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STRUCTURAL BREAKS IN THE MARKETS: OIL'S EXAMPLE

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Abstract

The importance of fossil fuels in the world's energy supply and the relationship between their fluctuations and geoeconomic and geopolitical phenomena make it important to analyze the major forces behind the often-unexpected behavior of oil prices. The aim of this paper is to study socio-economic events that are contemporaneous with structural changes in the price of oil, and which may indicate a causal relationship with them. This study uses the Bai & Perron methodology to detect structural breaks. The sample consists of observations of the closing prices of oil futures contracts traded in the US, West Texas Intermediate, corresponding to various maturities. We have identified three key points in the formation of oil prices. Firstly, we note the significant impact of macroeconomic factors, especially those more closely related to demand, as the main drivers of structural changes in the oil markets. The influence of OPEC in determining prices is also noted, highlighting its prominent role in the global oil landscape, although with less impact on the structural changes identified. Finally, the research suggests that, in a broader context, geopolitical events tend not to trigger significant structural changes in the oil market..

Keywords

Structural breaks, WTI futures, Bai & Perron methodology, oil.

Resumo

A importância dos combustíveis fósseis na oferta mundial de energia e a relação entre as suas flutuações e os fenómenos geoeconómicos e geopolíticos, tornam aliciante analisar as forças maiores por detrás do comportamento, amiúde inesperado, do preço do petróleo. É objetivo deste trabalho estudar os acontecimentos socioeconómicos contemporâneos a alterações de estrutura no preço do petróleo, que com elas possam indiciar relações de causalidade. Neste estudo é utilizada a metodologia de Bai & Perron para a deteção de alterações de estrutura. A amostra consiste em observações dos preços de fecho de contratos de futuros negociados nos EUA, West Texas Intermediate, correspondentes a várias maturidades. Três pontos são por nós identificados como essenciais sobre a formação do preço do petróleo. Em primeiro lugar, observa-se o impacto significativo de fatores macroeconómicos, especialmente os mais relacionados com a procura, como principais impulsionadores de alterações de estrutura nos mercados de petróleo. Também é assinalada a influência da OPEP na determinação dos preços, realçando o seu papel proeminente no panorama global do petróleo, embora com menor impacto nas alterações de estrutura identificadas. Por fim, a pesquisa sugere que, num contexto mais amplo, eventos geopolíticos tendem, por norma, a não desencadear alterações estruturais significativas no mercado do petróleo.

Palavras-chave

Alterações de estrutura, futuros WTI, metodologia de Bai & Perron, petróleo.

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The determinants of oil prices

Fossil fuels continue to have an overwhelming weight in the world's energy supply, despite progress in alternative sources, particularly renewables. According to data from the International Energy Agency (IEA), in 2021, the total aggregate supply of oil, coal and natural gas was around 80percent of the world's total energy supply, which was only one percentage point less than in 1990. And, unsurprisingly, among fossil fuels, oil continues to be the most representative, albeit in decline in recent years (29percent of total supply in 2021, 37percent in 1990).

Although today we are far from witnessing the disruptions in industrialized countries caused by the supply shock of the 1970s or even the fear with which the world awaited the possible production cuts decided at the Organization of the Petroleum Exporting Countries (OPEC) meetings, the truth is that geoeconomics and geopolitics continue to be greatly influenced by, and condition, the evolution of fossil fuel prices, particularly oil.

It is therefore essential to understand the major forces behind the perhaps often erratic or unexpected behavior of oil prices. One possible approach is to identify the main determinants of this price and its evolution over time.

Liu, Ding, Lv, Wu & Qiang (2019) points to three types of determinants, namely political factors, financial factors and the inability of supply to keep up with demand (particularly due to problems of insufficient storage and different reaction times, being longer in the supply side, which causes sudden over- or under-production crises), a determinant which is shared by more commodities. They also note the divergence between the main determinants before the 2007/2008 financial crisis, in this case demand and supply factors, and those that are the determinants of the oil price in the post-crisis period, where the behavior of demand and supply proves to be important but insufficient to explain the evolution of the oil price. Ding, Liu, Zhang & Long (2017) tell us that oil resources have the characteristics of a commodity (as a productive element) but also financial characteristics.

