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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.

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, 2014b).

Moreover, oil market movements are widely known to spillover to other commodity markets (see, for example, Kang and Yoon, 2013; Kang, McIver, & Yoon, 2016, 2017; Mensi, Beljid, Boubaker, & Managi, 2013, Mensi et al., 2014b, Mensi et al., 2015), as well as financial markets (see, for example, Balcilar and Ozdemir, 2013; Balcilar, Gupta, & Miller, 2015, 2017; Balli, Uddin, Mudassar, & Yoon, 2017; Bekiros and Uddin, 2017; Bekiros, Nguyen, Junior, & Uddin, 2017; Berger and Uddin 2016; Kang et al., 2016; Lahmiri, Uddin, & Bekiros, 2017; Mensi et al., 2015; Narayan and 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

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

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lower transaction costs and greater ease of short selling associated with futures contracts. Moreover, it is believed that futures market movements predict spot market movements for oil (see, for example, Baumeister and Kilian, 2014, 2015; Baumeister, Kilian, & Lee, 2014, 2017). 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 and Ullman, 2009; Loutia, Mellios, & Andriosopoulos, 2016; Mensi, Hammoudeh, & Yoon, 2014a; Schmidbauer and Rösch, 2012; Wirl and 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 and Panchenko, 2005, 2006; Hiemstra and 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:

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

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

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 $E[\mathbf{1}\{y_t \leqslant Q_\theta(Y_{t-1})|Z_{t-1}\}] = \theta$ or, equivalently, $\mathbf{1}\{y_t \leqslant Q_\theta(Y_{t-1})\} = \theta + \theta_t$, 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: