OIL EXTRACTION AND CRUDE OIL PRICE BEHAVIOR IN THE UNITED STATES: A FRACTIONAL INTEGRATION AND COINTEGRATION ANALYSIS

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ABSTRACT

This study reviews the relationship between the different types of oil extraction such as horizontal drilling or fracking, or directional drilling, which is a hybrid between vertical and horizontal, on the behavior of West Texas Intermediate crude oil prices. In doing so the study adds a new dimension to the literature on the relationship between oil price and extraction techniques. The analysis is based on statistical properties using the VAR model of Fractional Cointegration, reflecting evidence of cointegration between the series, and indicating a long-term equilibrium relationship. In addition, we apply the wavelet transform to analyze the structural changes in the price of West Texas Intermediate brought about by changes in drilling technology. Our results show that all three forms of extraction and West Texas Intermediate prices reach high levels of correlation, particularly around 2014. We conclude that a decrease in production based on any form of crude oil extraction leads to an increase in the price of crude oil.

Keywords: Drilling trajectory; crude oil production; crude oil prices; fractional integration; FCVAR model, wavelet analysis
JEL Classification: C00; C22; E30; Q40

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1. Introduction

In the United States the largest source of energy is crude oil. According to the International Energy Agency (IEA, 2019), crude oil consumption in the United States averages 20.54 million barrels per day (mbpd), including 1.1 mbpd which corresponds to biofuels. In global terms, global oil consumption stands at 98.8 million barrels per day (mbpd), making this natural resource a key asset for many economies.

However, the transformation that the energy sector is undergoing (the Paris Agreement, lithium battery energy storage, hybrid and electric mobility, etc.) motivated by global warming, climate change and concerns about the sustainability of our environment have diminished the role of oil as the predominant energy resource in recent years. This has raised concern among oil extraction companies over the optimization of their resources and led them to analyze more carefully their extraction efficiency and how this can affect their competitive position in the global energy resources market (see, e.g., Heijnen et al., 2015).

Even though we are dealing with a natural resource, which has been used since ancient times, it was not until the middle of the 19th century that the first commercially viable oil extraction well was developed (Owen, 1975). The progressive growth of the automobile industry and the successful application of this mineral to internal combustion engines, caused the demand for crude oil to rocket throughout the 20th century. If prior to the First World War (1914) there were approximately one million vehicles that used gasoline, by 1964 that figure had exceeded 170 million globally. Consequently, from 1957 to 1966 the same amount of oil was used as in the previous 100 years. Furthermore, the numerous geopolitical conflicts associated with the extraction of this highly-demanded resource, together with the enormous dependence of many non-producing countries, has led to the search, since the beginning of the century, for new more efficient extraction methods that enable access to larger reserves (Stevens, 2013).

Extraction technologies

Drilling of wells is required for the extraction of hydrocarbons. The first drilling was carried out in 1895 using the percussion drilling technique (Gatlin 1960). Drilling can be classified according to the method of rock breaking used, percussion drilling or rotary drilling, the latter being the more widely used (Lyons, Plisga and Lorenz, 2016). Drilling must also consider the characteristics of the well trajectory, hence important drilling methods such as vertical drilling, horizontal drilling and directional drilling have been developed.

1. Vertical drilling

Vertical drilling has traditionally been used for the search and production of oil in deposits. However, this extraction method is limited by the existence of rocks with low permeability and porosity. For the exploitation of ultra-deep oil resources, vertical drilling is necessary and is associated with reducing accidents at the bottom of the wells (Ma and Zhao, 2016). Vertical wells are those in which a target directly below the drill location on the surface is aimed for (Gatlin, 1960). The first vertical wells were drilled to a depth of 65 feet using the percussion drilling technique in 1895.

2. Horizontal drilling

Horizontal extraction began during the last century and is fundamentally based on vertical exploration up to a certain point at which the drilling bit is changed to a horizontal position. Subsequently, hydraulic fracturing then manages to extend the length of the well and access reserves that could not previously be reached using only a vertical extraction method. The technique used to drill a well from the surface to a certain subsurface location just above the oil or gas well is called horizontal drilling. The entry point is the one where the reservoir intersects after moving the well from the vertical plane around a curvature and a horizontal slope is generated. Ishak et al. (1995) described how this process is carried out until reaching the desired location in the well.

