Terrorism and the behavior of oil production and prices in OPEC

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Abstract

This paper contributes to the discussion of the role that terrorism plays in oil production and oil prices literature by studying the dynamics of terrorist attacks and oil production in OPEC. To this purpose, we use techniques based on fractional integration, fractional cointegration VAR (FCVAR) and wavelet analysis. Monthly data related to OPEC oil production, OPEC basket crude oil prices and terrorist attacks from January 1970 to December 2018 are used. The results, using fractional integration and cointegration techniques, indicate that the time series analyzed are highly persistent and there are no long-term deviations. Finally, using wavelet analysis, we conclude that the impact of the terrorist attacks in oil production and oil prices are non-significant and has a short-term component, recovering the original trend values between 1 and 10 months after the terrorist shock.

Keywords: Oil production; oil prices; terrorist attacks; fractional integration; FCVAR model; wavelet analysis.

JEL Classification: C00; C22; N4; E0.

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1. Introduction

According to Aon (2020) in 2016 the world suffered a 14.2% increase in the number of terrorist attacks. In recent decades, terrorism has represented a significant and growing threat to society, as it affects not only the life or integrity of people, but also has a direct impact on economies (Orbaneja et al., 2018). To take one of the most noteworthy examples in the literature, it is estimated that the short-term economic cost of the terrorist attacks of September 11 in New York cost approximately $21.4 billion dollars (Richman et al., 2011).

From the beginning of the industrial revolution, and despite the progress in the implementation of clean energy during the last years, oil continues to be the most widely used energy source globally (IEA, 2019). It plays a fundamental role in political and economic stability, being also a potential cause of wars and civil conflicts (Collier and Hoeffler, 1998; Ross, 2004 a,b; Fearon, 2005; Humphreys, 2005; Colgan, 2013). This is mainly due to the fact that most developed economies are heavily dependent on oil and of course it is a limited natural resource. This situation makes these countries extremely vulnerable to external production and price volatilities, especially those coming from the main market players: OPEC, U.S. and Russia (Bahgat, 2004). In this sense, and given that oil has a strategic value for many powerful countries that are dependent on it, it is very common for terrorists to target oil facilities (pipelines, tankers, refineries, oil fields, chokepoints, etc.) in oil-producing countries with the aim of economically disrupting foreign energy supplies (Adams, 2003; Luft and Korin, 2004). Therefore, there exists a deep interest in knowing what role terrorism plays in oil production and oil prices behavior.

As we mention before, terrorism seems a priori one of the main candidates likely to affect oil prices and production, since the production infrastructures in producing countries can be damaged or influenced by terrorist activities, either by appropriation or by destruction. Specifically, in 2016, terrorist attacks on oil and gas infrastructure comprised almost 42% of all terrorist attacks on commercial interests (Aon, 2020). In addition, authors such as Tichy (2019) claim that attacks on the energy sector form a very relevant part of the military strategy of such notorious terrorist organizations as the Islamic State (IS), since oil is an important source of financing for them.

In addition, the producing countries are in many cases very poorly diversified economies and unable to cope with certain turbulences or conflicts, which greatly reduces the productive capacity of the oil industry, affecting production and prices (Ross 2001; Jensen and Wantchekon 2004; Morrison 2009; Aslaksen 2010 and Ramsay 2011). Phan et al. (2021) affirm that terrorism events that take place in oil producing countries have a greater effect on oil prices. The U.S. Energy Information Administration (EIA 2019) affirms that, of today's current top twenty oil producing countries, seven are located in the Middle East and the North Africa region, putting this area at potential risk to terrorism damages. Moreover, Şen and Babalı (2007) indicated that it is important to note that OPEC members such as Saudi Arabia, Iran, Iraq, Kuwait, UAE or Qatar comprise 65%-70% of the world's oil reserves.

OPEC seeks to actively manage oil production in its member countries by setting production targets. This organization is responsible for about 40% of the world's crude oil production and, historically, crude oil prices have seen increases at times when OPEC's production targets are reduced, thereby affecting world economies. Coleman (2012) concluded that prices reflect supply-demand equilibrium and that shocks are caused by exogenous shortfalls in supply, the initiators of which lie in the behavior of markets, inventories and suppliers or when demand rises faster than expected.

Moreover, there is historical evidence that terrorist attacks in OPEC countries have affected their production capacity, and consequently the supply of crude. For example, a pipeline attacked in February 2016 in Nigeria paralyzed oil production, with production losses of around 250,000 barrels. Along these lines, Al-Quaeda also attacked a gas field in Algeria in 2016, causing significant curbs on its production. ISIS also attacked major oil distribution ports in Libya in 2016. In February 2016, a pipeline was attacked in Kurdistan, reducing oil production by 600,000 barrels per day (Bassil et al., 2018).

The goal of this paper is to understand the behavior of OPEC oil prices and OPEC oil production under the assumption of terrorist attacks in these countries. To this purpose, we analyze the statistical properties of these time series, measuring the degree of persistence by using fractional integration techniques (see Monge et al. 2017a, b; Monge and Gil-Alana, 2020; Monge and Gil-Alana, 2021, among others). Moreover, we analyze the long-term relationship of the time series using the Fractional Cointegration VAR (FCVAR) approach (see Johansen and Nielsen, 2010, 2012). Finally, we examine the possible structural changes in oil prices and oil production caused by the terrorist attacks in OPEC countries using methodologies based on Bai and Perron (2003) and wavelet transform (see Aguiar-Conraria and Soares, 2014).

To the best of our knowledge, this is the first paper that analyzes the statistical properties of terrorist attacks and crude oil production and prices in OPEC using the methodologies mentioned above. Therefore, the key objective of our study is to examine whether the impact of terrorism on the OPEC oil prices and OPEC oil production is temporary or permanent. This knowledge is extremely relevant to analyze what the effects of terrorist attacks may be for oil production and oil prices in OPEC. The study is both crucial and timely as, despite the importance of oil in the literature in economics, political science and international relations, there is surprisingly little scholarly discussion regarding the role terrorism plays in oil production in OPEC.