Due to its fundamental role in the oil market since its foundation in 1960, OPEC's actions and importance in the oil markets have been the subject of numerous studies. Among them, Coleman (2012) points to OPEC's market share as the main determinant of oil prices in the long term. Ben Salem, Nouira, Jeguirim & Rault (2022) conclude that OPEC's decisions, together with determinants such as the price of futures, the Iraq war and the financial crisis, have had a short-term impact, while other factors such as the price of gold and the exchange rate of the US dollar (USD) have both short- and long-term impacts. Demirbas, Omar Al-Sasi, & Nizami (2017) study the impact, among other factors, of OPEC's production decisions on market volatility and the economies of oil-producing countries. Quint & Venditti (2020), on the other hand, refer to the decisive role of OPEC and OPEC+[1], arguing that the production cuts between 2017 and 2020 had a less significant impact than apparent, in the order of 4 USD per barrel. Di Nino, Álvarez & Venditti (2020) find an essential role of this organization's price targeting in the oil price formation. This paper discusses two main strategies: Firstly, Market Share Targeting, where OPEC tries to maintain its market share against non-OPEC producers, with the second strategy being Price Targeting, where OPEC aims to directly stabilize or increase oil prices with its policies. The findings of this study indicate that while global demand remains the main factor driving oil prices, OPEC's Price Targeting actions can also have a significant impact in oil price changes, especially during periods of market instability. Smith (2009) cites the rapid economic growth of China and other developing nations as one of the determinants of oil prices. Other economic factors, such as the impact of a recessionary or expansionary period (Kilian, 2009), the return on bonds or the size of the oil futures markets (Coleman, 2012) or uncertainty (Kang & Ratti, 2013), are also mentioned. Garavini (2020) identifies the impact of the COVID-19 pandemic, due to the drastic reduction in oil demand caused by lockdowns and other restrictions, as well as due to the price war between Russia, Saudi Arabia and OPEC.

Coleman (2012) associates the long-term price of oil with the frequency of terrorist attacks in the Middle East and the presence of American soldiers in the region. Ozawa & Tardy (2022) and Karda (2023) explain the geopolitical scenario and the energy crisis that loomed over Europe due to Europe's dependence on Russian oil and gas. Yagi & Managi (2023) explain the rise in oil prices caused by the invasion of Ukraine.

The relationship between political factors and oil markets is well documented in the literature. Cheon, Lackner & Urpelainen (2015) study the dichotomy faced by policymakers when subsidizing oil products which, while a politically advantageous measure, can cause economic distortions and be ineffective in fighting poverty. Arezki, Djankov, Nguyen & Yotzov (2022) study the relationship between oil price movements and the probability of re-election of incumbent administrations, concluding that shocks to the price of oil imports cause a decrease in the probability of re-election. Dragomirescu-Gaina, Philippas & Goutte (2023) observe that US President Donald Trump's tweets (now X posts) about oil are associated with greater speculative activity in the energy derivatives markets.

Referring to the financial aspects associated with oil price formation, Liu (2019) considers them to be more relevant in this asset than in most commodities, due to the existence

[1] OPEC member countries (Algeria, Angola, Congo, Equatorial Guinea, Gabon, Iran, Iraq, Kuwait, Libya, Nigeria, Saudi Arabia, United Arab Emirates and Venezuela) plus a group of ten countries that take joint decisions with them, namely Azerbaijan, Bahrain, Brunei, Kazakhstan, Malaysia, Mexico, Oman, Russia, South Sudan e Sudan.

of derivative instruments associated with oil (which is not the case with most commodities) which makes it more sensitive, for example, to speculation. In addition to speculation, another financial factor that should be highlighted as a determining factor in the behavior of the oil markets is the attention[2] (and subsequent behavior) of investors in relation to these markets.