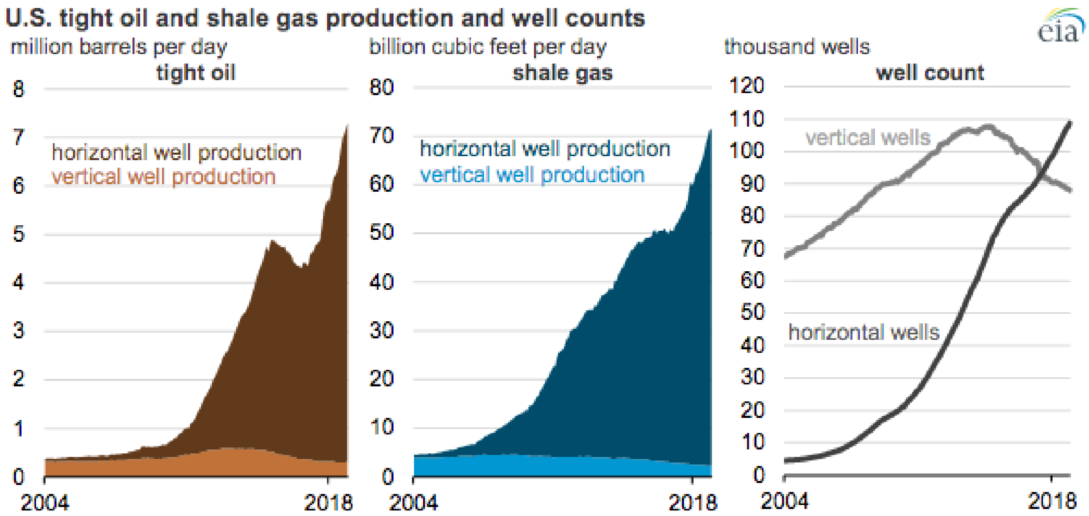
3. Directional drilling

Directional extraction is a mixture of the two previous models. This technique is used to increase extraction capacity and to avoid obstacles that impede access to the reserves or to avoid damaging sensitive environmental areas (Ma and Zhao, 2016). Traditionally, the most widely used method to obtain oil in the U.S. has been vertical extraction. However, as we can see in Figure 1, this technology has diminished in use due to the introduction and promotion of other methods such as fracking (horizontal extraction). Nowadays, oil wells drilled horizontally in tight oil formations account for an increasing share of the crude production in the United States. Horizontal wells accounted for 15% of U.S. crude oil production in 2004, increasing to 96% in 2018. Horizontal drilling, parallel to geological layers in narrow formations, allows producers to access more rock that contains oil and natural gas than vertical drilling: this is what is commonly known as hydraulic fracturing (IEA, 2020).

All the extraction methods referred to are enormously capital resource intensive, which implies risk and leads to concern about how these costs may affect production and prices in the market (Apergis et al., 2016). However, there are cost differences in extraction depending on the technology used. Bear in mind that drilling and completing a well can cost between $100-$150 per foot at the deepest sections and then around $450-

$625 per lateral foot (IEA, 2020). For all these reasons, companies dedicated to the extraction of crude pre-oil have been re-evaluating their extraction strategies in terms of the technologies used, since these can be a determining factor when positioning themselves in an increasingly competitive energy market.

Figure 1: U.S. tight oil and shale gas production and well counts



Source: U.S. Energy Information Administration, 2020.
Note: "The classification of vertical wells includes those wells that are created by directional and unknown drilling. The volumes of natural days include the values extracted from shale gas, and the liquid production of the formations of this gas are included in the volumes of tight oil."

Crude oil price analysis

To understand the behavior of each of the forms of crude oil extraction in the United States and how these affect the price of crude oil, we analyze the statistical properties of drilling rig counts in the U.S. according to their extraction technology and the West Texas Intermediate (WTI) U.S. oil price. With this objective, persistence is analyzed using fractional integration techniques such as those used by Monge et al. (2017 a,b) and Monge and Gil-Alana, (2020). Following the investigation of Johansen and Nielsen (2010, 2012) based on the Fractional Cointegration VAR (FCVAR) approach, the study of the long-term relationships of these variables is carried out. Finally, a wavelet analysis is carried out (Aguiar-Conraria and Soares, 2014) with the aim of examining whether possible changes in technology carried out in the excavations can lead to structural changes in the price of WTI.

To the best of our knowledge, there are no previous research papers that have studied oil production series in the United States according to the method of obtaining oil through a fractional integration and cointegration analysis and that have also included a study on what implications prices have on the West Texas Intermediate (WTI) market using Wavelet transforms. Kaufman et al. (1994) studied the possibility of applying policies that would increase the exploration and development of the oil industry by estimating a model that would allow the completion of wells in the United States; in their analysis they include the consequences of price expectations from the data obtained from the wells. Krane and Agerton (2015) state that, in general, the supply of crude oil tends to be more elastic in the face of price changes in wells of these characteristics. Baffes et al. (2015) also state that the changes in supply in recent years have been mainly due to the increase in production in the United States due to the development of new extraction techniques. Accordingly, Arezki and Blanchard (2015) affirm that only between 20% and 30% of supply is determined by factors associated with demand. Along the same lines, Hamilton (2014) explains that only 2/5 of the falls in the price of crude oil observed in 2014 are explained by the fall in demand. Baumeister and Kilian (2016) showed evidence that, in addition to the deceleration in the demand for crude oil, there are other shocks to world oil production and oil price expectations. All this evidence suggests that there are factors other than demand that determine the price, and these could be, among others, the type of extraction used.

Das et al. (2018) use the West Texas Intermediate (WTI) index for their review of the relationship between U.S. economic growth and crude oil prices considering the Industrial Production Index and WTI spot prices, adding a new dimension to the relationship between oil prices and economic growth.

In an interesting study carried out by Apergis et al. (2021), the asymmetries between the different drilling techniques are examined depending on their trajectory, the price of oil and its production in the U.S.. The research shows the independence of oil prices with respect to the extraction technique, revealing however a short-term asymmetry with respect to oil prices and production. Focusing more on the subject matter of our analysis, there are numerous studies which focus on the analysis of factors that affect the behavior of energy and oil prices in various countries, and, in particular in the United States. Kyrtsou et al. (2009) carried out different univariate tests for non-linearity and chaotic structure using energy sector price data to determine if the shocks produced by internal and external factors affect the prices of energy resources. On the other hand, Monge and Gil-Alana (2015) used gradual integration and cointegration techniques to conduct an analysis of how the price of crude oil in the United States affects mergers and acquisitions (M&A). Their results show that, between two and three months after an increase in the price of oil there is a significant increase in the number of mergers and acquisitions. In order to analyze the regionalization of the world crude oil market, the authors used high-frequency data to find co-movements among crude oil prices.

Hailemariam et al. (2019) studied the existence of a relationship between the economic policies applied in the G7 countries and their relationship with oil prices, completing the existing literature with Kang and Ratti (2013), Degiannakis et al. (2018) and Antonakakis et al. (2014), among others. The results showed that the years in which increases in crude oil prices were carried out were the consequence of a global increase in demand, since an estimated function of the negative oil price coefficient was obtained.