The rest of the paper is organized as follows. Section 2 reviews the literature about terrorist attacks and oil production. Section 3 provides a brief introduction to the mathematics of wavelets and explains how the metric is derived that is used to compare terrorist attacks and OPEC's crude oil production. The data are described in Section 4 and the main results are also presented in that section, while Section 5 concludes.

2. Literature review

There are numerous authors who have studied the different factors that affect the evolution of oil production and oil prices. These factors include oil demand and supply (Baumeister and Kilian, 2014; Cooper, 2003; Hamilton, 2009; Baumeister and Peersman, 2013; Huang et. al, 2017), oil inventory (Baumeister and Kilian, 2012), interest rates (Arora and Tanner, 2013), convenience yield (Murat and Tokat, 2009), news (Narayan, 2020), oil shocks (Hamilton, 2009), oil futures (Jun, 2017), exchange rates (Beckmann and Czudaj, 2013) and equity markets (Zhang and Wei, 2011). Lee et al. (2017) analyze how country risk affects fluctuations in the price of oil, concluding that exporting countries are positively affected by these shocks. Lambrechts and Blomquist (2017) have also deeply reflected on the importance of political-security risk in the oil and gas industry. Narayan (2020) answer the question: can stale oil price news predict stock returns? Using time-series predictive regression models estimated for 45 countries, they show that oil price news turns out to be more powerful in predicting returns in a horserace with oil price. More recently, authors such as Gil-Alana and Monge (2020), Kingsly, K. and Henri, K. (2020) and Salisu et al. (2020) have studied the effect of the

COVID-19 crisis on crude oil prices. Along the same lines, other authors such as Bakas and Triantafyllou (2020) argue that in times of higher uncertainty caused by pandemics, supply and demand fall rapidly and steadily over time due to the increase in the price elasticity.

The presence of terrorist events, wars and military conflicts also seem to have an important effect on the fluctuations associated with oil production and prices (Hendrix, 2017). In recent decades, terrorism has increased its influence on the oil industry, decisively affecting the behavior of production and prices (Adams, 2003; Luft and Korin, 2004). For instance, events such as the Suez Canal crisis 1956-1957, the OPEC oil embargo of 1973–1974, the Iranian Revolution of 1978–1979, the Iran and Iraq war of 1980, the first Persian Gulf War in 1990–1991 are conflicts that for authors such as Bagchi (2017) are unequivocally associated with an increase in the price of oil.

Despite the enormous importance of the OPEC countries in global oil production and reserves, coupled with the fact that it is precisely in these countries where there is a greater presence of attacks and terrorist groups, there are not many specific studies that analyze the behavior of oil production and prices for this group of countries. As far as we know, none of them use techniques based on fractional integration, fractional cointegration VAR (FCVAR) or wavelet analysis.

Hoffman (2006) argues that important and strategic sectors such as energy, and more specifically the producers of fossil fuels such as oil, have become targets for terrorism as in many cases they represent the main funding source for these terrorist groups. Şen and Babalı (2007) conclude in their study that terrorist attacks also have direct effects over oil supply security issues. On the other hand, Fattouh (2007) warns how high oil prices, threats of terrorist attacks, instability in many oil-exporting countries and the rise in so-called ‘oil nationalism’, have raised serious concerns about the security of oil supplies, which can lead to the supply in these countries being compromised thereby affecting prices. Cook (2008), carries out a descriptive study on the trajectory of terrorist attacks on oil targets perpetrated by radical groups.

Blomberg et al., (2009) found that terrorism has a positive impact on oil stock prices. Toft (2011) investigates how often and how many outbreaks of intra-state conflict in oil producing states translate into oil supply shortfalls. He concludes that outbreaks of conflict do not translate into production losses with any degree of certainty and, in fact, in many cases conflict was often followed by increasing oil production. Barros et al. (2011) use monthly data from 1973 to 2008 for thirteen OPEC members to study the time series behavior of oil production within a fractional integration modelling framework recognizing the potential for structural breaks and outliers. Contrary to most authors, Tahir Suleman (2012) affirms that information on terrorist attacks does not significantly affect operations in the oil industry. Kollias et al. (2013) argue that geopolitical events, especially war and terrorism, can have an important effect on oil market behavior. Moreover, they affirm that the time length of this effect and its intensity can vary and that terrorism is a one-off event that cannot be forecasted by the market.

Chen et al. (2016) quantitatively analyze the impacts of OPEC's political risk on Brent oil prices through Structural Vector Autoregression (SVAR) models. Monge et al. (2017a) investigate crude oil price behavior before and after military conflicts and geopolitical events since World War II using techniques based on unit roots and fractional integration, and finding evidence of persistence and breaks in the oil prices series and stationary long memory in the absolute returns. However, they do not observe significant differences before and after the conflicts and geopolitical events. In their study on Middle East and North Africa, Miao et al. (2017) show that in countries where oil prices rise, terrorist attacks have a clear effect on these rises. Orbaneja et al. (2018) studies the impact of terrorism on the oil market, focusing on the type of attack, distance, type of attack, size of the same; among others. Their results suggest that the various types of attacks lead to a large positive abnormal return of crude oil prices. Javid and Ahmad, (2020) study the impact of terrorist attacks and political events on returns and volatility in the oil and gas sector of the Karachi Stock Exchange from the period of 2004 to 2014. Their results indicate that the oil and gas sector reacts to terrorism and political events, although these effects become insignificant in the long run. By using a unique dataset that merges terrorism activity with oil prices, they collet daily data from West Texas Intermediate and GTD (Global Terrorism Database), Phan et al. (2021) carry out a study that proves that terrorist attacks, both through oil production and investment channels, can be a predictor of the behavior of oil prices. They affirm that terrorist attacks have a positive effect on oil prices, with those that occur in producing countries having the greatest effect.

