OPEC News and Jumps in the Oil Market

May 17, 2021

Konstantinos Gkillas*, Rangan Gupta**, Christian Pierdzioch*** and Seong-Min Yoon****

Highlights

- We study the role of OPEC meeting dates and production announcements for predicting jumps in the oil market
- We use a nonparametric causality-in-quantiles test
- We find strong evidence that the OPEC meeting dates, and production announcements do predict oil market jumps

Abstract

We study the role of OPEC meeting dates and production announcements for predicting jumps in the oil market. The period of analysis spans from the daily period of 2nd December 1997 to 26th May 2017, with the start and end date corresponding to our availability of the intraday data on oil-price data. We, first, apply the standard linear Granger causality test to detect evidence of the OPEC-based predictors in causing jumps. This test fails to detect predictability from OPEC-based predictors to oil market jumps. Yet given the strong evidence of nonlinearity between jumps and the dummies capturing news regarding the OPEC production announcements and meeting dates, we next use a nonparametric causality-in-quantiles test. Upon employing this data-driven robust approach, we find strong evidence that the variables do predict oil market jumps, ranging from the lower end of the conditional distribution of jumps to around the median.

Keywords: Oil market jumps; OPEC announcements; Nonparametric quantile causality
JEL Codes: C22; Q02

* Corresponding author. Department of Business Administration, University of Patras, University Campus, Rio, P.O. Box 1391, 26500 Patras, Greece. Email: Email: gillask@upatras.gr.
** Department of Economics, University of Pretoria, Pretoria, 0002, South Africa. Email: rangan.gupta@up.ac.za.
*** Department of Economics, Helmut Schmidt University, Holstenhofweg 85, P.O.B. 700822, 22008 Hamburg, Germany. Email address: pierdzic@hsu-hh.de.
**** Department of Economics, Pusan National University, 2, Busandaehak-ro 63beon-gil, Geumjeong-gu, Busan, 46241, Republic of Korea. Email: smyoon@pusan.ac.kr.

1. Introduction

The recent financialization of the oil market has increased participation of hedge funds, pension funds and insurance companies in the market, thus resulting in oil to be a profitable alternative investment in the portfolio decisions of financial institutions (see Akram, 2009; Tang and Xiong, 2012; Silvennoinen and Thorp, 2013; Fattouh et al., 2013; Büyüksahin and Robe, 2014; Bahloul et al., 2018; Bonato, 2019, among others). Naturally, accurate predictability of large oil-price movements and volatility is of vital importance to traders in the oil-sector. Oil-price volatility can be also considered as a measure of uncertainty, which in turn has been found to negatively influence economic activity (Elder and Serletis, 2010; Aye et al., 2014; van Eyden et al., 2019). Thus, not surprisingly, a large literature exists on the predictability of daily oil-price conditional volatility using different kinds of univariate and multivariate models from Generalized Autoregressive Conditional Heteroskedasticity (GARCH)-family, as well as the Markov-switching multifractal (MSM) model, and variations of the Heterogeneous Autoregressive (HAR) model to predict the realized volatility of oil returns (see Lux et al., 2016 and Gkillas et al., 2020a for detailed reviews).

The modelling of unexpected movements in oil prices is also crucial for portfolio risk management and financial decision making. Volatility as a measure of risk is an unobservable variable and several problems arise when trying to assess its impacts on financial markets. In light of this, market agents are known to care not only about the nature of volatility, but also about its level, with traders often differentiating between good and bad volatility (Giot et al., 2010). More specifically, “good” volatility is directional, persistent and relatively easy to anticipate, yet “bad” volatility is jumpy and relatively difficult to foresee (Caporin et al., 2016). Consequently, “good” volatility is associated with the continuous and persistent part of the price process, while “bad” volatility is associated with discontinuous movements known as jumps (Huang et al., 2019). In this context, it has been stressed that incorporating jumps into volatility models can improve their overall performance, given their dominance in the price process (Asai et al., 2019; 2020). Hence, the accurate prediction of jumps stands for a key research question. The inclusion of jumps in the price process is also important for asset allocation and portfolio risk management. Jumps help to forecast (i) returns (Andersen et al., 2015), (ii) volatility (Duong and Swanson, 2015), (iii) equity risk premium (Santa-Clara and Yan, 2010) and (iv) variance risk premium (Li and Zinna, 2017). Nevertheless, it is necessary to differentiate jumps information from risk. In other words, according to Bollerslev et al. (2008), jumps add a locally source of non-diversifiable risk in volatility making the prediction more difficult.

Recently, some studies have highlighted the role of news on the Organization of the Petroleum Exporting Countries (OPEC) production decisions in driving the (returns and) volatility of the crude oil market (see Schmidbauer and Rösch, 2012; Mensi et al., 2014; Ji and Guo, 2015; Loutia et al., 2016; Gupta and Yoon, 2018; Gupta et al., 2019; Derbali et al., 2020, among others). While in the existing empirical literature there is a body of evidence showing that jumps are linked to fundamentals (see e.g. Andersen et al., 2007), we still need to shed light on additional sources of unexpected movements in the oil market. Against this backdrop, given the importance of oil market jumps in portfolio risk management and asset allocation, the objective of our paper is to empirically test whether OPEC production decisions involving cut, maintain, and increase, and also OPEC meeting dates can predict jumps, and in hence provide a channel through which the “bad” volatility is affected. For our predictability analysis, we rely on the nonparametric causality-in-quantiles test proposed by Jeong et al., (2012), which allows us to test for predictability over the entire conditional distribution of jumps and control for misspecification due to uncaptured nonlinearity (which we show to exist below in our data from a statistical perspective). This is of paramount importance when the dependent variable, i.e., jumps in our case may exhibit fat tail behavior (see Bollerslev et al., 2013). This method also permits us to capture various market phases (sizes), such as booms and crashes, associated with the jumpy behavior of the prices process of the oil market. Moreover, this method can be considered as an inherently time-varying method since various parts of the conditional distribution can be related to different time points throughout the evolution of the dependent variable. In particular, the method applied in this study has the following two key advantages. First, it is considered as robust to misspecification errors as it is based on a nonparametric data-driven method. Second, by applying this method, we can detect casual effects across the entire conditional distribution of jumps and more importantly in the right end point of the distribution of jumps (see also Heimstra and Jones, 1994; Diks and Panchenko, 2005, 2006, among others). To the best of our knowledge, this is the first paper that evaluates the predictive power of OPEC production decisions on oil market jumps using a quantiles-based nonparametric framework.