With the emergence of an increasingly digital age, where information flows more quickly, investors' attention to the markets is increasingly impactful, which can be explained from the point of view of behavioral finance, as defined by Liu *et al.* (2019). These same authors cite Li, Ma & Zhang (2015), who studied the relationship between the Google search volume index (GSVI) and oil prices, concluding that the same index represents the concerns of non-commercial investors (without a direct interest in the commodity they are trading - essentially speculators), with a positive feedback mechanism between the GSVI and the volatility of this market. Li *et al.* (2015) also report the GSVI's ability to predict crude oil prices in the short term. In the same vein, Cepni, Nguyen & Sensoy (2022) developed two measures of investor attention based on the news function of the Bloomberg terminal (which is mostly used by institutional investors), proving their usefulness in predicting returns on oil futures (although they noted that their effectiveness decreases with the maturity of the contracts).

Before moving on to the core of our article, the presentation and modeling of structural changes in the oil market, a final word, necessarily summarized, on what the literature tells us about the most impactful shocks in this market. [3]

Kilian (2009) analyzes the impacts of demand and supply shocks on the price of oil, using WTI spot prices. The author concluded that not all shocks affect the price of this commodity (and the economy as a whole) in the same way, the most significant and persistent on real economic activity being that caused by a sudden movement in aggregate demand. Kang & Ratti (2013) corroborate Kilian's conclusions, in that they associate a positive, oil-specific demand shock with greater uncertainty in economic policy, which also influences oil prices.

About the relationship between inflation and the price of oil, Montoro (2012) studies the relationship between shocks in the oil market and inflation, finding a trade-off between stabilizing inflation and stabilizing production in the presence of these phenomena.

Karali, Ye & Ramirez (2019) conclude that truly unanticipated events (they use the September 11 terrorist attacks as an example) have short-term impacts, while the events that truly mark the markets more permanently are financial crises

Regarding the different players operating in these markets, Dedi & Mandilaras (2022) conclude that different investors react in different ways to shocks: producers and swap dealers reduce their positions in the presence of positive price shocks, while portfolio managers move in the opposite direction. Despite these movements, the same authors state that there is little evidence that these players' positions affect the price of oil.

[2] Investor attention and market sentiment are defined as the general attitude of investors towards how they expect market prices to develop.
[3] Shocks are defined as the unanticipated component of a substantial change in the price of oil (Baumeister & Kilian, 2016).

Structural changes: a brief literature review

After this brief literature review on the determinants of oil prices, we will now look at how the literature investigates the existence of structural changes in time series.

Bai (1997) refers to the very common instability of parameters in economic models, especially in time series that extend over a long period. This is because, over a longer time horizon, the data is much more likely to be influenced by factors such as policy changes. Another author with seminal contributions to the subject, Chow (1960), argues that whenever a linear regression is used to represent an economic relationship, we can question whether the relationship holds for two different time periods or for two different economic groups. For example, is consumer behavior today identical to what it was before the Second World War? According to the author, statistically, these questions can be answered by testing whether two sets of observations can be considered to belong to the same regression model. When there is a sudden and permanent change in the relationship between the points that make up a time series, we have a structural break (or structural change). The point at which this event occurs is called the breakpoint.

Ferreira, Menezes & Oliveira (2013) clearly summarize in their work how changes in structure seem to affect models based on economic and financial time series. They also point out that these changes can reflect legislative, institutional, technological, political or even macroeconomic shocks. Along the same lines, Hansen (2001) states that structural changes can be decisive in time series and that inferences about economic relationships, forecasts and policy recommendations can be flawed if these changes are not considered.

Regarding the tests for structural breaks, we can summarize them in two groups: the tests for detecting a single break and the tests for detecting multiple breaks.

In the first group, Chow (1960) proposed a test based on the assumption that the possible breakpoint date is known, which, without prior information, is difficult to sustain. Thus, this test only allows a possible breakpoint to be assessed simultaneously and is less effective when this point is unknown or has to be estimated (Gabriel, 2002).

Quandt (1960) developed the work of Chow (1960), proposing a method known as the *Quandt Likelihood Ratio* (QLR), based on calculating Chow stability test statistics for all possible breakpoints and analyzing the largest resulting value in absolute terms, estimating the breakpoint by maximum likelihood and then performing a *likelihood ratio* test (Gabriel, 2002). In short, Quandt assumes that a Chow test will be carried out for all possible breakpoints in the sample and the chosen breakpoint will be the one that maximizes the likelihood ratio test.