3. Methodology

3.1. Unit Roots

The unit roots could be tested in many different ways. We use ADF tests based on Fuller (1976) and Dickey and Fuller (1979), assuming that these methodologies are effective when the data are stationary. There are many other tests available to calculate unit roots that have greater power such as Phillips (1987) and Phillips and Perron (1988) in which a non-parametric estimate of spectral density of u_t at the zero frequency has been used. Also, considering the deterministic trend we use the methodology based on Kwiatkowski et al. (1992), Elliot et al. (1996) and Ng and Perron (2001) and produce the same results. In addition, we use two unit root tests with structural breaks in the time series. The methodology proposed by Narayan and Popp (2010) is an ADF-type unit root test that uses two different specifications for the deterministic component, allowing for two structural breaks in the level (Model 1) and two structural breaks in the level and in the slope of the deterministic trend component (Model 2). On the other hand, the LM test, proposed by Lee and Strazicich (2003) take into consideration two breaks in the intercept and two breaks in the intercept and trend (Model 1 and Model 2, respectively).

3.2. ARFIMA (p, d, q) model

An important characteristic of many economic and financial time series is their non-stationary nature, which can be described by a variety of models. Until the 1980s the standard approach was to use deterministic (linear or quadratic) functions of time, thus assuming that the residuals from the regression model were I(0) stationary. Later on, and especially after the seminal work of Nelson and Plosser (1982), a general consensus was reached that the non-stationary component of most series was stochastic, and unit roots (or first differences, I(1)) were most appropriate for them. However, the I(1) case is merely one particular model that can describe such behavior. In fact, the number of differences required to achieve I(0) stationarity is not necessarily an integer value but could be any point on the real line, including fractional values. In the latter case, the process is said to be fractionally integrated or I(d).

Long memory is a feature of observations that are far apart in time but highly correlated. This can be captured by fractionally integrated or I(d) models of the form:

$$(1-L)^d x_t = u_t, \qquad t = 1, 2, \dots, \tag{1}$$

where x_t refers to a time series, d refers to any real value, L refers to the lag-operator ($Lx_t = x_{t-1}$) and u_t refers to I(0) which is the covariance stationary process where the spectral density function is positive and finite at the zero frequency, displaying in the weak form a type of time dependence. So, for example, if u_t is ARMA (p, q), x_t is then said to be ARFIMA (p, d, q).

Although fractional integration can also occur at other frequencies away from zero, as in the case of seasonal and cyclical fractional models, the series used for our analysis do not have these features and hence we estimate standard I(d) models as in (1). The idea of fractional integration was introduced by Granger and Joyeux (1980), Granger (1980, 1981) and Hosking (1981), though Adenstedt (1974) had already showed awareness of its representation. The polynomial $(1-L)^d$ in equation (1) can be expressed in terms of its binomial expansion, such that, for all real d, x_t depends not only on a finite number of past observations but on the whole of its past history. In this context, d plays a crucial role since it indicates the degree of dependence of the series: the higher the value of d is, the higher the level of association between the observations will be.

Given the parameterization in (1) one can distinguish between several cases depending on the value of the parameter *d*, several specifications based on (1) can be observed. Thus, if $d < 0$, x_t is said to be anti-persistent, with the series exhibiting zero spectral density at the origin (Dittmann and Granger, 2002) and switching signs more frequently than a random process. The process is short memory or I(0) when $d = 0$ in (1). This occurs because $x_t = u_t$. Long memory process (d>0) is the name given when there is a high degree of association over a long time. With this last assumption, the process is still covariance stationary if $d < 0.5$ because the infinite sum of the autocovariances is still finite. Our interpretation of this can also be related to the issue of mean reversion. If the series reverts to the mean, shocks will be transitory and this happens when *d* is smaller than 1. In contrast to the above, the shocks are expected to be permanent when $d \geq 1$.

Although there are several procedures for estimating the degree of long-memory and fractional integration (Geweke and Porter-Hudak, 1983; Phillips, 1999, 2007; Sowell, 1992; Robinson, 1994, 1995a,b; etc.) we follow the Akaike information criterion (AIC) (Akaike, 1973) and the Bayesian information criterion (BIC) (Akaike, 1979) to select the most appropriate ARFIMA model and we follow Sowell (1992) and his likelihood process to present our results.

3.3. Fractional Cointegration (FCVAR) model

A method known as Fractionally Cointegrated Vector AutoRegressive (FCVAR) was introduced by Johansen (2008) to check for a multivariate fractional cointegration model. It was further expanded by Johansen and Nielsen (2010, 2012). It is one step ahead of the Cointegrated Vector AutoRegressive model (Johansen, 1996), which is named CVAR, and it allows for series integrated of order d and that cointegrate with order d - b, with b > 0. To introduce the FCVAR model, we present first the non-fractional CVAR model.

Let Y_t, $t = 1, \ldots, T$ be a p-dimensional I(1) time series. The CVAR model is:

$$\Delta Y_t = \alpha\beta' Y_{t-1} + \sum_{i=1}^{k} \Gamma_i \, \Delta Y_{t-i} + \varepsilon_t = \alpha\beta' L Y_t + \sum_{i=1}^{k} \Gamma_i \, \Delta L^i Y_t + \varepsilon_t. \qquad (1)$$

Δ^b and $L_b = 1 - \Delta^b$, representing the difference and the lag operator, is used to derive the FCVAR model. We then obtain:

$$\Delta^b Y_t = \alpha\beta' L_b Y_t + \sum_{i=1}^{k} \Gamma_i \, \Delta L_b^i Y_t + \varepsilon_t, \qquad (2)$$

which is applied to $Y_t = \Delta^{d-b} X_t$ such that

$$\Delta^d X_t = \alpha\beta' L_b \Delta^{d-b} X_t + \sum_{i=1}^{k} \Gamma_i \, \Delta^b L_b^i Y_t + \varepsilon_t, \qquad (3)$$

Where, ε_t is a term with mean zero, and variance-covariance matrix Ω is p-dimensional independent and identically distributed. As in the CVAR model, the parameters can be interpreted as follows. α and β are $p \times r$ matrices, where $0 \leq r \leq p$. The relationship in the long-run equilibria in terms of cointegration in the system is due to the matrix β. The parameter Γ_i controls for the short-run behavior of the variables. Finally, the deviations from the equilibria and their speed in the adjustment is because of the parameter α. Thus, the FCVAR model allows simultaneous modelling of the long-run equilibria, the adjustment responses to deviations from those and the short-run dynamics of the system. As an intermediate step towards the final model, we consider a version of model (2) with d = b and a constant mean term for the cointegration relations. That is to say:

$$\Delta^d X_t = \alpha(\beta' L_d X_t + \rho') + \sum_{i=1}^{k} \Gamma_i \Delta^d \, {L_d}^i X_t + \varepsilon_t \qquad (5)$$

Johansen and Nielsen (2012) and Nielsen and Morin (2014) discuss estimation and inference of this model.

It is noteworthy that fractional differencing is defined in terms of an infinite series but any actual sample will include only a finite number of observations. In order to calculate the fractional differences one can assume that $X_t$was zero before the start of the sample. The bias introduced by this assumption is analyzed by Johansen and Nielsen (2014) using higher-order expansions. They showed that it can be completely avoided by including a level parameter μ that shifts each of the series by a constant.

The estimated empirical model is the following:

$$\Delta^d (X_t - \mu) = L_d \alpha \beta' (X_t - \mu) + \sum_{i=1}^{k} \Gamma_i \Delta^d \, {L_d}^i X_t + \varepsilon_t \qquad (6)$$

The asymptotic analysis in Johansen and Nielsen (2012) shows that the maximum likelihood estimators of $(d, \alpha, \Gamma, \dots, \Gamma_2)$ are asymptotically normal, while the maximum likelihood estimator of (β, ρ) is asymptotically mixed normal when $d_0 < 1/2$ and asymptotically normal when $d_0 > 1/2$. FCVAR models have recently been estimated in numerous empirical papers (Baruník and Dvořáková, 2015; Maciel, 2017; Aye et al., 2017; Dolatabadi et al., 2018; Jones, Nielsen and Popiel, 2014; Gil-Alana and Carcel, 2020; Poza and Monge, 2020; etc.).

Nielsen and Popiel (2018) provide Matlab computer programs for the calculation of estimators and test statistics.

3.4. Wavelet Analysis

Wavelet methodology is used to analyze time series in the time-frequency domain. Following Vacha and Barunik (2012), Aguiar-Conraria and Soares (2011, 2014), Dewandaru et al. (2016), Tiwari et al. (2016), Jammazi et al. (2017) and others that apply Continuous Wavelet Transform (CWT) in finance and economics research, two tools are used in this paper: wavelet coherency and wavelet phase-difference.

There are two reasons for using this methodology: first, stationarity is not a requirement to carry out a wavelet analysis and, second, it is interesting to study the interaction of both the time and the frequency domains of the time series themselves to find evidence of the potential changes in its pattern.

The wavelet coherency is a two-dimensional diagram that correlates time series and identifies hidden patterns or information in the domain of time and frequency. The $WT_x(a,\tau)$ of a time series $x(t)$, that is obtained by projecting a mother wavelet ψ, is defined as:

$$WT_x(a,\tau) = \int_{-\infty}^{+\infty} x(t) \frac{1}{\sqrt{a}} \psi^* \left(\frac{t-\tau}{a}\right) dt,$$

where $WT_x(a,\tau)$ are the wavelet coefficients of $x(t)$; the position of a wavelet in the frequency domain is defined by a, and τ is the position in the time domain. Thus, the wavelet transform provides information concurrently on time and frequency by mapping the original series into a function of τ and a. A Morlet wavelet has been chosen as a mother wavelet to carry out our analysis since it is a complex sine wave within a Gaussian envelope, so we will be able to measure the synchronism between time series. (See Aguiar-Conraria and Soares 2014 for the properties of this wavelet and for a more complete understanding of this procedure).

To understand the interaction and the integration between the two series we use the wavelet coherence defined as:

$$WCO_{xy} = \frac{SO\left(WT_x(a,\tau)WT_y(a,\tau)^*\right)}{\sqrt{SO(|WT_x(a,\tau)|^2)SO\left(\left|WT_y(a,\tau)\right|^2\right)}},$$

where *SO* is a smoothing operator in both time and scale. Without the smoothing operator, the wavelet coherency would be always one for all times and scales (see Aguiar-Conraria et al. 2008 for details). Matlab computer programs for the calculation of estimators and test statistics in the CWT are provided in Aguiar-Conraria's website[1].

4. Data

The data examined in this work correspond to OPEC crude oil production[2] and OPEC basket oil price and the total number of terrorist events registered by month in each country over the period 1970:01-2018:12. The crude oil production and the crude oil prices dataset were obtained from Thomson Reuters Eikon database.

On the other hand, the total number of terrorist events by month was obtained from the Global Terrorism Database (National Consortium for the Study of Terrorism and Responses to Terrorism (START) 2020)[3], which records both domestic and transnational terrorism[4]. This database is made up of more than 100 structured variables (each attack's location, tactics and weapons, targets, perpetrators, casualties and consequences, and general information) and unstructured variables (summary descriptions of the attacks and more detailed information on the weapons used, specific motives of the attackers, property damage, and ransom demands, among others). For this last dataset we have had to select this qualitative information for each of the OPEC member countries, convert each event or attack into a numerical value analyzed over time, and then