From a practical point of view, our study sheds light on the types of events that can trigger unexpected movements in the oil market. According to Andersen et al. (2007), “it would be interesting to attempt a more systematic characterization of the types of events that cause the different markets to jump”. Therefore, there is a practical interest in identifying jumps, which in turn is important for developing hedging strategies and modelling market risk premia (see Eraker et al., 2003). Taking also into account that oil is a major production factor, policymakers have to make decisions during periods of jump-inducing turbulence in the oil market, hence it is economically important to proceed to a better econometric and statistical understanding of the behavior of jumps along with the events that cause the oil market to jump (see Gkillas et al., 2020b; Todorov and Tauchen, 2011).

The remainder of the paper is organized as follows. Section 2 lays out the basics of the methodology involving jumps and the causality-in-quantiles approach. Section 3 presents the data and reports the empirical results, with Section 4 concluding the paper.

2. Methodology

2.1. Jumps

In the related empirical literature, there is strong evidence that the assumption of a continuous diffusion is violated. The need for a more detailed description of the price process emerged from volatility asymmetries. Based on the theoretical studies implement by Barndorff-Nielsen and Shephard (2004b), Andersen et al. (2007) proposed a jump detection non-parametric scheme for realized volatility. In this sub-section, we briefly present the methodology for detecting oil price jumps from realized volatility.

In particular, we construct daily realized volatility with the use of realized variance (RV), as in Andersen et al. (2007), among many others. RV is the benchmark measure of realized volatility. More analytically, we define the price process in days t. Within each day, there are $N+1$ intraday prices or N intraday returns. In any day t, the observed prices concern these intraday time periods: $t_0 < t_1 < \cdots < t_{N+1}$. If we assume a constant number of intraday prices per day across all days considered, intraday returns can be constructed as the logarithmic difference between two consecutive observed prices given by the following equation:

$$r_{t,i} = \log(P_{t,i}) - \log(P_{t,i-1}) \quad (1)$$

where $r_{t,i}$ stands for the intraday return, $P_{t,i}$ stands for the intraday price with $i = (1, \dots, N)$, for the day t.

Next, a daily point estimate of RV_t is constructed for each day t by summing all intraday returns available as follows:

$$RV_t \equiv \sum_{i=1}^{N} r_{t,i}^2 \tag{2}$$

where $r_{t,i}$ stands again for the intraday return i within day t for $i = 1, \dots N$, and N is the total number of intraday returns within a trading day.

Turning now our attention to jumps, it is important to mention that when volatility at the given point estimate t includes jump variation, then it cannot be considered as an unbiased estimator of integrated variance. Therefore, price increments can be distinguished between jump variation and continuous variation. The former can be computed as the difference between the total variation - which is estimated by the RV_t as it measures both the continuous and jump variation - and the continuous variation. The standardized realized bipower variation (RBV_t) used in this study captures only the amount of continuous variation, therefore it has been considered to be a jump-robust estimator of realized volatility. More precisely, the asymptotic results of Barndorff-Nielsen and Shephard (2004) enable the nonparametric distinction between continuous and jump variation. Following Barndorff-Nielsen and Shepherd (2004, 2006), we use the RBV_t as a jump-free volatility estimator for the continuous sample path variation. RBV_t can be considered as a jump-robust estimator of integrated variance, that is, it is a less biased estimator than other realized measures of in the presence of jumps. The RBV_t is constructed by the following:

$$RBV_t \equiv \xi_1^{-2} \sum_{i=2}^{N} |r_{t,i}||r_{t,i-1}| \tag{3}$$

where $\xi_1 \equiv \sqrt{2/\pi} = E(|Z|)$ is the mean of the absolute value of a random variable (Z) which follows a normal distribution.

We use the Andersen et al.'s (2007) jump statistic to detect realized jump intensity. The jump statistic, as used here, is given as follows:

$$U_t \equiv \sqrt{N} \frac{(RV_t - RBV_t)RV_t^{-1}}{[(\xi_1^{-4} + 2\xi_1^{-2} - 5)max\{1, TQ_t RBV_t^{-2}\}]^{1/2}} \tag{4}$$

where TQ_t is the integrated quarticity which is estimated using the standardized realized tri-power quarticity measure as $N\xi_{4/3}^{-3} \sum_{i=3}^{N} |r_{t,i}|^{4/3} |r_{t,i-1}|^{4/3} |r_{t,i-2}|^{4/3}$, while $\xi_{4/3}$ is equal to $2^{2/3}\Gamma(7/6)\Gamma(1/2)^{-1} = E\left(|Z|^{4/3}\right)$. The U_t is a ratio statistic which follow the standard normal distribution ($U_t \to N(0,1)$, as $N \to \infty$). The U_t is used as a pre-test, testing the null hypothesis of no jumps against the alternative hypothesis of existence of jumps. A significant jump is identified by an indicator function, $\mathbf{1}\{U_t > \Phi_a\}$, under the following condition:

$$J_t \equiv \mathbf{1}\{U_t > \Phi_a\}[RV_t - RBV_t] \tag{5}$$

Analogically, the continuous component denoted by $C_{t,a}$ is equal to $\mathbf{1}\{U_t \leq \Phi_a\}RV_t$, where $RV_t \equiv J_{t,a} + C_{t,a}$. The non-negativity of both components corresponds directly to a significance level of $a = 0.05$ (Andersen et al., 2007). To put it differently, the difference between the RV_t and RBV_t is equal to zero when there is no jump and strictly positive when a jump occurs in the oil market (asymptotically).