The test described above is also of limited power, since it only tests the hypothesis that there were no changes against the existence of a change (although, unlike Chow, 1960, we don't have to previously indicate a specific date in order to test for a break on that date), ignoring the possibility of there being more than one break in the same sample. This approach was the basis for several other tests (the so-called "sup" tests), which, according to Casini & Perron (2018), culminated in the work of Andrews (1993), who, although limited (like Quandt) to detecting a single break, had the important merit of showing that the Chow test can be based on maximum values of the Wald tests and the Lagrange multiplier, in addition to the maximum likelihood, as Quandt illustrated.

Andrews & Ploberger (1994) followed the work described in the previous paragraph, developing a distribution for, among other cases, the likelihood ratio test on which Quandt (1960) is based, making it viable. Their study is based on the construction of tests, which, as Gabriel (2002: 23) explains, "*are constructed as a weighted average of the classic tests, and can take two different forms, depending on whether the potency is directed towards alternatives that are closer to or farther from the parameters under the null hypothesis*" (which is that there are no changes in structure).

In the second group of tests, with them being the detection of multiple breaks, we will highlight the contributions of Bai & Perron, also because we followed their methodology in our article, as we will see below.

Bai & Perron (1998) state at the outset of their work that it deals with multiple changes that occur at an unknown point in the sample, in a linear regression estimated by the method of least squares (OLS), deriving the rate of convergence and the limit distributions of the estimated breakpoints. This approach, as the two authors point out, differs from the rest of the literature of the time (in particular the one that we already reviewed in the previous section of this paper) in that, as we have seen, it only dealt with the case of a single change (a single breakpoint).

Their study, in addition to being based on a linear model estimated by OLS, allows for general forms of serial autocorrelation and heteroscedasticity in the errors, as well as lagged dependent variables, regressors with a trend and different distributions for the errors and for the regressors between segments, as the authors themselves summarize in the paper in question. It is a model of partial structural change, where not all parameters are subject to change and, on the other hand, it allows tests of multiple structural breaks, if there are no regressors with a trend.

In the test, the null hypothesis is that there are no changes, and the alternative is an unknown number of changes (at least one) up to a certain maximum, and a test for the null hypothesis of l changes versus the alternative l +1 changes.

Bai & Perron (2003a) refine the practical application of the methodology proposed in 1998, suggesting computational methods for estimating global minimizers. The supF test of the non-existence of structural changes *versus* the existence of a fixed number l of changes (there will always be at least one) is presented[4]. A limitation of this methodology is that it requires the assumption of a predefined number of l breakpoints, so in cases where it is challenging to do so, it may become interesting to run the methodology explained in the next paragraph.

The authors then present two tests of the null hypothesis of no changes against a given number of changes with the upper limit M (the so-called double maximum tests), useful for situations in which the researcher doesn't want to assume a given number of changes beforehand in order to draw conclusions and based on the calculation of a UDmax and a WDmax. The unweighted version of the test, the UDmax, estimates the number of breakpoints using the global minimization of the sum of squared residuals. The WDmax test, on the other hand, applies weights to the individual statistics so that the implied marginal values are equal before calculating the number of breaks (Perron, 2005). The

[4] *Global* test *L breaks vs. none.*

aforementioned Perron (2005) explains the usefulness of this approach to determining the number of breaks.

The last of the tests is that of l versus l + 1 changes, called supFT (l + 1|l) which consists of applying (l + 1) tests of the null hypothesis of no changes in structure versus the alternative hypothesis of a single change[5] . The authors settle in a rejection in favor of the model with (l + 1) breaks if the minimum global value of the sum of the squared residuals (in all segments where another break is included) is sufficiently smaller than the sum of the squared residuals of the model with l breaks. After this analysis, the date of the break selected is the one associated with the said global minimum.