Although Ivanovski and Hailemariam (2021) studied the theoretical ambiguity in the relationship between oil prices and stock returns, there is an extensive literature that denies the relationship (see, for example, Basher et al., 2012). However, some authors provide evidence of the existence of a relationship between the variables (see Narayan and Narayan, 2010). Thus, Monge et al. (2017b) applied wavelet tools to study shale oil production and the behavior of WTI prices. Apergis et al. (2016) analyzed how oil and natural gas prices may be affected by changes in the number of rigs and their refurbishments. Smith and Lee (2017) developed a model that allowed them to state that the volume of crude oil reserves is inelastic with respect to the price of oil. More specifically, they stated that the vast majority of extraction wells have fairly low productivity and represent a relatively small percentage of total reserves, which is why a drop in prices that leads to the elimination of some of these production points has no particular impact on the remaining volume of reserves. Ewin and Malik (2017) showed the effect of the news, both positive and negative, on the volatility of oil prices through the implementation of an asymmetric GARCH model. Monge et al. (2020) analyzed the (spatial) divergence of crude oil production in the United States, focusing especially on crude oil production between PADD 2 and PADD 3 zones, which are those in which a distribution bottleneck occurs, which directly affects the price of crude oil. West Texas Intermediate (WTI).

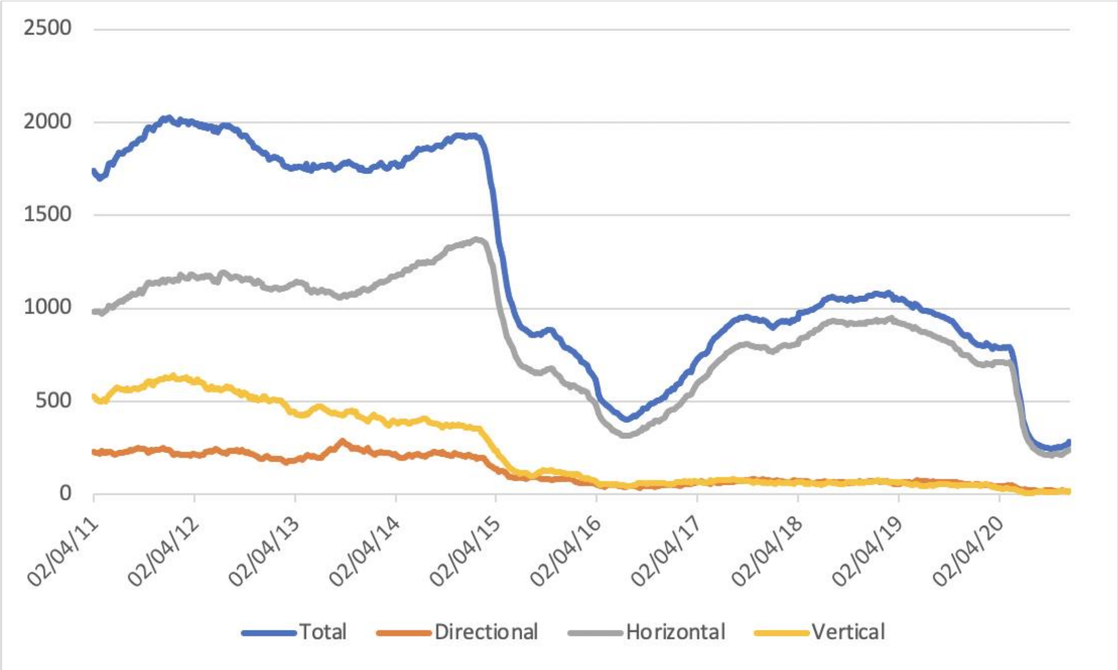
The rest of the paper is organized as follows: the data used for the research are described in Section 2 in addition to the methodology that has been used to carry out the study. The results are discussed in Section 3. Finally, the conclusions are found in Section 4.

2. Data and Methodology

2a. Dataset

The data used to carry out this study have been obtained from Baker Hughes[1] and refer to the total count of drilling rigs in the U.S. as well as vertical, horizontal and directional drilling rig counts. In addition, we have also used the West Texas Intermediate (WTI) crude oil price index obtained from the U.S. Energy Information Administration[2]. The data used in this research paper has a weekly frequency and the analyzed period is from February 4, 2011 to October 16, 2020.

Figure 2: Weekly data for vertical, directional, horizontal and total drilling rig counts



The data used are presented in Figure 2, displaying the time series plots of weekly data for vertical, directional, horizontal and total drilling rig counts. We observe in the figure that while vertical and directional extraction first decreases and then remains stable

[1] http://rigcount.bakerhughes.com
[2] https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=RWTC&f=W

during the period of analysis, horizontal extraction represents the most productive technology in the United States.

2b. Unit Roots

To carry out the objectives set forth in this research work, the ADF tests are used following the line in Fuller (1976) and Dickey and Fuller (1979), to verify the characteristics of the time series used and to confirm if they are stationary or not. Other methods are also conducted such as those proposed in Phillips (1987) and Phillips and Perron (PP, 1988), Kwiatkowski et al. (KPSS, 1992), Elliot et al. al (ERS, 1996) and Ng and Perron (NP, 2001)). The results were very similar in all cases.

2c. ARFIMA (p, d, q) model

To study the statistical properties of time series, we follow a mathematical notation where a time series $x_t,\ t = 1, 2, \dots$ follows an integrated of order d process (and denoted as $x_t \approx I(d)$) if:

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

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

The result of the parameter d allows us to conclude that if $d < 0$, x_t is anti-persistent, and this occurs when the series changes sign more frequently than occurs in a random process and when it has zero spectral density at the origin. (see Dittmann and Granger, 2002);

x_t is short memory or I(0) when $d = 0$ in (1) because $x_t = u_t$.

x_t is long memory when d > 0 and we find a high degree of association in observations far distant in time. Related to this last assumption we say that the process is still covariance stationary if $d < 0.5$. When d has a value less than 1, it displays reversion to the mean and it implies that if there is a shock, its effect will be transitory; on the contrary, when d ≥ 1, the effect of the shock will be permanent.