2.2. Causality-in-Quantiles

In this sub-section, we briefly present the methodology for testing nonlinear causality as developed by Jeong et al., (2012).[1] As already stated, this approach is a robust approach far away from the center of the distribution. Furthermore, it enables us to capture nonlinear dynamic casual effects between two time series. In our study, let y_t be the dependent variable which stands for jumps (J_t), while x_t stands for the predictor variable, in our case the dummies used in turn corresponding to OPEC meeting dates, and production decisions made on those dates involving a cut, maintain or increase (as described in detail in the Data segment of the paper below).

Let $Y_{t-1} \equiv (y_{t-1}, \dots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \dots, x_{t-p})$, $Z_t = (X_t, Y_t)$, and $F_{y_t|\cdot}(y_t|\bullet)$ denote the conditional distribution of y_t given $\bullet$. Defining $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ 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 1. The (non) causality in the θ-th quantile hypotheses to be tested are:

$$\begin{aligned} H_0&: \; P\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} = 1 \\ H_1&: \; P\left\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1})|Z_{t-1}\} = \theta\right\} < 1 \end{aligned} \tag{6}$$

Based on the study implement by Jeong et al. (2012), the feasible kernel-based test statistics is given as follows:

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

where $K(\bullet)$ is the kernel function with bandwidth h, T is the sample size, p is the lag order, and $\hat{\varepsilon}_t = \mathbf{1}\{y_t \leq \hat{Q}_\theta(Y_{t-1})\} - \theta$ is the regression error, where $\hat{Q}_\theta(Y_{t-1})$ is an estimate of the θ-th conditional quantile and $\mathbf{1}\{\bullet\}$ is the indicator function. The $\hat{Q}_\theta(Y_{t-1})$ is estimated by the Nadarya-Watson kernel estimator as follows:

$$\hat{Q}_\theta(Y_{t-1}) = \frac{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{Y_{t-1} - Y_{s-1}}{h}\right) \mathbf{1}\{y_s \leq y_t\}}{\sum_{s=p+1, s\neq t}^{T} L\left(\frac{Y_{t-1} - Y_{s-1}}{h}\right)} \tag{8}$$

with $L(\bullet)$ denoting the kernel function.

Note that, asymptotic normality holds for $\hat{J}_T$. The empirical implementation of causality testing via quantiles entails specifying three key parameters: the bandwidth (h), the lag order (p), and the kernel types for $K(\cdot)$ and $L(\cdot)$. We use a lag order of six based on the Schwarz Information Criterion (SIC). We determine h by leave-one-out least-squares cross validation. Finally, for $K(\cdot)$ and $L(\cdot)$, we use Gaussian kernels.

[1] What is more, the exposition in this section closely follows Nishiyama et al. (2011) and Jeong et al. (2012). Our description is compact because the details of the test have been laid out in, e.g. recent contributions by Balcilar, et al. (2016a) and Balcilar et al. (2016b), Balcilar et al. (2016c) and Balcilar et al. (2017), among others.

3. Data and Results

3.1. Data

Our analysis involves the measure of oil market jumps and four OPEC related variables over the daily period of 2nd December 1997 to 26th May 2017, with the start and end date corresponding to our availability of the intraday data on oil price. Intraday data reveal important information about the market compare to, for example, to daily data, such as intraday price changes and market microstructures. In this vein, Hansen and Huang (2016) noted that realized volatility is more accurately estimated at a daily frequency employing intraday data. We use intraday data on oil futures traded in NYMEX over a 24-hour trading day (pit and electronic) to extract our daily measure of jumps. We use futures data as futures have lower transaction costs related to futures trading, and therefore, our paper can be considered more relevant for analysts for practical applications (e.g. hedging analyses). Additionally, price discovery takes places mainly in futures markets as futures respond faster to new information than the spot markets because of the ease of short selling and lower transaction costs that they have (see Shrestha, 2014). The futures price data, in continuous format, is obtained from: Disktrading database (http://www.disktrading.com) and Kibot database (http://www.kibot.com). Close to expiration of a contract, the position is rolled over to the next available contract, provided that activity has increased. We define daily returns as the end of day (New York time) price difference (close to close). In the case of intraday returns, last-tick interpolation gives 1-minute prices (if the price is not available at the 1-minute stamp, the previously available price is imputed), and finally we compute 5-minute returns by taking the log-differences of these prices, and then these returns to construct a daily point estimate of realized oil volatility.

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, along with a dummy variable corresponding to the meeting date. The data for conference decisions were obtained from the OPEC website (http://www.opec.org). There were 75 announcements during our period of consideration, involving 16 cut, 12 increase, 47 maintain decisions.

The summary statistics of jumps is reported in Table A1, and as can be seen from this table, the variable is positively skewed and has excess kurtosis, resulting a non-normal distribution. This is also indicated by the overwhelming rejection (at 1 percent level of significance) of the null of normality under the Jarque-Bera test. Such statistical properties provide a preliminary justification for the causality-in-quantiles test used in this empirical analysis.

3.2. Results

Before we present the findings of the causality-in-quantiles test, for the sake of completeness and comparability, we first conduct the standard linear Granger causality test. The resulting $\chi^2(6)$ statistics are presented in Table 1, and as can be seen from the table, the null of no-Granger causality running from the four OPEC-based dummies to jumps cannot be rejected in any of the cases, even at the 10% level of significance.

Given the insignificant results obtained from the linear causality tests, we statistically examine the presence of nonlinearity in the relationship between jumps and the four OPEC dummies. For this purpose, we apply the Brock et al., (1996) test (known also as BDS test) to the residuals from the jump equation involving six lags of jumps and the four alternative OPEC dummies, considered by turn. Table A2 in Appendix 1 presents the results of the BDS test of nonlinearity. As shown in this table, we find strong evidence for the rejection of the null of independent and identically distributed (i.i.d.) residuals at various embedded dimensions (m), which in turn, is indicative of nonlinearity in the relationship jumps and the dummies associated with cuts, increases, maintain and meeting dates. This results further indicate that the results based on the linear Granger causality test cannot be deemed robust and reliable.