The authors then present the Bayesian Information Criterion (BIC) proposed by Schwarz (1978) and the LWZ proposed by Liu, Wu & Zidek (1997), the latter being a modification of the Schwarz criterion. Perron (1997) presents a simulation of the behavior of these two criteria. It is concluded that both criteria perform poorly in the presence of autocorrelation in the errors but have different powers when it does not exist. In such cases, when there is no autocorrelation but there is a lagged dependent variable, the BIC malfunctions when the coefficient of this variable is greater, and in these cases the LWZ is preferable (with the disadvantage of underestimating the number of breaks if there are any).

Bai & Perron (2003a) conclude by recommending the approach corresponding to the sequential application of the supFT (l + 1|l) test, using the sequential estimation of the breaks. According to them, this strategy works better than applying the BIC and LWZ criteria. In cases where it is challenging to apply this methodology, they recommend first carrying out the UDmax and WDmax tests to see if at least one break is present. If this is the case, then the number of breaks can be calculated using the Global L breaks vs. None test, using the global minimizers as the dates of the breaks.

There are many applications of the Bai & Perron test, especially in the specific case of oil, which is the subject of our article, the studies by Plante & Strickler (2021), who use the Bai & Perron methodology to determine the frequency and *timing of* structural breaks, to prove that the different types of oil are becoming increasingly homogenized. Weideman & Inglesi-Lotz (2017) apply this methodology to renewable energies in South Africa. Focacci (2022) studies the relationship between non-commercial investors and *spot* oil prices, determining the respective breaks with the Bai & Perron tests. Zarei, Ariff, Hook & Nassir (2015) study the evolution of interest rates using the same methodology. Xiong, Sun, Wang, Wang & Liu (2016) study the correlation between the price of crude oil and the *U.S. weekly leading index*. Shaeri, Adaoglu & Katircioglu (2016) determine the existence of breaks in equity returns to compare the exposure of the US financial and non-financial sectors to oil price risk. Finally, Tule, Ndako & Onipede (2017) use the methodology studied here to detect breaks in the Brent and WTI time series, so that these breaks do not jeopardize their conclusions about possible spillovers between oil shocks and the Nigerian bond market.

[5] *Sequential L+1 breaks vs L* test.

The model: data and methodology

The aim of this article is to determine the existence of possible structural changes in the West Texas Intermediate (WTI) oil futures market between March 2004 and March 2024.

To do this, we will work on the closing prices of WTI futures contracts for various maturities and we will carry out the multiple break tests proposed by Bai & Perron (1998, 2003), with the aim of estimating any structural changes in the sample, for later analysis.

The timeframe chosen was intended to cover several significant events, both economic and financial, as well as geopolitical milestones that naturally resulted in various fluctuations in the oil markets.

These events include the onset of a severe financial crisis in 2007/2008 and subsequent recovery, the occurrence of the Arab Spring at the end of 2010 and a sharp drop in oil prices from 2014 onwards, driven by several factors, most notably an excess of supply over demand. In addition, 2016 brought the Brexit referendum and the first election of Donald Trump, while the end of 2019 marked the beginning of the COVID-19 pandemic, which, in 2020, caused a deep economic contraction due to the impacts of the disease, including confinement measures and restrictions on activities. More recently, in 2022, the invasion of Ukraine by Russian forces took place. In addition to these landmark events, we also must consider other factors such as the macroeconomic movements of economies, OPEC's production decisions and energy adjustment and transition efforts.

The sample consists of 5038 daily observations of the closing prices of WTI futures contracts with maturities of 1, 2, 6 and 12 days (hereinafter *Daily 1*, *Daily 2*, *Daily 6* and *Daily 12*, respectively).

The choice of WTI over Brent Crude (these are the two main benchmarks, respectively, for the North American and European markets), in a context where there is no significant difference in terms of liquidity between the two contracts, was based on WTI's greater volatility, due in part to storage dynamics and its greater sensitivity to overproduction problems. This makes WTI a more suitable choice for analyzing disruptive events, especially those that originate in the US or significantly impacted the country before spreading globally, such as the 2007/2008 financial crisis.

