OPEC News and Predictability of Oil Futures Returns and Volatility: Evidence from a Nonparametric Causality-in-Quantiles Approach

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Abstract

This paper provides a novel perspective to the predictive ability of OPEC meeting dates and production announcements for (Brent Crude and West Texas Intermediate) oil futures market returns and GARCH-based volatility using a nonparametric quantile-based methodology. We show a nonlinear relationship between oil futures returns and OPEC-based predictors; hence, linear Granger causality tests are misspecified and the linear model results of non-predictability are unreliable. When the quantile-causality test is implemented, we observe that the impact of OPEC variables is restricted to Brent Crude futures only (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 returns. While, predictability of volatility covers the majority of the quantile distribution, barring extreme ends.

Keywords: Oil futures markets Returns and volatility; OPEC announcements; Nonparametric quantile causality.

JEL Codes: C22, C58, G14, G15.

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1. Introduction

Recently, commodity futures have emerged as a highly popular asset class for investors and fund managers (Andreasson, Bekiros, Nguyen, & Uddin, 2016). The rapidity in the financialisation of commodity markets has also significantly increased the number of market participants. In addition to being used for hedging and speculative purposes, commodity futures can also diversify away the risk of diversified stock/bond portfolios, particularly during financial crises and bearish equity markets. Thus, knowledge of the factors that drive commodity futures markets is likely to constitute valuable information for investors and fund managers.

Amongst the various commodities, oil is perhaps the most important given its influential role in the world economy relative to other commodities, particularly in terms of causing recessions (Hamilton, 1983, 2008, 2009, 2013).[1] Additionally, oil is indispensable for industrial, transportation, and agricultural sectors, whether used as feedstock in production or as a surface fuel in consumption (Mensi, Hammoudeh, & Yoon, 2014).

Moreover, oil market movements are widely known to spillover to other commodity markets (see, for example, Kang & Yoon, 2013; Kang, McIver, & Yoon, 2016, 2017; Mensi, Beljid, Boubaker, & Managi, 2013; Mensi et al., 2014b; Mensi, Hammoudeh, & Kang, 2015a), as well as financial markets (see, for example, Balcilar & Ozdemir, 2013; Balcilar, Gupta, & Miller, 2015; Balcilar, Gupta, & Wohar, 2017; Kang et al., 2016; Mensi, Hammoudeh, & Yoon, 2015b; Narayan & Gupta, 2015). Furthermore, as Shrestha (2014) notes, one can expect price discovery to occur primarily in the futures market because futures prices respond to new information faster than spot prices given lower transaction costs and greater ease of short selling associated with futures contracts. Moreover, it is believed that

[1] See Gupta and Wohar (2017) for a detailed review of the literature on the role of oil price movements and recessions.

futures market movements predict spot market movements for oil (see, for example, Baumeister & Kilian, 2014, 2015; Baumeister, Kilian, & Lee, 2014; Baumeister, Guérin, & Kilian, 2015). Thus, determining the factors that drive the oil markets and, in particular, the crude oil futures market, is of paramount importance for both investors and policy makers, which is our aim for this paper through analysis of the importance of information from OPEC announcements and meeting dates.

Some studies analyse the impact of news on OPEC production decisions on the crude oil market (Kaufmann & Ullman, 2009; Loutia, Mellios, & Andriosopoulos, 2016; Mensi et al., 2014; Schmidbauer & Rösch, 2012; Wirl & Kujundzic, 2004). These studies assume that this relationship is linear and test the significance of the impact. Thus, it must be noted that one could have also used nonlinear causality tests (for example, Diks & Panchenko, 2005; 2006; Hiemstra & Jones, 1994) to analyse the impact of OPEC announcements and meeting date information on oil futures returns and volatility.