Table 1: Granger Causality Test Estimates for Oil Market Jumps

Independent variable	$\chi^2(6)$-statistic	*p*-value
Meeting	9.9319	0.1275
Cut	8.3267	0.2151
Maintain	5.9475	0.4291
Increase	3.4897	0.7453

Notes: This table reports the estimates for the standard linear causality test between oil market jumps and OPEC news announcements. The 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, along with a dummy variable corresponding to the meeting date. ***, ** and * indicate the rejection of the null hypothesis of no-causality from OPEC news announcements to oil market jumps.

Given the strong evidence of nonlinearity in the relationship between jumps and OPEC news announcements,[2] we now turn our attention to the causality-in-quantiles test, which is robust to linear misspecification due to its nonparametric (i.e., data-driven) approach, besides providing evidence of predictability (if any) over the entire conditional distribution of jumps. As can be seen from Table 2, all the four OPEC related variables provide strong evidence of causality over the quantile range from 0.05 to 0.55, with the strongest impact in terms of statistically significant observed at the lowest considered quantile. More importantly, unlike the linear Granger causality test, where evidence of predictability is non-existent, we find evidence of predictability from the lowest quantile to the quantile just above the median. Recalling that quite a number of recent studies have suggested that OPEC news announcements drive volatility, one can argue that a channel through which this happens is that OPEC production decisions affect primarily the jump component in a similar manner, and hence, “bad” volatility. From a practical point of view such evidence indicates that the role of OPEC production decisions becomes important for sudden movements oil-prices associated with adverse events as when volatility is interpreted as uncertainty, it becomes a key input to investment decisions and portfolio choices (Poon and Granger, 2003). But, although OPEC production decisions can significantly help in the predictability of jumps, large jumps due to large price movements that happened in the oil market cannot be linked with OPEC production decisions.

[2] In addition, by applying the Bai and Perron’s (2003) test of multiple structural breaks on the jump equation (with six lags each of jumps and cut, increase, maintain, or meeting date dummies), two breaks (in September, 2001 and August, 2006) were detected between jumps series and each of the four OPEC news related variables. This result in turn, further warranted the need of a nonlinear approach to detecting causality in our context. Complete details of the structural break tests are available upon request from the authors. We also apply standard unit root tests to reveal whether oil market jumps series is stationary. The results are also available upon request and suggest that jumps can be employed directly without further transformation in the causality-in-quantiles procedure.

Table 2. Nonparametric Causality-in-Quantiles Results for Oil Market Jumps

Quantile	Meeting	Cut	Maintain	Increase
0.05	2685.1220***	2692.4390***	2676.4040***	2697.4810***
0.10	1502.1840***	1507.2630***	1496.8810***	1510.2930***
0.15	934.8305***	938.0227***	930.9399***	940.0763***
0.20	586.4426***	588.2303***	583.3897***	589.6616***
0.25	402.5122***	403.0630***	399.7872***	404.1003***
0.30	279.5168***	279.3823***	278.4010***	281.8445***
0.35	181.0650***	180.3274***	179.9614***	182.2018***
0.40	204.5213***	207.7911***	204.3135***	205.5889***
0.45	293.8399***	298.0508***	293.3934***	296.0927***
0.50	21.2322***	20.9058***	20.9493***	21.3410***
0.55	503.8821***	510.0203***	503.7456***	508.2684***
0.60	0.0391	0.0487	0.0390	0.0409
0.65	0.0398	0.0219	0.0238	0.0195
0.70	0.0458	0.0499	0.0364	0.0384
0.75	0.0484	0.0490	0.0382	0.0463
0.80	0.0868	0.1126	0.0910	0.1251
0.85	0.0452	0.0098	0.0178	0.0077
0.90	0.0670	0.0274	0.0343	0.0154
0.95	0.0304	0.0086	0.0104	0.0009

Notes: This table reports the estimates for the causality-in-quantiles test between oil market jumps and OPEC news announcements. The 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, along with a dummy variable corresponding to the meeting date. ***, ** and * indicate the rejection of the null hypothesis of no-causality from OPEC news announcements to oil market jumps for various quantiles at 1 percent, 5 percent and 10 percent levels of significance, respectively. The corresponding critical values of the test are 2.575, 1.96 and 1.645.

In a recent paper, Plante (2019) introduced a newspapers (the Financial Times, the Houston Chronicle, the New York Times and the Wall Street Journal) articles count index related to OPEC that rises in response to important OPEC meetings and events connected with OPEC production levels. Plante (2019) showed that this index can predict oil market volatility. This index is constructed at a monthly frequency and is available over the period from January 1986 to December 2016. In addition to this benchmark index, the author also developed two other indices, with the first one being the raw number of articles written about OPEC and divided by the total number of articles produced by the four newspapers over the same time period, and the second one based on Google search volume data on "OPEC" covering January, 2004 to December, 2016.[3] As a robustness check to our daily analysis of jumps obtained from intraday data, we now computed the monthly jumps from daily data on WTI oil prices. The daily data are obtained from the FRED database of the Federal Reserve Bank of St. Louis ((https://fred.stlouisfed.org/). To detect monthly jumps from realized volatility we employ the jump detection scheme presented in Appendix 2. The application of this scheme to monthly realized volatility is possible in the same way as it is to daily realized volatility estimates

[3] The newspaper- and Google search volume-based indices are available for download from the website of Dr. Michael D. Plante at: https://sites.google.com/site/michaelplanteecon/research.

constructed from intraday data, on the grounds that it is not dependent on direct estimates of the transition density function and directly builds on the theoretical results of Barndorff-Nielsen and Shephard (2004). Barndorff-Nielsen and Shephard (2004) noted that the conception of realized bi-power variation and jumps can be applied to finite number of observations and a fixed interval of time, even in case it is a trading day or a calendar month. Following Giot and Laurent (2007), the explanatory power of the monthly jumps is consistent with implied volatility in encompassing regressions. Monthly jumps are also studied by (Gkillas et al., 2018; Gkillas et al., 2020b, among others). Furthermore, when we repeated the causality-in-quantiles test in Table A3 in the Appendix 1, we find that in general, our results are similar to those obtained under the daily data. The strongest impact in terms of statistically significant observed at the lowest quantile and the causality ranges to till just above the median (especially under the two newspapers based indices).