As mentioned, the methodology used is that of Bai & Perron (1998, 2003), which makes it possible to detect and locate multiple unknown break points. The *Global L Breaks vs. None Test* proposed by these authors analyses the hypothesis of the existence of at least one break (meaning a given optimized number l of breaks) in the time series under study, such that:

H_0: There is no break in the time series

H_1: There is at least one break in the time series

This test is described as sequential, since it works in such a way as to look for the existence of a break (and rejection of H_0) and once this is achieved, the sample is split in two at estimated break date and a new test is carried out on this new sub-sample. The sequence is only interrupted when a sub-sample is found that does not reject H_0.

To avoid the problem, described earlier in this paper, of a previous inference of the number of breaks, the UDmax and WDmax statistics are calculated, which estimate the number of breaks present in the sample.

We thus have the following linear regression (with m breaks and m +1 regimes):

$$y_t = x'_t\beta + z'_t\delta_j + u_t \quad , t = T_{j-1} + 1, \dots, T_j \qquad (1)$$

With $j = 1, \dots, m+1$. For this model we have y_t as the observable dependent variable at time t; $x_{(t)}$ p x 1) and z_t (q x 1) are vectors of covariates and β and δ_j ($j = 1, \dots, m+1$) are the corresponding vectors of coefficients; u_t is the disturbance at time t. The indices ($T_1, \dots, t_m$), corresponding to the breakpoints, are treated as unknown (taking $T_0 = 0$ and $t_{(m)(+1)} = T$), in order to estimate the unknown coefficients of the regression together with the breakpoints when T observations in ($y_t, x_{(t)}, z_{(t)}$)) are available. The authors also add in the same reference that the model is a partial structural change model since β is not subject to change and is estimated using the entire sample. When $p = 0$ we have a pure structural change model where all the coefficients are subject to change. Finally, it is also explained that for the model in question the variance of u_t does not need to be constant, and there can be breaks in it as long as they coincide with moments of breaks (changes) detected in the regression parameters.

The estimation is based on the OLS, and the sum of the squares of the residuals (SQR) is given by:

$$SQR = \sum_{i=1}^{m+1}\sum_{t=T_{i-1}}^{T_i}(y_t - x'_t\beta - z'_t\delta_i)^2 \qquad (2)$$

There will be $\hat{\beta}$ ($\{T_j\}$) and $\hat{\delta}$ ($\{T_j\}$) estimates for each of the m breaks and ($T_1, \dots, T_m$) denoted as $\{T_j\}$. Taking SQR by $S_T(T_1, \dots, T_m)$ we have the estimated breakpoints ($\hat{T}_1, \dots, \hat{T}_m$), such that:

$$(\hat{T}_1, \dots, \hat{T}_m) = argmin_{(T_1,\dots,T_m)} S_T(T_1, \dots, T_m) \qquad (3)$$

Minimization is performed on all partitions ($T_1, \dots, T_m$) such that $T_i - T_{i-1} \geq q^2$ (where q is the number of changes present in the sample). Thus, all the breakpoint estimators are global minimizers of the objective function and the regression parameters become least squares estimates associated with partition m, that is:

$$\hat{\beta} = \hat{\beta}(\{\hat{T}_j\}) \text{ and } \hat{\delta} = \hat{\delta}(\{\hat{T}_j\}). \qquad (4)$$

This article will use the *Global L breaks vs. None* test, with the number of breaks determined by the *UDmax* and *WDmax* statistics.[6]

Results and discussion

Table 1 shows the main characteristics of the observations of the closing prices of the WTI futures that make up the sample.

Table 1. Descriptive statistics of the sample data.

Series	Average	Median	Maximum	Minimum	Deviation-Standard	Variance	Kurtosis	Asymmetry
Daily 1	70,47446	68,705	145,29	-37,63	0,3126461	492,45226	-0,3744491	0,3036176
Daily 2	70,79323	68,885	145,86	11,57	0,3065895	473,55737	-0,4481892	0,3385176
Daily 6	71,02392	69,005	146,85	24,73	0,2926012	431,33083	-0,3169087	0,3636459
Daily 12	70,45986	68,65	146,32	29,63	0,2822116	401,24338	-0,1477076	0,3886963

Source: Own elaboration.