Geweke and Porter-Hudak (1983), Phillips (1999, 2007), Sowell (1992) and others carried out various techniques for calculating the degree of long memory and fractional integration. To represent the results, Sowell's (1992) likelihood technique has been used, while in order to choose the most appropriate ARFIMA model for the analysis, the Akaike information criterion (AIC, Akaike, 1973) and the Bayesian Information Criterion (BIC; Akaike, 1979) have been employed.

2d. Fractional Cointegrated Vector AutoRegressive Model

The Fractional Cointegrated Vectorial AutoRegressive (FCVAR) method was studied by Johansen (2008) and later expanded by Johansen and Nielsen (2010, 2012), this being the natural evolution of the model described earlier by Johansen (1996) of the Cointegrated Vector AutoRegressive (CVAR). This method has the ability to admit integrated time series of order d that cointegrate with order d - b, with b > 0. It is necessary to present the non-fractional CVAR model before carrying out the FCVAR.

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

$$\Delta Y_t = \alpha\beta' Y_{t-1} + \sum_{i=1}^{k} \Gamma_i \, \Delta Y_{t-i} + \varepsilon_t = \alpha\beta' L Y_t + \sum_{i=1}^{k} \Gamma_i \, \Delta L^i Y_t + \varepsilon_t. \qquad (2)$$

To derive the FCVAR model, we need Δ^b and $L_b = 1 - \Delta^b$ which are the fractional counterparts to replace the difference and lag operator Δ and L in (2). We then obtain:

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

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

$$\Delta^d X_t = \alpha\beta' L_b \Delta^{d-b} X_t + \sum_{i=1}^{k} \Gamma_i \Delta^b L_b^i Y_t + \varepsilon_t, \tag{4}$$

where ε_t is a term with mean zero and variance-covariance matrix Ω that 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 short-run behavior of the variables depends on the parameter Γ_i. Finally, the deviations from the equilibria and their speed in the adjustment depends on the parameter α.

2e. Wavelet Analysis

Time series are an aggregation of components operating on different frequencies. Thus, the most outstanding information is hidden in the frequency content of the signal. Wavelet coherence and wavelet phase difference have been used to further this research in the time-frequency domain. This study allows us to analyze the interaction of the time series in the time domain and to reveal structural changes without the need for it to comply with the stationarity characteristic. [3]

Based on the analysis carried out by Kyrtsou et al. (2009) on the energy markets and nonlinear dependencies, several authors have used nonlinear methods to analyze the impact of oil shocks using wavelet analysis. Other authors such as Aguiar-Conraria and Soares (2014) and Crowley and Mayes (2009) have used wavelets to test and to study business cycle synchronization. To identify hidden patterns and/or information, we use the wavelet coherency plot that measures the correlation between the time series in the time-frequency domain. To get this result, we calculate the $WT_x(a, \tau)$ which is the

[3] Continuous Wavelet Transform (CWT) has been applied in several finance and economics research papers such as Vacha and Barunik (2012), Aguiar-Conraria and Soares (2011, 2014), Dewandaru et al. (2016), Tiwari et al. (2016), Jammazi et al. (2017), among others.

wavelet transform of a time series $x(t)$, projecting the mother wavelet ψ to map the original time series onto a function of τ and a:

$$WT_x(a,\tau) = \int_{-\infty}^{+\infty} x(t) \frac{1}{\sqrt{a}} \psi^* \left(\frac{t-\tau}{a}\right) dt, \qquad (5)$$

To measure the synchronism between the time series, the Morlet wavelet is chosen as the mother wavelet, as this is a complex sinusoidal wave within a Gaussian envelope. (Aguiar-Conraria and Soares, 2014).

Taking into account the results that we get using Wavelet Transform, Wavelet coherence helps us understand how one time series interacts with respect to the other. We can define this term as:

$$WCO_{xy} = \frac{SO\left(WT_x(a,\tau)WT_y(a,\tau)^*\right)}{\sqrt{SO(|WT_x(a,\tau)|^2)SO\left(\left|WT_y(a,\tau)\right|^2\right)}}, \qquad (6)$$

The SO parameter represents the smoothing operator in time, being relevant since if it were dispensed with, the wavelet coherence for all scales and times would be one (Aguiar-Conraria et al., 2008). The codes developed with Matlab for the CWT solution can be found on the Aguiar-Conraria website[4].

3. Empirical Results

3a. Unit roots

Three standard unit root tests have been calculated to examine the statistical properties of the total, horizontal, vertical and directional drilling rig counts. We select the ADF (Augmented Dickey-Fuller, 1979) test, the PP (Phillips Perron, 1988) test and the KPSS (Kwiatkowski-Phillips-Schmidt-Shin, 1992). Table 1 displays the results, which suggest that the five selected time series are non-stationary I(1).

[4] https://sites.google.com/site/aguiarconraria/joanasoares-wavelets

Table 1: Unit roots tests.

	ADF			PP		KPSS	
	(i)	(ii)	(iii)	(ii)	(iii)	(ii)	(iii)
Total	-1.5658	0.0166	-1.3991	0.0938	-1.2827	5.255	0.6531
Directional	-1.7676	-0.6955	-1.7014	-0.7515	-1.7348	6.182	0.7338
Horizontal	-1.1129	-0.0576	-1.2067	0.117	-1.0859	3.2651	0.4419
Vertical	-2.7296	-0.8456	-0.5569	-0.9263	-0.7225	6.5833	1.3532
WTI	-1.0123	-1.4415	-2.5739	-1.3973	-2.3808	4.6837	0.6433

(i) Refers to the model with no deterministic components; (ii) with an intercept, and (iii) with a linear time trend. We reflect t-statistic with a test critical value at 5%.