However, these tests rely on conditional mean-based estimation and, hence, fail to capture the entire conditional distribution of returns and volatility – something that our approach can accomplish. In the process, our test is a more general procedure to detect causality in both returns and volatility at each quantile of their respective conditional distributions. Hence, we are able to capture the existence or non-existence of causality in various market states, i.e., bear (lower quantiles), normal (median), and bull (upper quantiles), in the Brent Crude and WTI futures markets. To that end, as a more general test, our method is more likely to pick up causality when conditional mean-based tests might fail to do so. Finally, because the model does not require the determination of the number of regimes – as in a Markov-switching model – and can test for causality at each point on the conditional distribution that characterises specific regimes, our test also does not suffer from any misspecification in terms of specifying and testing for the optimal number of regimes.

Against this backdrop, the nonparametric causality-in-quantiles test of Jeong, Härdle, and Song (2012) is used to examine for the first time the predictability of returns and the volatility of Brent Crude and West Texas Intermediate (WTI) oil futures on the basis of OPEC production announcements involving a cut, maintain, and increase decision, and OPEC meeting dates. Note that following Sadorsky (2006), a measure of volatility can be obtained from a GARCH(1,1) model, which is believed to appropriately capture the pattern of the second moment of the oil market. However, predictability is approached from the perspective of causality by analysing the quantiles of the conditional distribution of returns and volatility and, hence, in the process capturing various phases of the oil futures market. Understandably, this causality-in-quantiles approach is inherently a time-varying approach because various parts of the conditional distribution are related to various points in time associated with the evolution of returns and volatility.

The causality-in-quantile approach has the following two novelties. Firstly, it is robust to misspecification errors because it detects the underlying dependence structure between the examined time series. This information could prove to be particularly important because oil returns are well known as being nonlinearly associated with their predictors (Balcilar, Bekiros, & Gupta, 2016) – a fact that also holds in our data. Secondly, using this methodology, we are able to test not only for causality-in-mean (1st moment) but also for causality that may exist in the tails of variables' joint distribution. This ability is particularly important if the dependent variable has fat-tails – which as per our empirical analysis exists for oil futures returns.

The remainder of the paper is organized as follows. Section 2 lays out the basics of the econometric methodology. Sections 3 and 4 present the data and results. Section 5 concludes the paper.

2. Methodology

This section provides a brief description of the quantile-based methodology using the framework of Jeong et al. (2012). As previously mentioned, this approach is robust to extreme values in the data and captures general nonlinear dynamic dependencies. Let y_t denote oil futures returns (Brent Crude or WTI) and x_t denote the predictor variable. In our case, the dummies used in turn 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.

Formally, let $Y_{t-1} \equiv (y_{t-1}, \cdots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \cdots, x_{t-p})$, $Z_t \equiv (X_t, Y_t)$, $F_{y_t|Z_{t-1}}(y_t, Z_{t-1})$, 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 one. Consequently, the (non) causality in the θ^{th} quantile hypotheses to be tested can be specified as:

$$H_0\text{: } \mathrm{P}\left[F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right] = 1, \tag{1}$$

$$H_1\text{: } \mathrm{P}\left[F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right] < 1. \tag{2}$$

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 on the basis of 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, $\mathbf{1}\{y_t \leq Q_\theta(Y_{t-1})\} = \theta + \theta_t$, 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:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1, s\neq t}^{T} K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s\ , \tag{3}$$

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:

$$\hat{\varepsilon}_t = \mathbf{1}\{y_t \leq Q_\theta(Y_{t-1})\} - \theta. \tag{4}$$

$\hat{Q}_\theta(Y_{t-1})$ 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:

$$\hat{Q}_\theta(Y_{t-1}) = \hat{F}^{-1}_{y_t|Y_{t-1}}(\theta|Y_{t-1}) \tag{5}$$

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

$$\hat{F}_{y_t|Y_{t-1}}(y_t|Y_{t-1}) = \frac{\sum_{s=p+1,s\neq t}^{T} L\left(\frac{(Y_{t-1}-Y_{s-1})}{h}\right)\mathbf{1}(y_s \leq y_t)}{\sum_{s=p+1,s\neq t}^{T} L\left(\frac{(Y_{t-1}-Y_{s-1})}{h}\right)}, \tag{6}$$

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 the kernel type for $K(\cdot)$ and $L(\cdot)$, respectively. 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.[2] The bandwidth value is chosen by employing least squares cross-validation techniques.[3] Finally, for $K(\cdot)$ and $L(\cdot)$, Gaussian-type kernels are employed.