4. Conclusion

Recent evidence tends to suggest that news on OPEC production decisions can affect oil market volatility. Given that the volatility-related literature also stresses the importance of jumps in forecasting oil price volatility, we study the role of announcements of production decision by the OPEC in predicting daily oil market jumps derived from intraday data. For our predictability analysis, we rely on a nonparametric causality-in-quantiles test, which is robust to not only misspecification due to nonlinearity being a data-driven procedure, but also provides evidence of causality over the entire conditional distribution of jumps. Our results indicate that dummy variables capturing information on OPEC meeting dates, as well as production decisions associated with cuts, increases, or maintaining the status quo indeed predict oil market jumps very strongly at the lower end of the conditional distribution, and ranges till just above the median. In summary, our analysis shows that OPEC's production decisions can affect "bad" oil market volatility as it can trigger jumps via small to normal jumps. But this result can only be detected when we rely on a nonparametric quantiles-based causality framework, instead of standard causality linear models. Standard linear models fail to capture any evidence of predictability due to misspecification that arises as they are unable to capture nonlinearities exist in the relation between jumps and OPEC meeting dates and production announcements.

From a practical point of view, our study sheds light on the types of events that cause unexpected movements in the oil market. To this end, we take the point of view of investors that are exposed to jump-risk that may occur due to OPEC meeting dates and production announcements. Thus, we proceed to a systematic characterization of the types of events that cause the oil market to jump. In other words, we determine whether OPEC announcements can be considered as a source of "bad" volatility for the oil market. Our findings do reveal predictability from OPEC meeting dates and production announcements to oil market jumps when controlling different market phases and regimes. Such evidence has ample practical implications for portfolio selection and risk management, as well as policy implications as it is widely accepted that oil market uncertainty negatively affects economic activity (see Elder and Serletis, 2010). Thus, our findings imply that both investors and policymakers can use the information contained in OPEC announcements to predict unexpected movements in the oil market. As part of future research, our paper can be extended to analyzing the role of news associated with OPEC in predicting volatility and jumps of other financial markets.

References

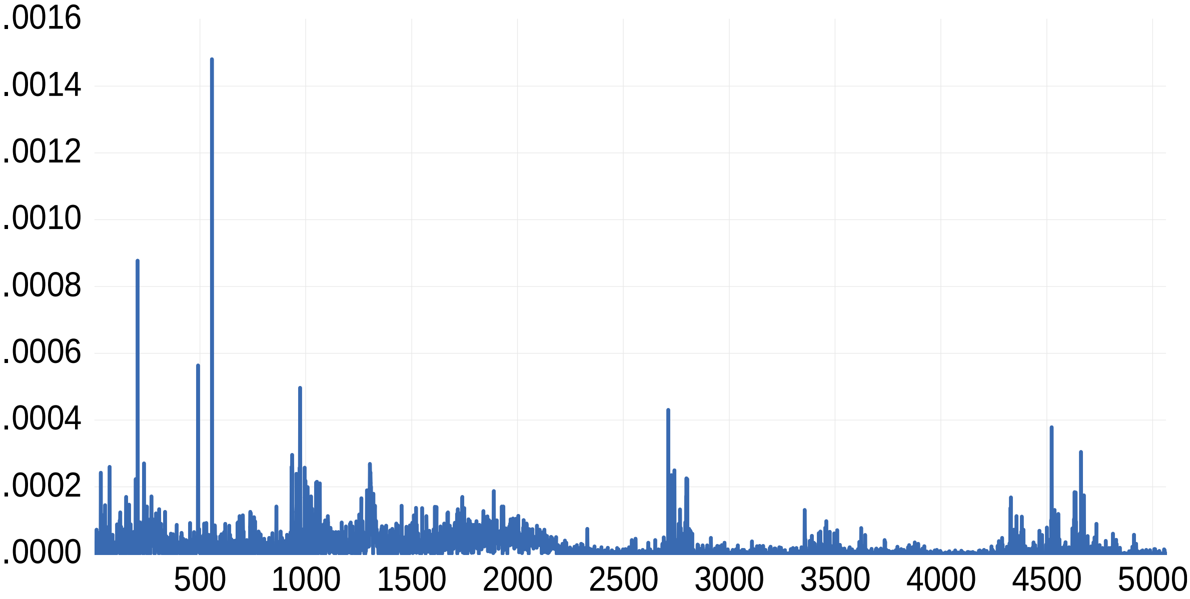
1. Akram, Q. F. (2009). Commodity prices, interest rates and the dollar. Energy economics, 31(6), 838-851.
2. Andersen, T. G., Bollerslev, T., and Diebold, F. X. (2007). Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility. The review of economics and statistics, 89(4), 701-720.
3. Andersen, T. G., Fusari, N., and Todorov, V. (2015). The risk premia embedded in index options. Journal of Financial Economics, 117(3), 558-584.
4. Asai, M. Gupta, R., and McAleer, M. (2019). The Impact of Jumps and Leverage in Forecasting the Co-Volatility of Oil and Gold Futures. Energies, 12, 3379.
5. Asai, M. Gupta, R., and McAleer, M. (2020). Forecasting Volatility and co-volatility of crude oil and gold futures: Effects of leverage, jumps, spillovers, and geopolitical risks. International Journal of Forecasting. DOI: https://doi.org/10.1016/j.ijforecast.2019.10.003.
6. Aye, G. C., Dadam, V., Gupta, R., and Mamba, B. (2014). Oil price uncertainty and manufacturing production. Energy Economics, 43, 41-47.
7. Bahloul, W., Balcilar, M., Cunado, J., and Gupta, R. (2018). The role of economic and financial uncertainties in predicting commodity futures returns and volatility: Evidence from a nonparametric causality-in-quantiles test. Journal of Multinational Financial Management, 45, 52-71.
8. Bai, J., and Perron, P. (2003). Computation and analysis of multiple structural change models. Journal of Applied Econometrics, 18(1), 1-22.
9. Balcilar, M., Gupta, R., and Pierdzioch, C. (2016a). On exchange-rate movements and gold-price fluctuations: evidence for gold-producing countries from a nonparametric causality-in-quantiles test. International Economics and Economic Policy. http://dx.doi.org/10.1007/s10368-016-0357-z.
10. Balcilar, M., Gupta, R., and Pierdzioch, C. (2016b). Does uncertainty move the gold price? New evidence from a nonparametric causality-in-quantiles test. Resources Policy, 49, 74–80.
11. Balcilar, M., Gupta, R., Pierdzioch, E., and Wohar, M. E. (2016c). Terror attacks and stock-market fluctuations: Evidence based on a nonparametric causality-in-uantiles test for the G7 countries. European Journal of Finance. http://dx.doi.org/10.1080/1351847X.2016.1239586.
12. Balcilar, M., Gupta, R., Pierdzioch, E., and Wohar, M. E. (2017). Do terror attacks affect the dollar-pound exchange rate? A nonparametric causality-in-quantiles analysis. North American Journal of Economics and Finance 41, 44-56.
13. Barndorff-Nielsen, O. E., and Shephard, N. (2004). Power and bipower variation with stochastic volatility and jumps. Journal of financial econometrics, 2(1), 1-37.
14. Barndorff-Nielsen, O. E., and Shephard, N. (2006). Econometrics of testing for jumps in financial economics using bipower variation. Journal of financial Econometrics, 4(1), 1-30.
15. Barroso, P., and Santa-Clara, P. (2015). Momentum has its moments. Journal of Financial Economics, 116(1), 111-120.
16. Bonato, M. (2019). Realized correlations, betas and volatility spillover in the agricultural commodity market: What has changed? Journal of International Financial Markets, Institutions and Money, 62, 184-202.
17. Bollerslev, T., Law, T. H., & Tauchen, G. (2008). Risk, jumps, and diversification. Journal of Econometrics, 144(1), 234-256.