3b. Fractional Integration

The use of fractional methods and ARFIMA (p,d,q) models is chosen given the low power of unit root tests[5] in long memory contexts. For the selection of the most appropriate AR and MA orders in the models, the Akaike information criterion (AIC; Akaike, 1973) and the Bayesian information criterion (BIC; Akaike, 1979) are applied[6].

The AR and MA terms and the fractional parameter d resulting from the use of Sowell's (1992) maximum likelihood estimator of various ARFIMA specifications (p,d,q) for all combinations of p, q ≤ 2 are shown in Table 2.

Table 2. Results of long memory tests

Data analyzed	Model Selected	d	Std. Error	Interval	I(d)
Total	ARFIMA (0, d, 0)	1.4399263	0.0293275	[1.39, 1.49]	I(d >1)

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

[6] A note 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).

Directional	ARFIMA (2, d, 2)	1.0456892	0.0370000	[0.98, 1.10]	I(1)
Horizontal	ARFIMA (1, d, 1)	1.4856419	0.0189182	[1.45, 1.51]	I(d >1)
Vertical	ARFIMA (2, d, 2)	1.222881	0.100698	[1.06, 1.39]	I(d > 1)
WTI crude oil price	ARFIMA (2, d, 2)	1.0537872	0.1766352	[0.76, 1.34]	I(1)

Table 2 reflects that in all cases the estimates of d are equal to or greater than 1. In the prices of directional oil and WTI, the hypothesis I(1) cannot be rejected, while for the remaining three series it can be rejected in favor of a greater order of integration. This seems to indicate that the shocks will be permanent as there is no evidence of reversion to the mean in any of the individual cases, causing a change in trend. Therefore, it can be concluded that extraordinary measures will be required to reestablish trends in the event of shocks.

3c. Fractional Cointegration VAR model

Table 3 shows the results obtained after analyzing the persistence of the long-term co-movements of the series from the FCVAR model.

Table 3: Results of the FCVAR model ($d \neq b$)

	d	**b**
Panel I: without crude oil prices	$d = 1.019$ (0.085)	$b = 0.669$ (0.100)

Panel II: with crude oil prices	$d = 0.729$ (0.163)	$b = 0.729$ (0.104)

From Panel I in Table 3 where the WTI crude oil price is not included in the analysis, an order of integration of around 0.35 is obtained since for the individual time series it is 1.02 and the reduction in the degree of integration in the regression is 0.67. With these results we may conclude that it is a time series with long-term equilibrium that follows a long memory process, so that a time forecast is obtained over long horizons (Baillie and Bollerslev, 1994). It is a long duration shock with a stationary process in the correction of the error according to the value obtained ($d - b = 0.35$).

In Panel II, where the WTI crude oil price is included in the analysis, we observe that the order of integration of the time series is $(d - b) = 0$, because the order of integration of the individual series is about 0.729 and the reduction term is of precisely the same magnitude. This result implies I(0) cointegration errors. Thus, we cannot reject the hypothesis where the shock duration is short-lived due to the error correction term showing short-run stationary behavior.

From an economic viewpoint, we can conclude that a shock to any type of oil production will have a lasting effect in the long run. However, when we introduce price into the analysis, we observe that it cannot be concluded that the behavior will be the same as oil production, since the results indicate that the shock will be of shorter duration.

3d. Wavelet Analysis

We use a multivariate wavelet analysis based on the time-frequency domain to estimate how the different ways of extracting oil affect the behavior of oil prices. Also, the possible presence of structural changes can be detected for the whole sample.

Figure 3. Wavelet Coherency, Phase-differences and Wavelet gain between different ways of extracting oil and WTI crude oil prices