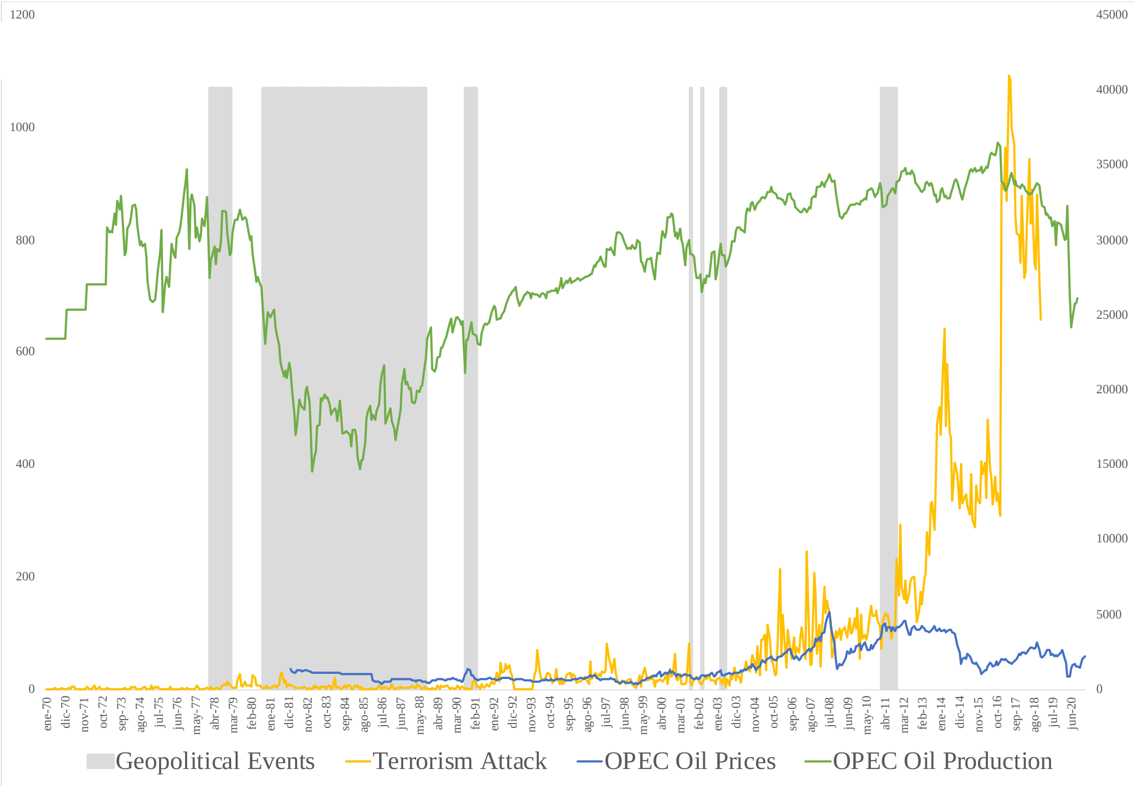
[1] https://sites.google.com/site/aguiarconraria/joanasoares-wavelets
[2] OPEC total crude oil production is measured in million barrels per day.
[3] Type of recorded events: assassination, hijacking, kidnapping, barricade incident, bombing/explosion, armed assault, unarmed assault, facility/infrastructure attack).
[4] Terrorism is transnational when an incident in the venue country concerns perpetrators or victims from another country.

aggregate this data into a monthly time series in order to carry out our analysis with total oil production in OPEC countries. The number of zero values with daily and weekly data for the time series of terrorist attacks and the unavailability of daily or weekly data for the time series of oil production in OPEC countries has limited our ability to carry out the analysis at other time frequencies.

Figure 1 displays the time series plots of the number of terrorist attacks and the total crude oil production in OPEC countries. The grey part of the figure identifies some relevant events identified in Monge et. al (2017a) such as the Iranian Revolution of 1978/79, the Iran-Iraq War of 1980-1988, the Persian Gulf War of 1990/91, the Venezuelan crisis of 2002 and the Iraq War of 2003, and the Libyan uprising of 2011. Also, we have identified relevant terrorist attacks such as September 11, 2001.

As is shown in the figure, the trends of terrorist attacks and crude oil production at OPEC countries increase, leading us to think that terrorist attacks may have some influence on the crude oil production due to the arguments given by Lee (2016) (see for example the periods between the years 1995-1998, 2000-2003, among others).

Figure 1: Terrorist Attacks in OPEC Countries and OPEC Total Crude Oil Production



5. Empirical results

5.1. Unit Roots

We have calculated the three standard unit roots tests to analyze the statistical properties of the terrorist attacks, OPEC oil prices and OPEC oil production.

We have obtained the results using the Augmented Dickey-Fuller (ADF) test, the Phillips Perron (PP) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test displayed in Table 1, which suggest that the selected time series are non-stationary I(1). Calculating the first differences we observe that the series become stationary I(0) (see Table 1).

Table 1. Unit root tests based on ADF, PP and KPSS

		ADF			PP			KPSS
	(i)	(ii)	(iii)	(i)	(ii)	(iii)	(ii)	(iii)
Original Data and First Differences in OPEC oil prices								

OPEC oil prices	-0.9578	-1.9084	-2.7911	-0.9399	-1.8907	-2.8405	1.7157	0.2759
d_OPEC oil prices	-17.6672*	-17.6491*	-17.6276*	-17.5198*	-17.4992*	-17.4758*	0.0554*	0.0510*
Original Data and First Differences in OPEC oil production								
OPEC oil production	0.1290	-1.9179	-2.3825	0.3544	-1.6383	-2.1358	1.5260	0.4075
d_OPEC oil production	-25.8849*	-25.8738*	-25.8516*	-26.8155*	-26.8594*	-26.8328*	0.0766*	0.0757*

*(i) Refers to the model with no deterministic components; (ii) with an intercept, and (iii) with a linear time trend. * Denotes a statistic significant at the 5% level. For ADF and PP, the 5% critical value is -1.9418 for no deterministic components; -2.8707 with an intercept; -3.4245 with a linear time trend. For KPSS, the 5% critical value is 0.4630 with an intercept component; 0.1460 with a linear time trend.*

Also, we apply two unit root tests with structural breaks onto our time series. The two unit root tests are Narayan and Popp (2010) and the Lee and Strazicich (2003) Lagrange Multiplier (LM) test. We have used these tests because, according to Narayan and Popp (2013) they provide better results in terms of power and size. Also, these methodologies allow for two structural breaks and neither accommodates heteroskedasticity which is particularly problematic with frequency higher than annual data.

The methodology proposed by Narayan and Popp (2010) is an ADF-type unit root test that uses two different specifications for the deterministic component, allowing for two structural breaks in the level (Model 1) and two structural breaks in the level and in the slope of the deterministic trend component (Model 2). On the other hand, the LM test take into consideration two breaks in the intercept and two breaks in the intercept and trend (Model 1 and Model 2, respectively).

These methodologies are important because most standard unit roots will bias towards non-rejection of the unit root

Table 2 presents the results of both methodologies. According to our results using most standard unit roots suggests that the selected time series are non-stationary I(1), but these more contemporary methods are important because they show that, taking into account two structural breaks, the time series analyzed in this research paper are stationary I(0) (see Table 2).