18. Bollerslev, T., Todorov, V., and Li, S. Z. (2013). Jump tails, extreme dependencies, and the distribution of stock returns. Journal of Econometrics, 172(2), 307-324.
19. Brock, W.A., Scheinkman, J.A., Dechert, W.D., and LeBaron, B. (1996). A test for independence based on the correlation dimension. Econometric reviews, 15(3), 197-235.
20. Büyükşahin, B., & Robe, M. A. (2014). Speculators, commodities and cross-market linkages. Journal of International Money and Finance, 42, 38-70.
21. Campbell, J. Y., Lettau, M., Malkiel, B. G., and Xu, Y. (2001). Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk. The Journal of Finance, 56(1), 1-43.
22. Caporin, M., Rossi, E., and Magistris, P.S.D. (2014). Volatility jumps and their economic determinants. Journal of Financial Econometrics, 14(1), 29-80.
23. Christensen, B. J., and Hansen, C. S. (2002). New evidence on the implied-realized volatility relation. The European Journal of Finance, 8(2), 187-205.
24. Derbali, A., Wu, S. and Jamel, L. (2020). OPEC news and predictability of energy futures returns and volatility: evidence from a conditional quantile regression. Journal of Economics, Finance and Administrative Science. DOI: https://doi.org/10.1108/JEFAS-05-2019-0063.
25. Diks, C. G. H., and Panchenko, V. (2005). A note on the Hiemstra-Jones test for Granger noncausality. Studies in Nonlinear Dynamics and Econometrics, 9(2), 1-7.
26. Diks, C. G. H., and Panchenko, V. (2006). A new statistic and practical guidelines for nonparametric Granger causality testing. Journal of Economic Dynamics and Control, 30(9-10), 1647-1669.
27. Duong, D., and Swanson, N. R. (2015). Empirical evidence on the importance of aggregation, asymmetry, and jumps for volatility prediction. Journal of Econometrics, 187(2), 606-621.
28. Elder, J., and Serletis, A. (2010). Oil Price Uncertainty. Journal of Money, Credit and Banking, 42(6), 1137-1159.
29. Eraker, B., Johannes, M., and Polson, N. G. (2003). The impact of stochastic volatility and jumps in returns. Journal of finance, 58, 1269-1300.
30. Fattouh, B., Kilian, L., and Mahadeva, L. (2013). The role of speculation in oil markets: What have we learned so far?. The Energy Journal, 34(3).
31. French, K. R., Schwert, G. W., and Stambaugh, R. F. (1987). Expected stock returns and volatility. Journal of financial Economics, 19(1), 3.
32. Giot, P., and Sébastien L. (2007). The Information Content of Implied Volatility in Light of the Jump/Continuous Decomposition of Realized Volatility. Journal of Futures Markets 27 (4). John Wiley & Sons, Ltd: 337–359. doi:10.1002/fut.20251.
33. Giot, P., Laurent, S., and Petitjean, M. (2010). Trading activity, realized volatility and jumps. Journal of Empirical Finance, 17(1), 168-175.
34. Gkillas (Gillas), K., Vortelinos, D. I., and Saha, S. (2018). The properties of realized volatility and realized correlation: Evidence from the Indian stock market. Physica A: Statistical Mechanics and its Applications, 492, 343-359.
35. Gkillas, K., Gupta, R., and Vortelinos, D. (2018). Uncertainty and Jumps in the Pound-Dollar Exchange Rate: Evidence from Over One Century of Data (No. 201843).
36. Gkillas, K., Gupta, R., and Pierdzioch, C. (2020a). Forecasting realized oil-price volatility: The Role of financial stress and asymmetric loss. Journal of International Money and Finance, 104, 102137.
37. Gkillas, K., Gupta, R., and Wohar, M. E. (2020b). Oil shocks and volatility jumps. Review of Quantitative Finance and Accounting, 54(1), 247-272.