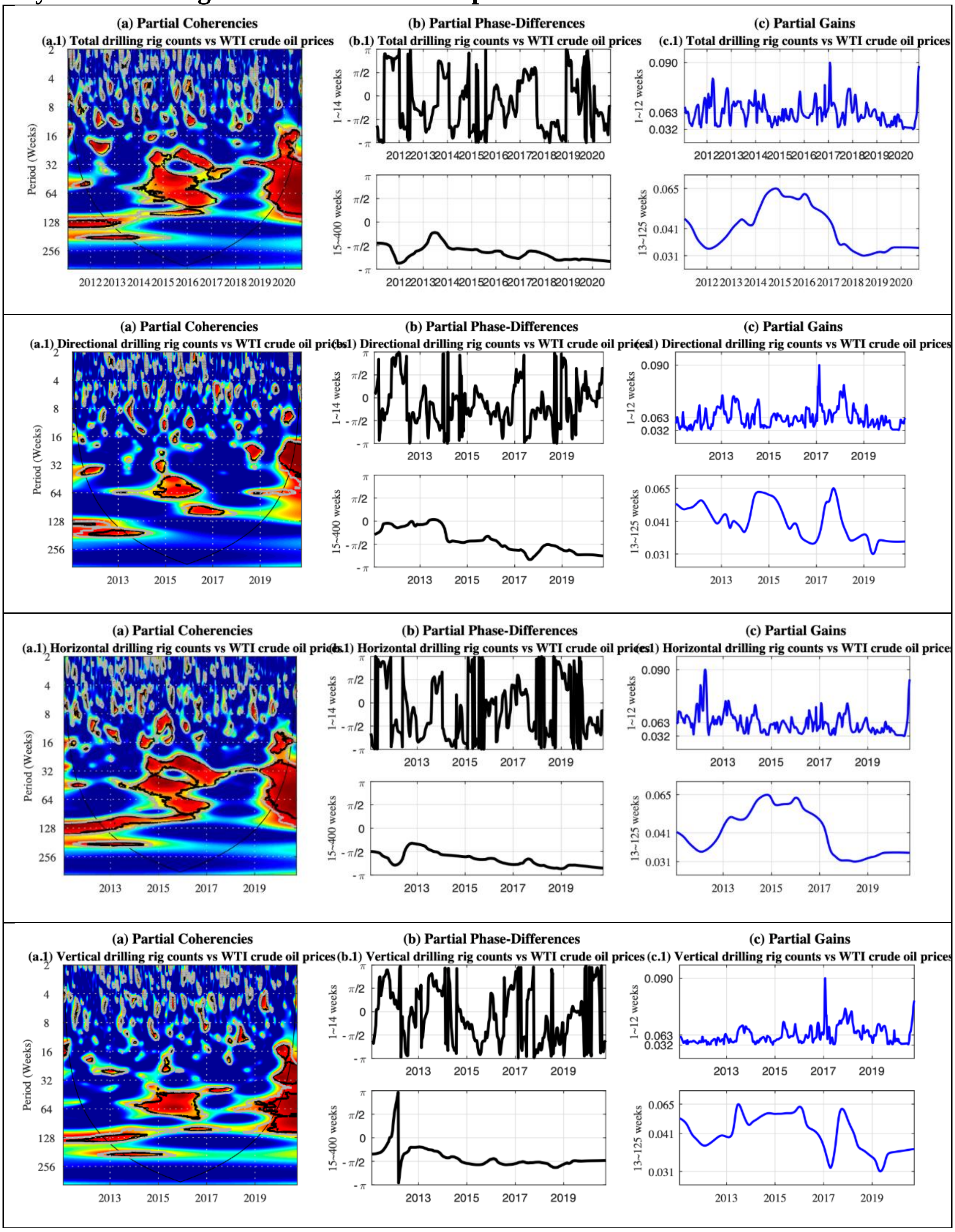


Figure 3 tells us when and at which frequencies the interrelations between the time series occur and when they are the strongest. Thus, in section (a) of Figure 3 we obtain the wavelet coherency, identifying the main regions with statistically significant coherency. Also, with this term we consider the importance and the strength of the interrelations between the analyzed time series. These regions are located at cycles corresponding to 24 and 128 weeks (low frequencies), starting at 2014 in all the series.

Once we have identified the regions, we look at the results obtained in sections (b) and (c) of the figure, the partial phase difference and the partial wavelet gain, respectively. These two results allow us to determine the impact and importance of the shock of one variable in relation to the other. On the results previously obtained at the 5% significance level, the phase difference is between $-\pi/2$ and $-\pi$. This means that the different ways of extracting oil and the prices of WTI crude oil, at the frequencies studied, give rise to an antiphase relationship where oil extraction is related to the prices of WTI crude oil. Economically, this means that a decrease in the production of any form of crude oil extraction implies an increase in the WTI price. The module of the regression coefficient in the different forms of extraction, corresponding to the partial profit, is 0.065 on the WTI prices at each moment.

4. Conclusion and policy implications

The average consumption of barrels of crude oil in the United States exceeds 20 million a day (mbpd). However, the increase in awareness regarding climate change has brought about a notable expansion in the use of clean energies in recent years, reducing the market share of the more polluting traditional energy sources, such as oil. As a result, the level of competitiveness in the energy market has grown in recent years, causing the oil industry to seek new ways of expanding its operations, in particular, the use of horizontal drilling techniques capable of reaching much more extensive reserves. In the United States, the number of extraction wells using this technology increased from 15% in 2004 to 96% in 2018, indicating a shift in production technology that has fostered the introduction of sweeping changes in the industry. The objective of our study is twofold. First, we examine the statistical properties of the horizontal, vertical and directional drilling rig counts by measuring the degree of persistence with fractional integration techniques, also using the FCVAR model to study their long-term relationships. Second, and through continuous wavelet transformation techniques, we aim to analyze whether this transition from vertical to horizontal extraction techniques has had repercussions on the behavior of the West Texas Intermediate (WTI) index for the price of crude oil in the United States.

To carry out this research, some unit root methods (ADF, Dickey and Fuller; PP, Phillips and Perron, 1988, and KPSS, Kwiatkowski et al., 1992) are first performed. From the results obtained, it can be concluded that these are non-stationary I(1) series. Fractional integration is also used in this study, obtaining that the five time series examined (counts of total, directional, horizontal and vertical drilling platforms and WTI crude oil prices) display orders of integration equal to or above 1, implying a lack of mean reversion in the series, and thus with shocks having permanent effects.

The long-term correlation between the variables in the multivariate case is confirmed by the FCVAR model. For the individual series, the order of integration is 1.02 and the reduction in the degree of integration is close to 0.67. Therefore, we obtain 0.35 for the degree of integration corresponding to the cointegration vector, which indicates a certain forecasting power in long horizons and implies that the shock could be of long duration following a stationary process with the error correction term. The order of the individual time series is close to 0.729 for WTI prices, with 0.729 being exactly the same for the reduction in the degree of integration in the cointegration regression, indicating I(0) cointegration errors. Therefore, it is not possible to reject the hypothesis in which the error correction term behaves stationary in the short term, and it is a shock of short duration.

Finally, we apply Continuous Wavelet Transform (CWT) to analyze the structural changes caused by changes in drilling technology on the price of the West Texas Intermediate (WTI). Our results show that the three different ways of extracting oil and WTI crude oil prices reach high levels of correlation, the most important one starting around 2014. We conclude that a decrease in the production of any form of crude oil extraction implies an increase in the price of WTI crude oil.