Given that Mensi et al. (2014) indicate the impact of OPEC variables on the volatility of the oil spot market, we decided to analyse the impact of these OPEC variables on the volatility of oil futures by first recovering a measure of conditional volatility from a GARCH(1,1) model, and then applying the causality-in-quantiles test to this measure of volatility. The basics of GARCH(1,1) model is as follows:

[2] 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.

[3] 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).

$$y_t = \mu + \varepsilon_t \quad , \tag{7}$$

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}, \tag{8}$$

where y_t represents the oil futures return series and ε_t is the stochastic disturbance term that is assumed to be normally distributed with zero mean. The conditional variance h_t depends on the mean volatility level (ω), the lagged error (ε_{t-1}^2), and the lagged conditional variance (h_{t-1}). The decision to use a GARCH (1,1) model is based on the findings of Sadorsky (2006), who shows that GARCH(1,1) fits very well with crude oil price volatility.

3. Data

Our daily data consist of four OPEC-related variables used in predicting returns and volatilities of Brent Crude and WTI futures. Oil futures data are sourced from Datastream of Thomson Reuters, 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, we collect data on the nearest and second nearest contracts. We suppose that traders hold futures contracts to the last day of a specific month, which is one month before contract expiration. On that date, the trader rolls his or her position to the second nearest contract and holds it to the last day of the month before the delivery month. The 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 included them in the analysis. The data for conference decisions were obtained from the OPEC website (http://www.opec.org). There were 92 announcements during our period of consideration (January 1991 through December 2016): 19 cut, 17 increase, 57 maintain decisions were made.

Table 1. Summary statistics

Statistic	Variable			
	Brent returns	GARCH-based Brent volatility	WTI returns	GARCH-based WTI volatility
Mean	0.0153	5.0387	0.0051	5.7686
Median	0.0592	3.6010	0.0363	4.1061
Maximum	12.8983	164.4725	16.4097	141.6737
Minimum	-42.7223	0.6913	-40.0478	0.9329
Std. Dev.	2.2014	7.2552	2.3685	7.5513
Skewness	-1.1838	10.6209	-0.7627	8.2969
Kurtosis	27.5596	170.7607	19.4196	111.4259
Jarque-Bera	165969.0	7795680.0	73296.1	3242998.0
p-value	0.0000	0.0000	0.0000	0.0000
Observations	6,543	6,543	6,469	6,469