38. Gupta, R., Lau, C.K.M., and Yoon, S.-M. (2019). OPEC News Announcement Effect on Volatility in the Crude Oil Market: A Reconsideration. Advances in Decision Sciences, 23(4), 1-23.
39. Gupta, R., and Yoon, S.-M. (2018). OPEC news and predictability of oil futures returns and volatility: Evidence from a nonparametric causality-in-quantiles approach. The North American Journal of Economics and Finance, 45(C), 206-214.
40. Hansen PR and Huang Z. 2016. Exponential GARCH Modeling With Realized Measures of Volatility. Journal of Business & Economic Statistics.
41. Huang, D., Schlage, C., Shaliastovich, I. and Thimmel, NJ., 2019. Volatility-of-volatility risk. Journal of Financial and Quantitative Analysis. 54(6), 2423-2452.
42. Hiemstra, C. and Jones, J. D. (1994). Testing for linear and nonlinear Granger causality in the stock price-volume relation. Journal of Finance, 49(5), 1639–1664.
43. Jeong, K., Härdle, W. K., & Song, S. (2012). A consistent nonparametric test for causality in quantile. Econometric Theory, 28(4), 861-887.
44. Ji, Q., and Guo, J.-F. (2015). Oil price volatility and oil-related events: An Internet concern study perspective. Applied Energy, 137, 256-264.
45. Li, J. and Zinna, G. (2017). The variance risk premium: components, term structures, and stock return predictability. Journal of Business and Economics Statistics. 1-15.
46. Loutia, A., Mellios, C., and Andriosopoulos, K. (2016). Do OPEC announcements influence oil prices? Energy Policy, 90, 262–272.
47. Lux, T., Segnon, M., and Gupta, R. (2016). Forecasting crude oil price volatility and value-at-risk: Evidence from historical and recent data. Energy Economics, 56, 117-133.
48. Mensi, W., Hammoudeh, S., and Yoon, S.-M. (2014a). How do OPEC news and structural breaks impact returns and volatility in crude oil markets? Further evidence from a long memory process. Energy Economics, 42, 343–354.
49. Poon, S.H., and Granger, C.W.J. (2003), Forecasting volatility in financial markets: a review. Journal of Economic Literature, 41, 478-539.
50. Plante, M.D. (2019). OPEC in the News. Energy Economics, 80, 163-172.
51. Santa-Clara, P. and Yan, S. (2010). Crashes, volatility, and the equity premium: lessons from S&P 500 options. Review of Economics and Statistics 92, 435-451.
52. Schmidbauer, H., and Rösch, A. (2012). OPEC news announcements: effects on oil price expectation and volatility. Energy Economics, 34(5), 1656–1663.
53. Shrestha, K. (2014). Price discovery in energy markets. Energy Economics, 45, 229-233.
54. Schwert, G. W. (1990). Stock market volatility. Financial analysts journal, 46(3), 23-34.
55. Schwert, G. W., and Seguin, P. J. (1990). Heteroskedasticity in stock returns. the Journal of Finance, 45(4), 1129-1155.
56. Silvennoinen, A., and Thorp, S. (2013). Financialization, crisis and commodity correlation dynamics. Journal of International Financial Markets, Institutions and Money, 24, 42-65.
57. Tang, K., and Xiong, W. (2012). Index investment and the financialization of commodities. Financial Analysts Journal, 68(6), 54-74.
58. Todorov, V., and Tauchen G. (2011). Volatility Jumps. Journal of Business and Economic Statistics 29 (3). Taylor & Francis: 356–371. doi:10.1198/jbes.2010.08342.
59. Van Eyden, R., Difeto, M., Gupta, R., and Wohar, M. E. (2019). Oil price volatility and economic growth: Evidence from advanced economies using more than a century's data. Applied energy, 233, 612-621.

Appendix 1

Figure A1. Data Plot of Jumps



Notes: This figure depicts data plots for oil market jumps over the daily period of 2nd December 1997 to 26th May 2017, with the start and end date corresponding to our availability of the intraday data on oil price.

Table A1. Summary Statistics of Oil Market Jumps

Statistic	**Value**
Mean	1.98E-05
Median	2.50E-06
Maximum	0.001480
Minimum	0.000000
Standard Deveation	4.23E-05
Skewness	12.18215
Kurtosis	332.2824
Jarque-Bera	22962445
p-value	0.0000***
Observations	5055

Notes: This table reports summary statistics for oil market jumps over the daily period of 2nd December 1997 to 26th May 2017, with the start and end date corresponding to our availability of the intraday data on oil price. The null hypothesis that the data is normally distributed is also tested by the Jarque-Bera test. The *p*-values of the test are given below in brackets. ***, ** and * indicate the rejection of the null hypothesis of the skewness being zero and the excess kurtosis being zero at 1 percent, 5 percent and 10 percent levels of significance, respectively.

Table A2. Brock et al. (1996) (BDS) test of nonlinearity

Dependent variable	**Independent variable**	**Dimension**				
		2	3	4	5	6
Jumps	Meeting	27.2511***	33.5470***	38.6822***	43.3977***	48.6534***
	Cut	27.2010***	33.5395***	38.6393***	43.3688***	48.5535***
	Maintain	27.4109***	33.6064***	38.6291***	43.2205***	48.4024***
	Increase	27.5014***	33.7918***	38.7891***	43.3925***	48.5096***

Notes: This table reports the estimates for Brock et al.'s (1996) test (BDS) of nonlinearity between oil market jumps and OPEC news announcements. The 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, along with a dummy variable corresponding to the meeting date. The test is applied on the residuals arising from the regression between oil market jumps as dependent variable and the OPEC news announcements as independent variables (including twelve lags) recovered from the VAR(6) model. The number of lags is defined from the Akaike Information Criterion (AIC). The null hypothesis of independent and identically distributed residuals ($\mathrm{i.i.d.}$) at various embedded dimensions (m) is tested by a z-statistic of the BDS test. ***, ** and * indicate the rejection of the null hypothesis of the BDS test at 1 percent, 5 percent and 10 percent levels of significance, respectively.