This research can be very useful for all those institutions and companies that are affected by the changes that occur in the oil market, achieving a better understanding of the behavior of the WTI price related to the effects of production. From a methodological viewpoint, the paper can also be extended in various directions. First, the presence of structural breaks can be examined by using standard methods such as Perron and Vogelsang (1992), Perron (1997) and Bai and Perron (2003) or using the fractional approach developed in Gil-Alana (2008), Ohanissian et al. (2008), Aue and Horvath (2013) and others. Moreover, noting that fractional integration is very much related to the presence of non-linearities, this is another avenue for future work, using, for example, the approach developed in Cuestas and Gil-Alana (2016) that allows for Chebyshev's polynomials in time in the context of I(d) models. All these lines of research will be pursued in future papers.

References

Aguiar-Conraria, L., Azevedo, N. and Soares, M. J. (2008). Using wavelets to decompose the time-frequency effects of monetary policy. Physica A: Statistical Mechanics and its Applications, 387, 2863-2878.

Aguiar-Conraria, L. and Soares, M. J. (2011). Oil and the macroeconomy: using wavelets to analyze old issues. Empirical Economics, 40, 645-655.

Aguiar-Conraria, L., and Soares, M. J. (2014). The continuous wavelet transform: moving beyond uni and bivariate analysis. Journal of Economic Survey, 28, 344-375.

Akaike, H. (1973). Maximum likelihood identification of Gaussian autoregressive moving average models. Biometrika, 60(2), 255-265.

Akaike, H. (1979). A Bayesian extension of the minimum AIC procedure of autoregressive model fitting. Biometrika, 66(2), 237-242.

Antonakakis, N., Chatziantoniou, I., and Filis, G. (2014). Dynamic spillovers of oil price shocks and economic policy uncertainty. Energy Economics, 44, 433-447.

Apergis, N., B.T. Ewing, and J.E. Payne (2016). A Time Series Analysis of Oil Production, Rig Count, and Crude Oil Prices: Evidence from Six U.S. Oil Producing Regions. Energy, 97, 339-349.

Apergis, N., Ewing, B. T., and Payne, J. E. (2021). The asymmetric relationship of oil prices and production on drilling rig trajectory. Resources Policy, 71, 101990.

Arezki, R. and Blanchard, O. (2015). Seven questions about the recent oil price slump. Energy, 36, 2-10.

Aue A. and L. Horváth (2013) Structural breaks in time series. Journal of Time Series Analysis 34(1):1–16.

Baffes, J., Kose, M. A., Ohnsorge, F. and Stocker, M. (2015). The great plunge in oil prices: Causes, consequences, and policy responses. Policy Research Note No.1, World Bank.

Bai, J. and P. Perron (2003). Computation and analysis of multiple structural change models. Journal of Applied Econometrics 18, 1–22.

Baillie, R. T., and Bollerslev, T. (1994). Cointegration, fractional cointegration, and exchange rate dynamics. The Journal of Finance, 49(2), 737-745.

Basher, S. A., Haug, A. A., and Sadorsky, P. (2012). Oil prices, exchange rates and emerging stock markets. Energy Economics, 34(1), 227-240.

Baumeister, C. and Kilian, L. (2016). Understanding the decline in the price of oil since June 2014. Journal of the Association of Environmental and Resource Economists, 3, 131- 158.

Crowley, P. M. and Mayes, D. G. (2009). How fused is the Euro area core?: an evaluation of growth cycle co-movement and synchronization using wavelet analysis. OECD Journal: Journal of Business Cycle Measurement and Analysis, 2008(1), 63-95.

Cuestas, J.C. and L.A. Gil-Alana (2016) A Non-Linear Approach with Long Range Dependence Based on Chebyshev Polynomials, Studies in Nonlinear Dynamics and Econometrics 23, 445-468.

Das, D., Bhatia, V., Pillai, J. and Tiwari, A. K. (2018). The relationship between oil prices and US economy revisited, Energy Sources, Part B: Economics, Planning, and Policy, 13:1, 37-45.

Degiannakis, S., Filis, G., and Arora, V. (2018). Oil prices and stock markets: a review of the theory and empirical evidence. The Energy Journal, 39(5).

Dewandaru, G., Masih, R., and Masih, A. M. M. (2016). Contagion and interdependence across Asia-Pacific equity markets: An analysis based on multi-horizon discrete and continuous wavelet transformations. International Review of Economics and Finance, 43, 363-377.

Dickey, D. A., and Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association, 74(366a), 427-431.

Dittmann, I., and Granger, C. W. J., (2002). Properties of nonlinear transformations of fractionally integrated processes. Journal of Econometrics. 110, 113-133.

Elliot, G., T.J. Rothenberg and J.H. Stock (1996), Efficient tests for an autoregressive unit root, Econometrica 64, 813-836.

Fuller, W. A. (1976). Introduction to Statistical Time Series, New York: JohnWiley. FullerIntroduction to Statistical Time Series1976.

Gatlin, C. (1960). Petroleum Engineering Drilling and Well Completions. Prentice-Hall Inc., Englewood Cliffs.

Geweke, J. and PorterHudak, S. (1983). The estimation and application of long memory time series models. Journal of Time Series Analysis, 4(4), 221-238.

Gil-Alana, L. A. (2008). Fractional integration and structural breaks at unknown periods of time. Journal of Time Series Analysis, 29(1), 163-185.

Hailemariam, A., Smyth, R., and Zhang, X. (2019). Oil prices and economic policy uncertainty: Evidence from a nonparametric panel data model. Energy economics, 83, 40-51.

Hamilton, J. (2014). Oil prices as an indicator of global economic conditions. Econbrowser

Heijnen, L., R. Rijkers, and R.G. Ohmann (2015). Management of Geological and Drilling Risks of Geothermal Projects in the Netherlands. In Proceedings of World Geothermal Congress 2015. Melbourne, Australia: International Geothermal Association (IGA).

Hosking, J.R.M. (1981), Modelling persistence in hydrological time series with using fractional differentiation, Water Resources Research 20, 1898-1908.