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

Figure 1a. Brent returns

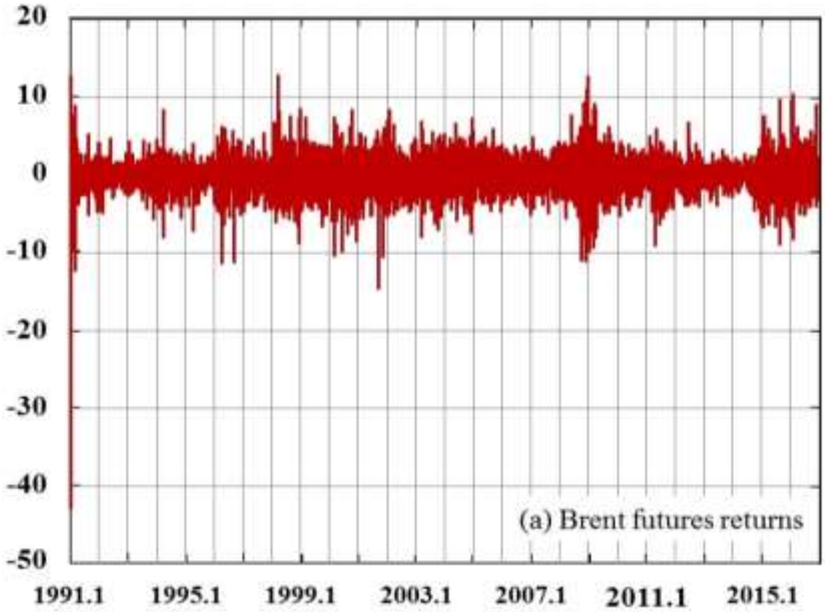


Figure 1b. WTI returns

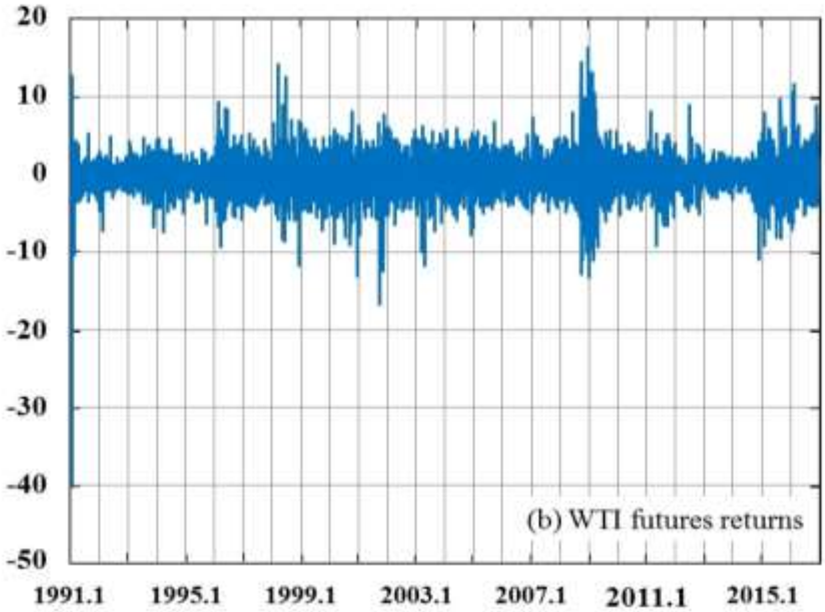


Figure 1c. GARCH-based volatility of Brent market

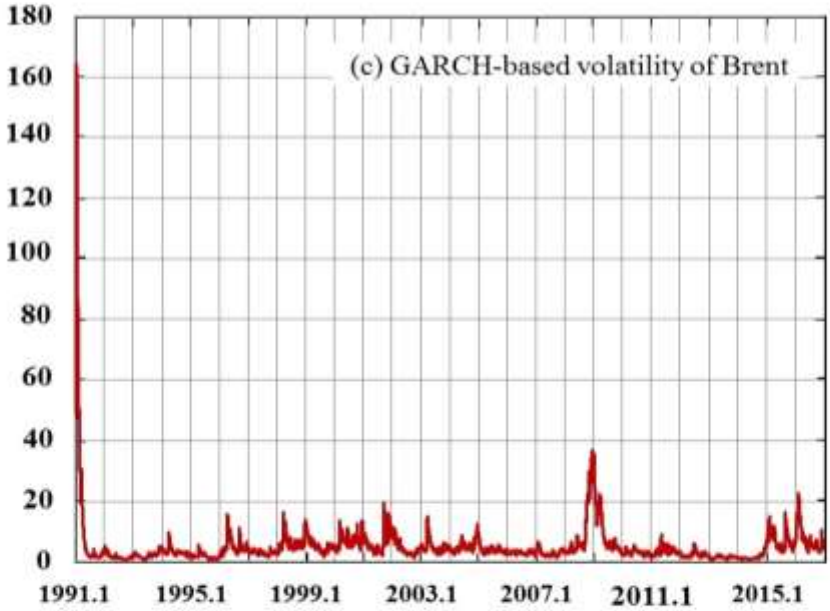
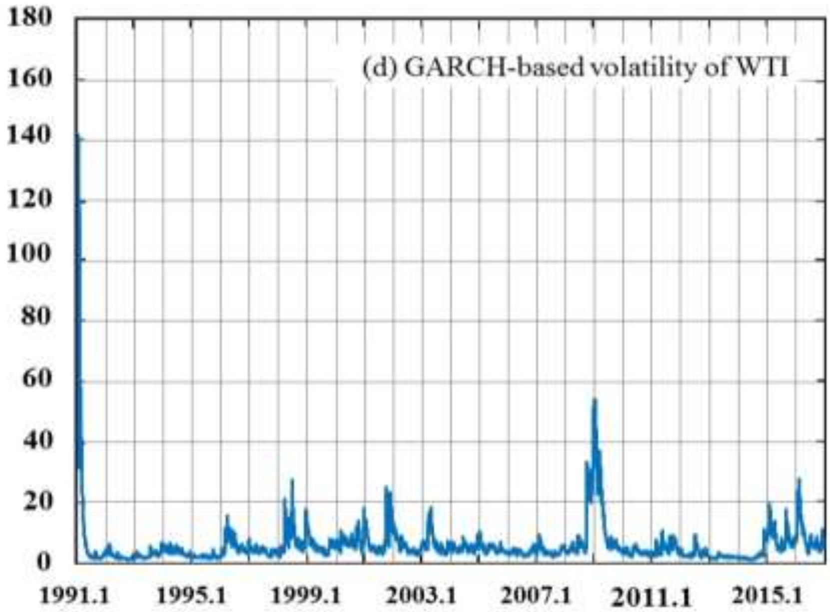