Table 2. Unit root tests based on Narayan and Popp (2010) and Lee and Strazicich (2003)

Narayan and Popp (2010)						
	Break in intercept			Break in intercept and trend		
Series	**Test statistic**	**TB1**	**TB2**	**Test statistic**	**TB1**	**TB2**
OPEC Oil Prices	-5.826	2006:11	2014:05	-7.072	2000:01	2014:07
OPEC Oil Production	-6.366	1979:12	1988:05	-5.987	1979:12	2008:08
Terrorism attacks	-5.213	2012:12	2014:10	-7.417	2012:07	2014:03
Lee and Strazicich (2003)						
OPEC Oil Prices	-2.734	2008:11	2011:09	-5.887	2004:10	2014:10
OPEC Oil Production	-2.554	1976:11	1982:12	-4.768	1980:04	1987:07
Terrorism attacks	-3.495	2011:11	2014:11	-6.937	2005:05	2012:12

For Narayan and Popp (2010) unit root test, the critical values for Model M1 $= -4.67, -4.08, -3.77$ *at* $1\%, 5\%, 10\%$, *respectively. The critical values for Model M2* $-5.29, -4.69, -4.40$ *at* $1\%, 5\%, 10\%$, *respectively. TB1 and TB2 are the dates of the structural breaks.*
For Lee and Strazicich (2003) unit root test, , the critical values for Model M1 $= -3.55, -3.005, -2.732$ *at* $1\%, 5\%, 10\%$, *respectively. The critical values for Model M2*$= -4.65, -4.14, -3.89$ *at* $1\%, 5\%, 10\%$, *respectively. TB1 and TB2 are the dates of the structural breaks.*

5.2. Fractional Integration

Following the results obtained using unit root methods in the three time series and due to the low power of the unit root methods under fractional alternatives[5], we also employed fractional methods, and used ARFIMA (p, d, q) models to study the persistence of the OPEC oil prices and OPEC oil production time series. The Akaike information criterion

[5] See Diebold and Rudebusch (1991), Hassler and Wolters (1994) and Lee and Schmidt (1996).

(AIC; Akaike, 1973) and the Bayesian information criterion (BIC; Akaike, 1979) were used to select the appropriate AR and MA orders in the models.[5]

Table 3 displays the fractional parameter d and the AR and MA terms obtained using Sowell's (1992) maximum likelihood estimator of various ARFIMA (p, d, q) specifications with all combinations of p, q ≤ 2, for each time series.

Table 3. Results of long memory tests

Long memory test						
Data analyzed	Sample size (weeks)	Model Selected	d	Std. Error	Interval	I(d)
OPEC oil prices	444	ARFIMA (2, d, 2)	0.8638194	0.1186592	[0.67, 1.06]	I(1)
OPEC oil production	588	ARFIMA (2, d, 2)	0.8699298	0.0456837	[0.79, 0.95]	I(d)

We observe from Table 3 that the estimates of d in OPEC oil prices are equal I(1) and I(d) for OPEC oil production time series. In both cases, the values of d are in the range (0, 1), implying fractional integration. Also, the value of d in both time series are below 1. With this result, we could conclude that these two time series are mean reverting, implying transitory shocks and thus, in the event of an exogenous shock the series will return to its original trend in the future. But if we look at the confidence intervals, we cannot reject the hypothesis of I(1) for the OPEC oil prices.

5.3. FCVAR model ($\boldsymbol{d \neq b}$)

[5] A point of caution should be adopted here since the AIC and BIC may not necessarily be the best criteria for applications involving fractional models (Hosking, 1981).

Next, the FCVAR model proposed by Johansen and Nielsen (2012), where the fractional integration and the classical CVAR model join is used in order to contrast the possible existence of persistence in the long run co-movements of the series. Table 4 summarizes the results of the FCVAR model.

Table 4. Results of FCVAR model

	d	**b**
Panel I: OPEC oil prices and Terrorism attacks	$d = 0.800$ (0.136)	$b = 0.800$ (0.000)
Panel II: OPEC oil production and Terrorism attacks	$d = 0.857$ (0.061)	$b = 0.857$ (0.000)

We follow the indications suggested by Jones, Nielsen and Popiel (2014) about the lag value (k = 3). Also, we consider deterministic components and cointegration rank (r) to get our results. We observe from Panel I and Panel II (cointegrating the OPEC oil prices and OPEC oil production with terrorism attacks) in Table 4 that the order of integration of the individual series are about 0.800 and 0.857, respectively while the reduction in the degree of integration in the cointegrating regression is exactly of the same magnitude, implying that the order of integration $(d - b) = 0$, which in turn implies I(0) cointegration errors. Thus, we cannot reject the hypothesis in which the error correction term shows short-run stationary behavior and where the shock duration is short-lived. These results are in line with those obtained using fractional integration.

5.4. Structural breaks and Continuous Wavelet Transform

In order to verify if the terrorism has caused any change in oil prices and oil production in OPEC countries, we use Perron and Vogelsan (1992) and Bai and Perron (2003) approaches for detecting breaks in the data. The break dates, for the monthly case are reported in Table 5.