International Energy Administration (IEA 2019), Global Energy Review 2019, IEA, Paris.

International Energy Administration (IEA 2020) Global Energy Review 2020, IEA, Paris.

Ishak, I.B., Steele, R.P., Macaulay, R.C., Stephenson, P.M., and S.M. Al Mantheri. (1995). Review of Horizontal Drilling. Paper presented at the Middle East Oil Show, Bahrain, March 1995.

Ivanovski, K., and Hailemariam, A. (2021). Forecasting the dynamic relationship between crude oil and stock prices since the 19th century. Journal of Commodity Markets, 24, 100169.

Jammazi, R., Ferrer, R., Jareño, F. and Shahzad, S. J. H. (2017). Time-varying causality between crude oil and stock markets: What can we learn from a multiscale perspective?. International Review of Economics and Finance, 49, 453-483.

Johansen, S. (1996). Likelihood-based inference in cointegrated vector autoregressive models. New York, NY: Oxford University Press.

Johansen, S. (2008). A representation theory for a class of vector autoregressive models for fractional processes. Econometric Theory, 24, 651-676.

Johansen, S. and Nielsen, M. Ø. (2010). Likelihood inference for a nonstationary fractional autoregressive model. Journal of Econometrics, 158, 51-66.

Johansen, S. and Nielsen, M. Ø. (2012). Likelihood inference for a fractionally cointegrated vector autoregressive model. Econometrica, 80, 2667-2732.

Kang, W., and Ratti, R. A. (2013). Oil shocks, policy uncertainty and stock market return. Journal of International Financial Markets, Institutions and Money, 26, 305-318.

Kaufmann, R.K, Gruen, W. and Montesi, R. (1994). Drilling Rates and Expected Oil Prices: The Own Price Elasticity of U.S. Oil Supply, Energy Sources, Part B: Economics, Planning, and Policy, 16:1, 39-58.

Krane, J. and Agerton, M. (2015). Effects of low oil prices on U.S. shale production: OPEC calls the tune and shale swings. Baker Institute Research Paper.

Kwiatkowski, D., Phillips, P. C., Schmidt, P. and Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. Journal of Econometrics, 54(1-3), 159-178.

Kyrtsou, C., Malliaris, A. and Serletis, A. (2009). Energy sector pricing: On the role of neglected nonlinearity. Energy Economics, 31, 3, 492-502.

Lyons, W.C., Plisga, G.J. and Lorenz, M.D., (2016). Standard Handbook of Petroleum and Natural Gas Engineering: Second Edition. Standard Handbook of Petroleum and Natural Gas Engineering: Second Edition. 1-1568.

Ma, C. and J. Zhao (2016). Overview on Vertical and Directional Drilling Technologies for the Exploration and Exploitation of Deep Petroleum Resources. Geomechanics and Geophysics for Geo-Energy and Geo-Resources, 2(4), 365-395.

Monge, M. and Gil-Alana, L. A. (2015). Fractional Integration and Cointegration in Merger and Acquisitions in the US Petroleum Industry. Applied Economics Letters, 23-10.

Monge, M., Gil-Alana, L. A. and de Gracia, F. P. (2017a). Crude oil price behaviour before and after military conflicts and geopolitical events. Energy, 120, 79-91.

Monge, M., Gil-Alana, L. A., and de Gracia, F. P. (2017b). US shale oil production and WTI prices behavior. Energy, 141, 12-19.

Monge, M. and Gil-Alana, L. A. (2020). Spatial Crude Oil Divergence and Crude Oil Price Behavior in the United States. Working Paper.

Narayan, P. K., and Narayan, S. (2010). Carbon dioxide emissions and economic growth: Panel data evidence from developing countries. Energy policy, 38(1), 661-666.

Ng, S. and P. Perron (2001), Lag length selection and the construction of unit root tests with good size and power, Econometrica 69, 519-1554.

Ohanissian, A., Russell J.R. and R.S.Tsay (2008) True or spurious long memory? A new test. Journal of Business and Economic Statistics 26(2):161–175.

Owen, E W. Wed . (1975). Trek of the oil finders: a history of exploration for petroleum. U.S. Department of Energy Office of Scientific and Technical Information.

Perron, P. (1997), Further evidence on braking trend functions in macroeconomic variables, Journal of Econometrics 80, 355-385.

Perron, P. and T.J. Vogelsang (1992), Testing for a Unit Root in a Time Series with a Changing Mean: Corrections and Extensions, Journal of Business and Economic Statistics 10, 4, 467-470.

Phillips, P. C. (1987). Time series regression with a unit root. Econometrica, 55(2), 277-301.

Phillips, P. C., and Perron, P. (1988). Testing for a unit root in time series regression. Biometrika, 75(2), 335-346.

Phillips, P. C. B. (1999). Discrete Fourier transforms of fractional processes. Department of Economics, University of Auckland.

Phillips, P. C. B. (2007). Unit root log periodogram regression. Journal of Econometrics, 138(1), 104-124.

Smith, J. and T. Lee (2017). The Price Elasticity of U.S. Shale Oil Reserves. Energy Economics, 67, 121-135.

Sowell, F. (1992). Maximum likelihood estimation of stationary univariate fractionally integrated time series models. Journal of Econometrics, 53(1-3), 165-188.

Stevens, P. (2013). History of the International Oil Industry. In: Dannreuther R., Ostrowski W. (eds) Global Resources. Palgrave Macmillan, London. https://doi.org/10.1057/9781137349149_2

Tiwari, A. K., Mutascu, M. I. and Albulescu, C. T. (2016). Continuous wavelet transform and rolling correlation of European stock markets. International Review of Economics and Finance, 42, 237-256.

Vacha, L., and Barunik, J. (2012). Co-movement of energy commodities revisited: Evidence from wavelet coherence analysis. Energy Economics, 34, 241-247.