Figure 1d. GARCH-based volatility of WTI market



Our data cover 3 January 1991 to 30 December 2016, giving 6,543 and 6,469 observations for Brent Crude and WTI futures returns, respectively. Figure 1 plots the returns and the conditional volatility recovered from the GARCH(1,1) model, whereas Table 1 presents the summary statistics for the variables of interest. For our context of causality-in-quantiles, returns and volatility series are found to be skewed to the left and right, respectively, 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 returns and volatility provide preliminary justification for the causality-in-quantiles test used in the empirical analysis.

4. Empirical results

4.1. Preliminary tests

Before we discuss the 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 2, the standard linear Granger causality tests yield no evidence of causality that goes from any of the OPEC-based variables to either Brent Crude or WTI futures returns, even at the 10 per cent level of significance. Therefore, standard linear tests support the conclusion that no significant OPEC-related effects exist on oil futures returns.

Given the insignificant results obtained from the linear causality tests, next we statistically examine the presence of nonlinearity in the relationship between oil futures returns and the OPEC variables. The presence of nonlinearity further motivates the use of the nonparametric quantile-in-causality approach because the quantile-based test formally addresses nonlinearity in the relationship between oil futures returns and OPEC meeting dates and announcements related to production decisions.

Table 2. Linear Granger causality test

Dependent variable	Independent variable	F-statistic	p-value
Brent returns	Cut	0.143	0.705
	Increase	0.254	0.614
	Maintain	0.199	0.655
	OPEC meeting	0.137	0.711
WTI returns	Cut	0.870	0.351
	Increase	0.316	0.574
	Maintain	0.919	0.338
	OPEC meeting	0.380	0.538

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

For this purpose, we apply the Brock, Dechert, Scheinkman, and LeBaron (1996) (BDS) test on the residuals from the returns equation involving one lag of returns and one lag of the OPEC variables. Table 3 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 i.i.d. residuals at various embedded dimensions (m). Thus, strong evidence exists of nonlinearity in the relationship between oil futures returns and the various OPEC variables. This evidence indicates that the findings based on the linear Granger causality test as presented in Table 2 cannot be deemed robust and reliable. Given the strong evidence of nonlinearity in the relationship between returns and OPEC meeting dates and announcements, we now turn our attention to the causality-in-quantiles test, which is robust to linear misspecification given its nonparametric (i.e., data-driven) approach.