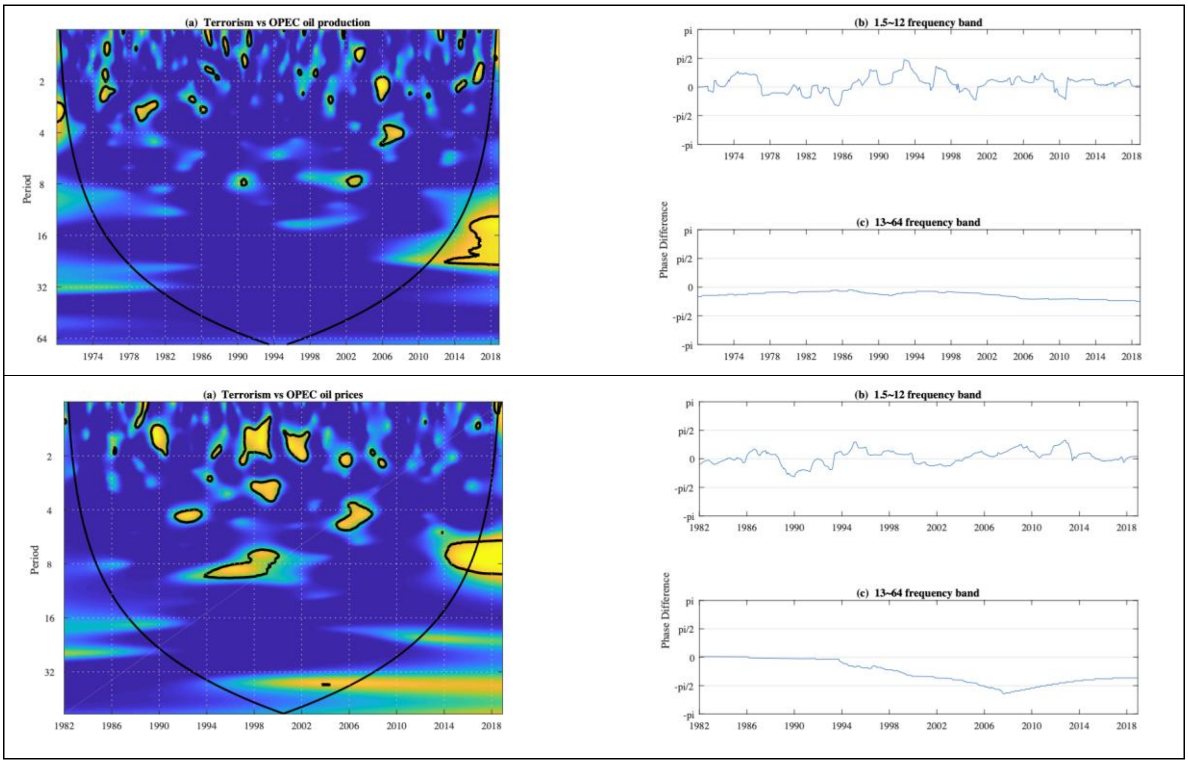
Table 5. Structural breaks

Time Series	Number of breaks chosen by BIC	Structural break dates
OPEC Oil Prices	3	February 2002 September 2007 May 2013
OPEC Oil Production	5	April 1981 August 1988 December 1995 April 2004
Terrorism	2	April 2004 January 2014

Following the BIC criterion to choose the number of structural breaks, we see that the most relevant ones in the terrorism time series are two, which are close to those found in the unit roots tests previously analyzed.

Figure 2 displays the wavelet coherency and the phase difference for the monthly data of terrorist attacks and OPEC oil production and OPEC oil prices showing evidence of varying dependence between the time series across different frequencies and over time. Also, with this methodology we can see when a structural change occurs in the behavior of crude oil prices and crude oil production with respect to terrorist attacks.

Figure 2: Wavelet coherency and phase difference between terrorist attacks in the OPEC oil production and oil prices.



The contour designates the 5% significance level. Coherency ranges from blue (low coherency) to yellow (high coherency). (a) Wavelet coherency. (b)-(c) Phase difference.

Figure 2 represents two different estimations. The left panel (a) has the wavelet coherency that represents the interrelations between OPEC oil production and OPEC oil prices with respect to terrorism, when they are stronger or not and at which frequencies these points occur. Frequencies are shown on the vertical axis, from scale 1 (a single month) up to scale 64 (approximately 5 years), whereas time is shown in the horizontal axis, from the beginning to the end of the sample period. The statistical significance of local correlations in the time-frequency domain was evaluated using Monte Carlo simulations. The regions surrounded by the black contour are the high frequency and the high coherence regions with significance values at 5%, that are the outcome obtained. The right panel has the phase differences: at the top (b) is the phase difference in the 1.5-12 frequency band for monthly data; at the bottom (c) is the phase difference in the 13-64 frequency band for monthly data. The frequency bands helps us to understand the movement of both time series, one in relation to the other.

Also, we consider the structural breaks found in the terrorist attacks time series (2004:04 and 2014:01), using Bai and Perron (2003), to analyze the relationship between OPEC oil prices and OPEC oil production and terrorism using wavelet analysis.

The main regions with statistically significant coherency are in low frequencies (corresponding to cycles between 1 to 12 months) in both cases, for production and prices.

A more accurate result is that, in the case of terrorism and OPEC oil production we find a region in the coherency figure corresponding to the first structural break (2004:04) in the short-term frequencies, between 3 and 6 months. In the case of Terrorism and OPEC oil prices, we can conclude that the two structural breaks that we found previously (2004:04; 2014:01) are represented in the figure of coherency, in the low frequency corresponding to cycles between 3 and 6 months and 7 and 12 months, respectively.

These results are in line with the results that we get in the previous sections, where we state that the impact of the terrorist attacks in the oil production and oil prices has a short-term component.

The second estimation is the partial phase-difference (represented in the right part of the Figure 2) that gives us information about the movement of one time series with respect to the other. Focusing on the regions mentioned above, with high coherency at the 5% significance level, we can appreciate that all these regions stay between 0 and $\pi/2$ which means that terrorist attacks are positively correlated and leading in the behavior of oil production and oil prices in OPEC.

Once we have identified the structural changes that have occurred due to the terrorist attacks, and we have concluded that the terrorist attacks affected production in OPEC countries in May 2004 and prices in OPEC countries in May 2004 and January 2014, we statistically analyze the behavior of these series after each shock. To do so, we apply

ARFIMA models. The results are reported in Table 6.

Table 6. Results of long memory tests before and after structural breaks

Long memory test						
Data analyzed	Sample size (weeks)	Model Selected	d	Std. Error	Interval	I(d)
OPEC oil prices						
OPEC oil prices – before break 2004	268	ARFIMA (2, d, 2)	0.6570056	0.1639512	[0.39, 0.93]	I(d)
OPEC oil prices – after break 2004	118	ARFIMA (2, d, 1)	0.4072463	0.1950897	[0.09, 0.73]	I(d)
OPEC oil prices – before break 2014	118	ARFIMA (2, d, 1)	0.4072463	0.1950897	[0.09, 0.73]	I(d)
OPEC oil prices – after break 2014	60	ARFIMA (2, d, 2)	0.296182	0.474025	[-0.48, 1.08]	I(0), I(1)
OPEC oil production						
OPEC oil production – before break 2004	412	ARFIMA (2, d, 2)	1.1720706	0.1683746	[0.89, 1.45]	I(1)
OPEC oil production – after break 2004	118	ARFIMA (2, d, 2)	0.802797	0.156333	[0.55, 1.06]	I(1)

We observe from Table 6 that the estimates of d after structural changes in oil prices and oil production in OPEC are in the range (0, 1), implying fractional integration in both time series, oil prices and oil production, respectively.