As can be seen in the table, the series under study are platicurtic and positively asymmetric. By being platicurtic, we can see that these series have relatively flat price distributions and a lower probability of extreme prices, which indicates that they are stable and have a lower risk of major fluctuations. Positive asymmetry shows that prices tend to be above average, which leads us to assume that there is a potential for frequent growth (growth, it must be said, is usually moderate, since being platicurtic we see that values are concentrated around the average, with extreme values being rare).

The maximum and minimum indicate the highest and lowest closing prices of the WTI futures contracts that make up our sample, where the negative minimum value of 37.36$ in the series of daily observations of contracts with a maturity of 1 day stands out, for reasons that will be discussed later.

On the other hand, as the days to maturity of the contracts increase, the variance and standard deviation decrease, indicating less volatility in the oscillations of the series as the days to maturity of the contracts increase.

The application of Bai & Perron's methodology led to the estimation of the regression model by OLS, which consists of a constant regressor that allows for serial correlation that differs between regimes, using covariance estimation by HAC[7] . A maximum of 5 breaks in the model were considered and a *trimming* percentage 15percent was applied (Bai & Perron, 2003b).

In the HAC options we set the *Lag Specification* to fixed, with the *Number of lags* equal to 1. The *Kernel* was set to *Quadratic-Spectral,* to allow for autocorrelation in the errors,

[6] Perron (2005) summarizes the usefulness of this approach.
[7] *Heteroskedasticity and Autocorrelation Consistent.* Guarantees the consistency of the regression in terms of heteroskedasticity and autocorrelation, ensuring that it meets the assumptions necessary for the Bai & Perron methodology.

the *Bandwith method* was set to *Andrews Automatic*, with an *offset* set to 0 and the specification of the equations was set to *close c,* where *close* was the name of the column where the closing prices of the futures contracts were recorded in each series and *c* was the constant regressor discussed in the previous paragraph.

After constructing the regressions, the tests were carried out. At this stage, the *Global L breaks vs. None* option was selected, with a *Trimming percentage of* 15, a significance level of 0.05 and a maximum number of breaks set at 5 (Bai & Perron, 2003b). The results are shown in Table 2.

Table 2. Results of the Global L breaks vs. None test applied to the sample.

Series	No. of breaks	Date of Breaks
Daily 1	4 (UDmax)	6/18/2007, 12/03/2010, 11/28/2014, 3/05/2021
	5 (WDmax)	6/18/2007, 12/03/2010, 11/28/2014, 11/28/2017, 3/05/2021
Daily 2	5	6/28/2007, 12/03/2010, 11/28/2014, 11/28/2017, 3/05/2021
Daily 6	5	6/15/2007, 12/02/2010, 11/28/2014, 11/28/2017, 3/05/2021
Daily 12	5	6/13/2007, 12/01/2010, 11/28/2014, 11/28/2017, 3/05/2021

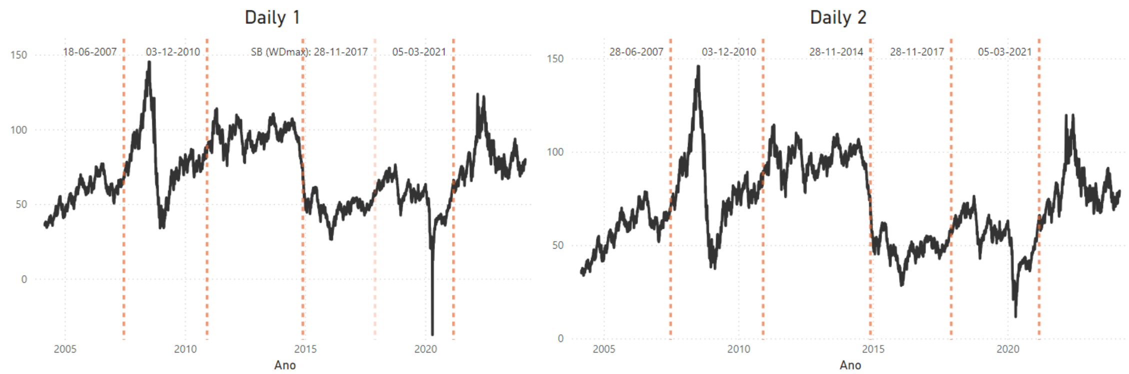
Source: Own elaboration.

