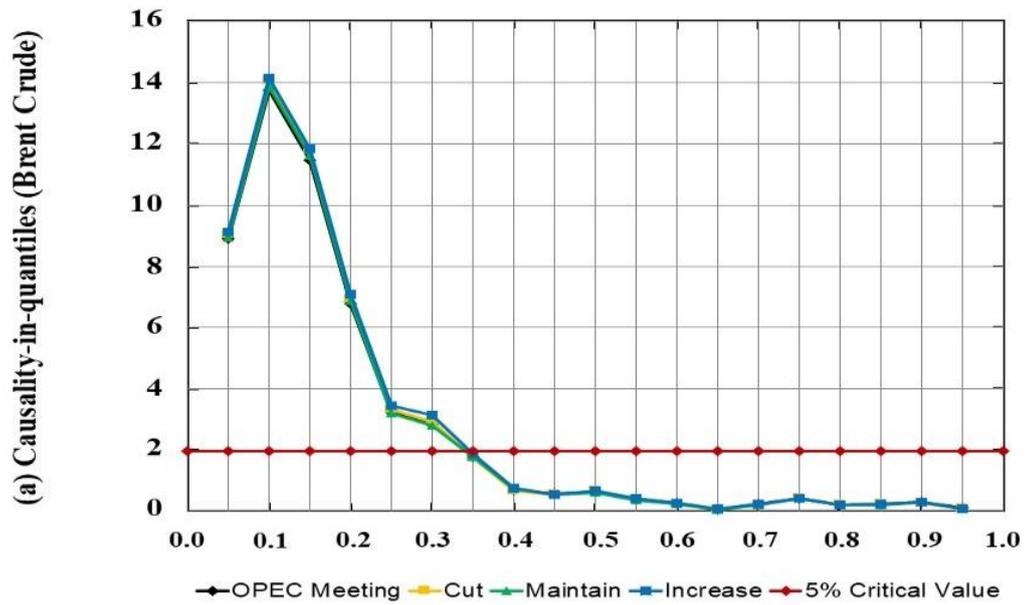


Figure 2(a)

Causality-in-quantiles: Brent Crude Futures Volatility and OPEC Variables

Note: The horizontal axis depicts the various quantiles and the vertical axis measures the test statistic.

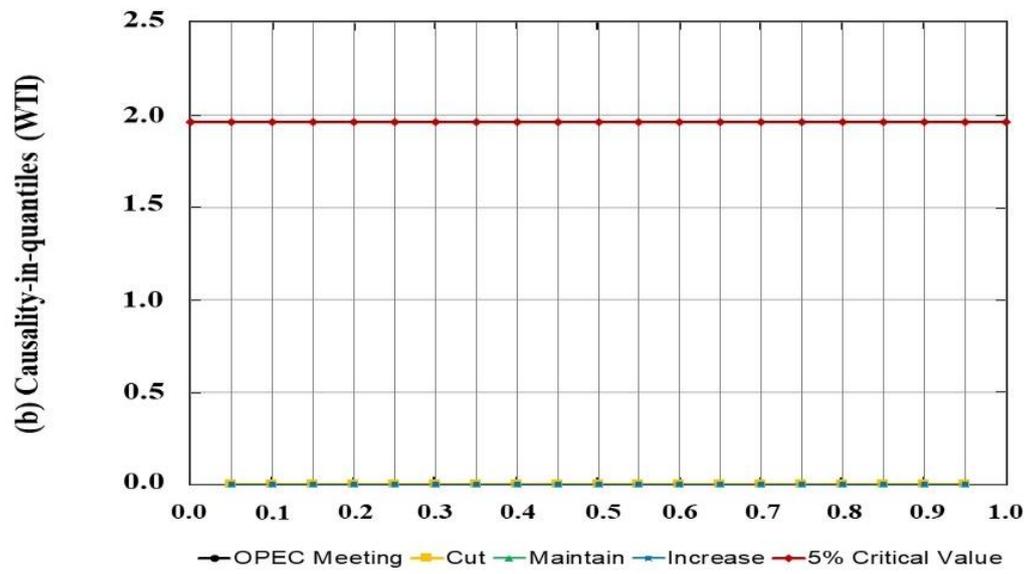


Figure 2(b)

Causality-in-quantiles: WTI Futures Volatility and OPEC Variables

Note: See the note for Figure 2(a).