Table A3. Nonparametric Causality-in-Quantiles Estimates for Monthly Oil Market Jumps

Quantile	OPEC Newspaper Index	Alternative Newspaper Index	Google Search Volume Index
0.05	27.0996***	29.1435***	36.8897***
0.10	14.9814***	16.4169***	18.9854***
0.15	9.5543***	10.7645***	10.9073***
0.20	6.3436***	7.4399***	6.2517***
0.25	4.2819***	5.3149***	3.3899***
0.30	2.9346***	3.9322***	1.6912*
0.35	2.2036**	3.1739***	0.9640
0.40	1.7457*	2.7437***	0.7737
0.45	1.6974*	2.5224**	0.8431
0.50	1.9715**	2.6516***	0.6129
0.55	1.7881*	2.3049**	0.5693
0.60	1.4271	1.9956**	0.3205
0.65	1.5730	1.9193*	0.2484
0.70	1.5422	1.4499	0.2461
0.75	1.8836*	1.7918*	0.2292
0.80	1.3745	1.1396	0.5821
0.85	1.6242	1.1269	0.5034
0.90	1.0378	0.9288	0.4475
0.95	0.8072	0.7524	0.4679

Notes: This table reports the estimates for the causality-in-quantiles test between oil market jumps and news OPEC-related indices. The indices considered are OPEC Newspaper Index, Alternative Newspaper Index and Google Search Volume Index. The first index is newspapers articles count index related to OPEC that rises in response to important OPEC meetings and events connected with OPEC production levels. This index is constructed at monthly frequency and is available over the period of January 1986 to December 2016. The second index is the raw number of articles written about OPEC and divided by the total number of articles produced by the four newspapers over the same period. The third index is based on Google search volume data on "OPEC" covering January 2004 to December 2016. ***, ** and * indicate the rejection of the null hypothesis of no-causality from OPEC news indices to oil market jumps for various quantiles at 1 percent, 5 percent and 10 percent levels of significance, respectively. The corresponding critical values of the test are 2.575, 1.96 and 1.645.

Appendix 2

This appendix offers a detailed overview of the procedure used in this study to detect monthly jumps from a monthly point estimate of realized volatility estimated employing daily returns. French et al. (1987), Schwert (1990) and Schwert and Seguin (1991) suggested the construction of realized volatility using daily returns. Campbell et al. (2001) were the first to employ various alternative measures to estimate the dispersion of returns in a monthly frequency, based on the conception of the nonparametric realized volatility estimation. Gkillas (Gillas) et al. (2018) studied the properties of monthly realized volatility.

In this paper, we estimate monthly realized volatility with the use of daily returns, as in Christensen and Hansen (2002), and Barroso and Santa-Clara (2015), among others. More specifically, we employ daily oil log returns of the to construct monthly point estimates of realized variance (RV). The RV is the benchmark and widely used realized volatility measure. More specifically, for each month t, we construct a monthly point estimate by using all daily returns, as follows:

$$RV_t \equiv \sum_{i=1}^{N} r_{t,i}^2 \tag{1}$$

where $r_{t,i}$ stands for the daily return for day i within month t for $i = 1, \dots N$, and N is the total number of daily returns within a month t.

The asymptotic results of Barndorff-Nielsen and Shephard (2004) enable the nonparametric distinction between continuous and jump variation of returns. Although the realized variance RV defined in Equation (1) measures both the continuous and jump variation, the standardized realized bipower variation (RBV) which captures only the amount of continuous variation, therefore it has been considered to be a jump-robust estimator of RV. The RBV is given by the following:

$$RBV_t \equiv \xi_1^{-2} \sum_{i=2}^{N} |r_{t,i}||r_{t,i-1}| \tag{2}$$

where ξ_1 is equal to $\sqrt{2/\pi} = E(|Z|)$ and $(|Z|)$ stands for the mean of the absolute value of a random variable (Z) which is follow a normal distribution.

We use the logarithmic transformation of Andersen et al.'s (2007) jump statistic to detect realized jump intensity. In an earlier version of their study, Andersen et al. (2007) found no difference between the plain jump statistic and its logarithmic transformation. The log-version of the jump statistic, used in this study, is given by the following:

$$U_t \equiv N \frac{(\log(RV_t) - \log(RBV_t))}{[(\xi_1^{-4} 2\xi_1^{-2} - 5) TQ_t (RBV_t)^{-2}]^{1/2}} \tag{3}$$

where TQ_t is the integrated quarticity which is estimated using the standardized realized tri-power quarticity measure as $N\xi_{4/3}^{-3} \sum_{i=3}^{N} |r_{t,i}|^{4/3} |r_{t,i-1}|^{4/3} |r_{t,i-2}|^{4/3}$, while $\xi_{4/3}$ is equal to $2^{2/3}\Gamma(7/6)\Gamma(1/2)^{-1} = E(|Z|^{4/3})$. The U_t is a ratio statistic which follow the standard normal distribution ($U_t \rightarrow N(0,1)$, as $N \rightarrow \infty$). The U_t is used as a pre-test, testing the null hypothesis of no jumps against the alternative hypothesis of existence of jumps. A significant jump is identified by an indicator function, $\mathbf{1}\{U_t > \Phi_a\}$, under the following condition:

$$J_t \equiv \mathbf{1}\{U_t > \Phi_a\}[\log(RV_t) - \log(BV_t)] \tag{4}$$

where continuous component $C_{t,a}$ is equal to $\mathbf{1}\{U_t \leq \Phi_a\}\log(RV_t)$ and $\log(RV_t)$ is equal to $J_t + C_{t,a}$. The non-negativity of both components corresponds directly to a significance level of $a = 0.05$ (Andersen et al., 2007). The application of this detection scheme to monthly realized volatility estimates is possible in the same way as it is to daily estimates, on the grounds that it is not dependent on direct estimates of the transition density function and directly builds on the theoretical results of Barndorff-Nielsen and Shephard (2004). Barndorff-Nielsen and Shephard (2004) showed that the conception of realized bi-power variation and jumps is applicable to finite number of observations and a fixed interval of time, even in case it is a trading day or a calendar month.