Table 3. Brock et al. (1996) (BDS) test of nonlinearity

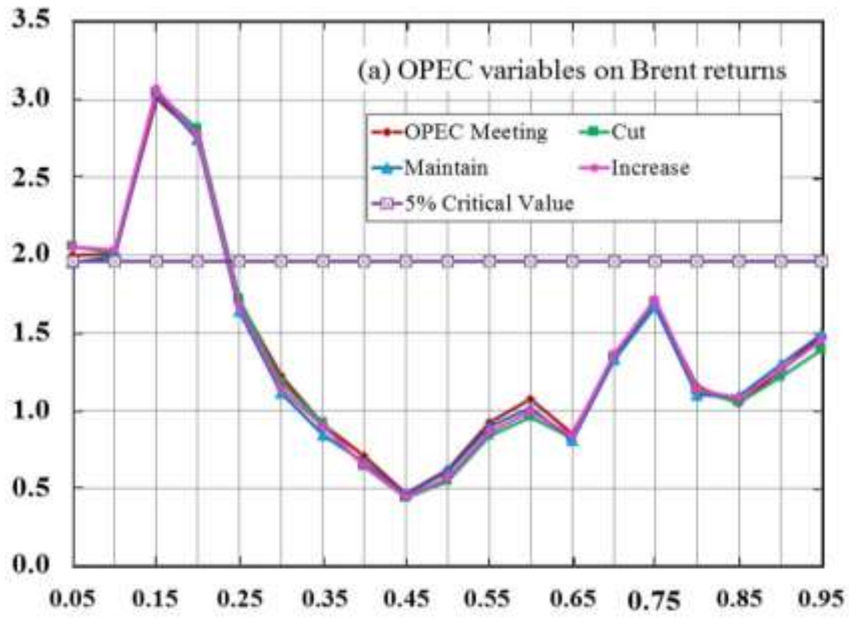
Dependent variable	Independent variable	Dimension				
		2	3	4	5	6
Brent returns	Cut	10.524*	15.146*	20.508*	28.843*	40.566*
	Increase	10.556*	15.197*	20.560*	28.939*	40.740*
	Maintain	10.562*	15.233*	20.579*	28.887*	40.529*
	OPEC meeting	10.572*	15.244*	20.596*	28.957*	40.654*
WTI returns	Cut	14.096*	18.195*	21.060*	23.201*	25.791*
	Increase	14.158*	18.229*	21.075*	23.196*	25.781*
	Maintain	14.163*	18.257*	21.106*	23.231*	25.827*
	OPEC meeting	14.173*	18.251*	21.100*	23.222*	25.816*

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

4.2. Quantile causality tests

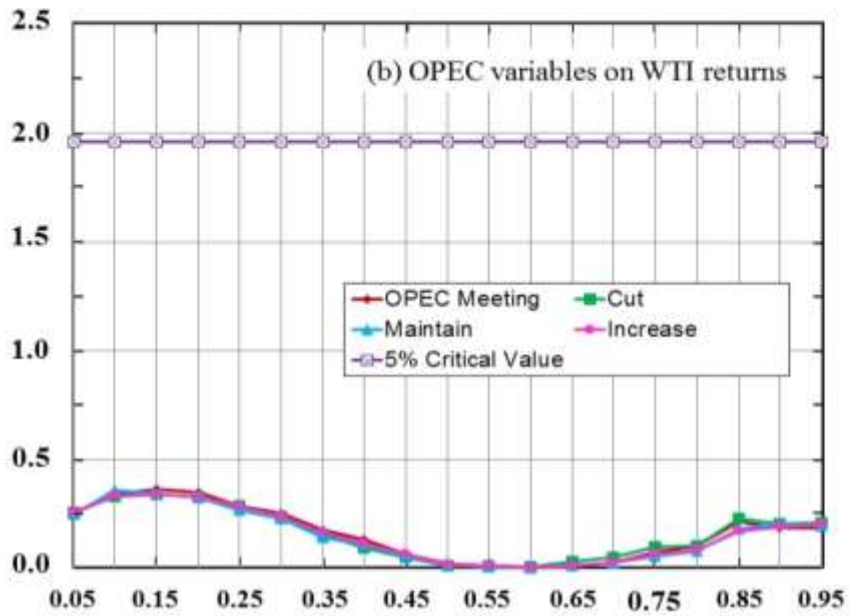
Figure 2 presents the findings from the causality-in-quantiles tests for oil futures returns and the volatility for the Brent Crude and WTI markets that emanates from the OPEC meeting dates and production decisions for the quantile range from 0.05 to 0.95. As Figures 2b and 2d show, irrespective of the OPEC variable used as a predictor, no evidence exists for the predictability of WTI returns and GARCH-based volatility. Therefore, the results of the linear causality test for WTI returns carry over to the causality-in-quantiles even after controlling for misspecifications in the linear model attributable to the existence of nonlinearity.