Focusing on the behavior of the time series after the first break (2004:04), we conclude that d=0.40 for oil prices, implying that the shock was transitory recovering its original trend in the short term. On the other hand, d=0.80 for oil production, but although apparently the result is similar to oil prices mentioned before, we cannot reject the hypothesis of I (1).

Finally, focusing on the behavior of the OPEC oil prices after the second break (2014:01), we observe that d=0.29. The value of d is below 1. With this result, we could conclude that after the structural break the time series is mean reverting, also implying transitory shocks. But if we look at the confidence interval, we cannot reject the hypothesis of I(1).

5. Conclusions

This paper contributes to the literature on understanding the behavior of the OPEC oil prices and OPEC oil production in response to terrorist attacks in these countries. To this purpose, we analyze the statistical properties of these time series, measuring the degree of persistence by using fractional integration techniques. Moreover, we analyze the long-term relationship of the time series using the Fractional Cointegration VAR (FCVAR) approach. Finally, we examine the possible structural changes in oil prices and oil production caused by the terrorist attacks in OPEC countries using methodologies based on Bai and Perron (2003) and wavelet transform.

In this research we have analyzed the number of terrorist events per month from the Global Terrorism Database (National Consortium for the Study of Terrorism and Responses to Terrorism (START), 2020) and its effects on crude oil production and crude oil prices behavior, from January 1970 to December 2018.

Given that OPEC is a dominant supplier in the oil market, assuming that OPEC has a superior understanding of the dynamics of the market and the ability to restrict supplies (Hansen and Lindholt 2008) and noting the terrorism and war events which have taken place in the main oil producing countries over the last 30 years, we analyze these three time series to gain a better understanding of the consequences of terrorist events on OPEC's crude oil production and OPEC's crude oil prices, examining the statistical properties of the time series using fractional integration techniques to measure the degree of persistence and analyzing the long-term relationships of the time series using the Fractional Cointegration VAR model (FCVAR). We also study the dynamics in the time-frequency domain applying wavelet tools for its resolution.

We started by performing several unit root methods, including ADF (Dickey and Fuller, 1979), PP (Phillips and Perron, 1988), and KPSS (Kwiatkowski et al., 1992). The results suggest that the time series are nonstationary I(1). In addition, we use two unit root tests with structural breaks onto the time series based on Narayan and Popp (2010) ADF-type unit root test and the LM test, proposed by Lee and Strazicich (2003). Taking into account that the analyzed time series could have structural changes, we carried out the analysis of unit roots with structural changes and the results indicate that the time series follow a stationary behavior.

As we have explained throughout this research paper, time series depend not only on a finite number of past observations but on the whole of its past history. In this context, techniques based on fractional integration play a crucial role since it indicates the degree of dependence of the series and allow us to know if the impact of terrorism on the OPEC oil prices and OPEC oil production is temporary or permanent. The results that we get using the ARFIMA model indicate that the values of d are in the range (0, 1), implying fractional integration. These values are below 1, implying mean reversion and thus, in the event of an exogenous shock the series will return to its original trend in the future.

In the multivariate case by using a FCVAR model and where we study the relationship of OPEC's crude oil production and OPEC's crude oil prices with terrorism attacks, we observe that the results are in line with the previous one where the order of integration of the individual series are below 1 (0.800 and 0.857, respectively) while the reduction in the degree of integration in the cointegrating regression is exactly of the same magnitude, implying that the order of integration $(d - b) = 0$. This implies I(0) cointegration errors. Thus, we cannot reject the hypothesis in which the error correction term shows short-run stationary behavior and where the shock duration is short-lived.

Following the results obtained and taking into account the structural changes caused by the terrorist attacks found by the unit roots tests of Narayan and Popp (2010) and Lee and Strazicich (2003), and in order to be more precise in our calculations we use Perron and Vogelsan (1992) and Bai and Perron (2003) approaches for detecting breaks in the data. The most relevant structural changes that have occurred in the time series of terrorist attacks have been in 2004: 04 and 2014: 01.

In order to know how terrorist attacks and OPEC oil prices and OPEC oil production are related at different frequencies and how such relationships have evolved over time, we use Continuous Wavelet Transform. We observe that terrorist attacks had an influence on oil prices in the periods 2004: 04 and 2014: 01. However, in oil production, we only find a clear influence in the period 2004: 04. Using this methodology, we state that terrorist attacks have a short-term component and they are positively correlated and leading in the behavior of oil production and oil prices in OPEC. The shocks found took between 1 and 10 months to disappear.

Finally, once we have identified the structural changes that have occurred due to the terrorist attacks, and we have concluded that the terrorist attacks affected production in OPEC countries in May 2004 and prices in OPEC countries in May 2004 and January 2014, we statistically analyze the behavior of these series after each shock, concluding that after the structural break the time series are mean reverting, implying transitory shocks.

This paper can be very helpful to institutions and companies that are exposed to crude oil market changes. Our findings might help market participants to understand better what the impact of terrorism on crude oil production movements may be and its subsequent potential effects on hedging strategies. It would be also reasonable to extend this research to other influence groups in the oil industry or high producing countries such as the U.S. or Russia, especially when the development of new production techniques such as fracking have been gaining relevance in the last years, increasing worldwide resources and shifting the balance of power and influence between countries.

Finally, we believe that it would be very interesting to incorporate variables that try to capture the effect of COVID-19, since there are already some studies that confirm that it could have important structural consequences for the oil industry. In future research, we will try to analyze and incorporate these variables, as we believe that they may be a determining factor in the future to define the effect of terrorism on oil production and prices in OPEC.

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