Figure 2a. Causality-in-quantiles: Brent futures returns and OPEC-related variables



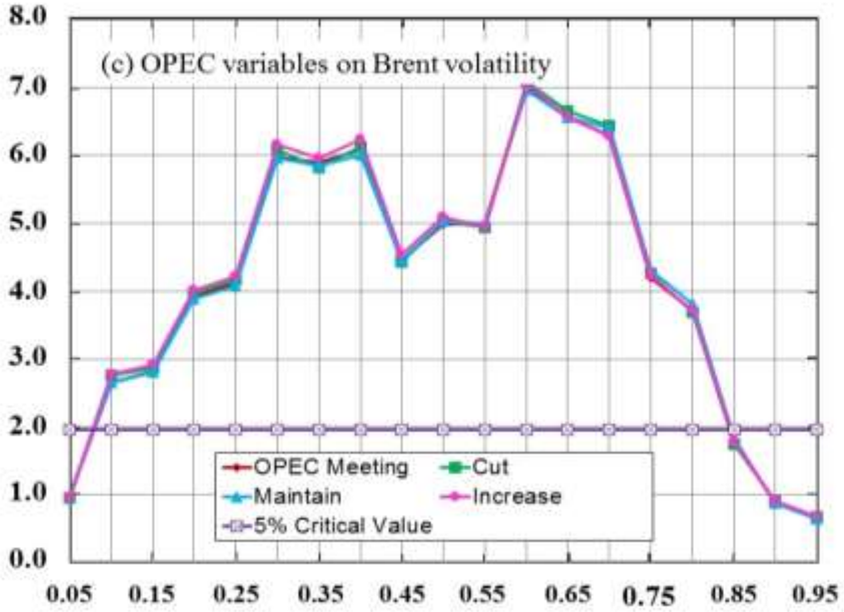
Note: The horizontal axis depicts the various quantiles and the vertical axis measures the test statistic.

Figure 2b. Causality-in-quantiles: WTI futures returns and OPEC-related variables



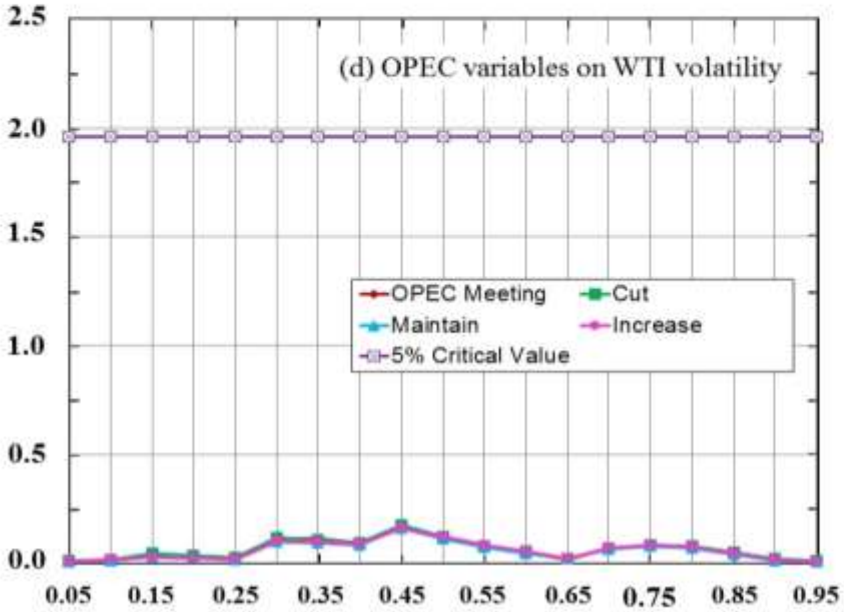
Note: See the notes for Figure 2a.

Figure 2c. Causality-in-quantiles: Brent futures GARCH-based volatility and OPEC variables



Note: See the notes for Figure 2a.

Figure 2d. WTI futures GARCH-based volatility and OPEC-related variables



Note: See the note for Figure 2a.

However, in Figures 2a and 2c, we observe quantile-specific effects on Brent Crude returns and volatility. For returns, unlike no evidence of predictability, all OPEC variables behave similarly in causing Brent Crude futures returns over the quantile range from 0.05 to less than 0.25, i.e., predictability is observed in the lower quantiles, representing the bear phase of the market, with the peak at the 0.15 quantile. Regarding volatility, again, all OPEC-related variables behave identically and cause uncertainty in the Brent Crude market over the quantile range from 0.10 to less than 0.85, with the strongest impact at the 0.60 quantile. Therefore, for volatility, the lower and upper ends are not predictable by meeting OPEC dates and production decision behaviour. This result tends to suggest the unpredictability in the risk profile of the Brent Crude market at very low and high levels of uncertainty on the basis of OPEC-related predictors.[4]

Intuitively, our results tend to suggest that investors in the Brent crude oil market probably herd when market performance is mediocre to good; hence, they do not require any other information that is available from OPEC-related variables. However, when the market is in a bearish mode, investors seek to obtain favourable information from the OPEC-based predictors to possibly improve their investment positions. At the same time, volatility in the Brent Crude futures market is predictable when it is around the normal phase (median and its relatively wide neighbourhood); however, when volatility is extremely low or high, OPEC-based news has no value.

Our results tend to suggest that WTI futures are good hedges against risks associated with OPEC announcements but that Brent Crude in general is not; if we take both returns and volatility effects together, the market is only a good hedge against such risks at very high quantile levels. From the perspective of an academic, WTI futures can be categorized as an

[4] We also carried out a causality-in-quantiles analysis for the WTI and Brent Crude spot markets using daily data from 21 May 1987 to 30 December 2012. Although no impact on GARCH-based volatility were observed for both markets, the OPEC variables were found to predict both their returns at the lower and upper ends of their respective conditional distributions. Complete details of these results are available on request from the authors.

efficient market, whereas Brent Crude futures are efficient only when performing exceptionally well – with high returns and risk. Finally, the policy maker who worries about the impact of oil price movements (both returns and volatility) on the real economy should be ready to undertake appropriate measures to circumvent the negative impact – if any – from a Brent Crude market that is not performing at its peak. However, it must be noted that the investor, the academic, and the policy maker should be using nonlinear/nonparametric movement to correctly capture the effect of OPEC announcements on oil futures because using a linear model is likely to lead to incorrect inferences, especially with respect to Brent Crude futures.

5. Conclusion

This paper provides a novel perspective of the predictive ability of OPEC announcements on production decisions and meeting dates for returns and GARCH-based volatility of the oil futures market using a nonparametric quantile-based methodology. This methodology formally distinguishes between different market states that can be characterized as bull, bear, and normal market conditions. Standard linear causality tests yield insignificant results for both Brent Crude and WTI future markets during the daily period from 3 January 1991 to 30 December 2016. However, we indicate that linear Granger causality test results cannot be relied on because formal tests reveal strong evidence of nonlinearity between oil futures returns and the OPEC-based predictor variables. Hence, linear Granger causality tests are misspecified.

When we use 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, and the meeting dates, predict only the lower quantiles of the conditional distribution of Brent futures market returns. Yet, the predictability of volatility covers the majority of the quantile distribution, barring the extreme lower and upper ends. Therefore, whereas the OPEC-related variables can predict the bear market associated with Brent futures returns, future market uncertainty (i.e., volatility) cannot be captured by OPEC-based predictors. As part of future research, it would be interesting to extend our analysis to a forecasting exercise because in-sample predictability does not guarantee the same over an out-of-sample (Balcilar et al., 2016).

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