During the tests, the number of breaks was calculated sequentially using the *double maximum*, *WDmax* and *UDmax* tests. The criterion for choosing the number of breaks is the results of the latter tests which, except for the case described in the next paragraph, are convergent. This convergence gives us confidence in the results.

In the series of contracts with a maturity of 1 day, the *WDmax* and *UDmax* tests show different results in terms of the number of breaks. This divergence in the number of breaks indicated by each of the *double maximum tests* is not relevant to the analysis of the results, since it will be done on common dates between all the tests and the break found by the WDmax statistic and which is not found in UDmax (November 28, 2017) appears as a break date in all the other series. Even so, for a positively asymmetric platicurtic series such as the one we are discussing now, we assume that the unweighted nature of the UDmax statistic becomes more conservative and thus more suitable for a series with a lower frequency of extreme values.

In addition to the convergence in the results of the *double maximum* tests, it is important to mention that the dates identified for the breaks refer to the same days or the same short period. This circumstances gives us confidence that, in fact, one (or more) event(s) occurred that significantly affected WTI prices on those dates/periods. Before analyzing the possible causes, the results of the tests listed in Table 2 are presented graphically (Figures 1 and 2).

Figure 1 Observations of the closing prices of WTI futures contracts with a daily maturity of 1 and 2 days, and their respective breaks.



Source: Own elaboration.

Figure 2. Observations of the closing prices of WTI futures contracts with daily maturities of 6 and 12 days, and their respective breaks.

Source: Own elaboration.

Before analyzing the breaks found, we would like to comment on the observations made on April 20 and 21, 2020. Historic lows were reached on these days, including a value of -37.63$ on April 20 in the case of daily observations of WTI futures with a one-day maturity. In the other series, although with values already in positive territory, the minimum values of the sample were found on April 20 and 21, 2020. This sample was caused by problems with WTI storage, which was under pressure due to the large reduction in demand caused by the restrictions imposed by the Covid-19 pandemic. The fact that the issue has been solved in a short time may explain the absence of a drop on this date.

Table 3 identifies and aggregates the breaks detected and associates each of these breaks with contemporary events that may have had a causal relationship with them.

Table 3. Contemporary events at the time of the breakdowns.

Break	Contemporary Events
June 13-28, 2007	Turkish troops gather on the border with Iraq OPEC refuses to increase production Nigerian workers' strike
December 1st to 3rd, 2010	Indications of global economic recovery.
November 28, 2014	166th OPEC meeting Record US production Global economic slowdown and reduced demand for oil
November 28, 2017	173rd OPEC meeting Strong economy and increased demand for oil
March 5th, 2021	14th ministerial meeting between OPEC members and non-members *American Rescue Plan Act of 2021* Strong economic recovery after the COVID-19 pandemic

Source: Own elaboration.

The first break, in the second half of June 2007, coincided with several notable events for the oil markets, especially of a geopolitical nature, namely tensions between Turkey and Iraq, with the concentration of Turkish troops on the border with Iraq. A workers' strike in Nigeria, the largest oil producer on the African continent, with armed demonstrators storming oil production facilities, also contributed to the rise in oil prices. To add to all these factors, Salem El-Badri, the then secretary-general of OPEC, announced on June 14 that OPEC was refusing to increase production levels. All these cyclical factors, plus the impact of Cyclone Gonu at the beginning of the month, caused a sharp rise in the price of oil and, once these phenomena had dissipated, prices naturally corrected significantly downwards.

The break in the first few days of March 2010 was associated with signs of global economic recovery, which had an impact on confidence in the performance of economies. As a result, expectations of oil demand were revised upwards, which led to an increase in the price of oil.

In November 2014, there was a break on the 28th, the day immediately after the 166th OPEC meeting. At that meeting, the organization decided, against expectations that production would fall, to maintain production levels, appearing comfortable with low prices. This decision came in a context where oil prices were already under pressure from the biggest increase in production since records began in the US (*Energy Information Administration*, 2015), as well as a reduction in demand for oil that began in May, caused by a slowdown in the global economy, as Mead & Stiger (2015) explain.

The break on November 28, 2017, can also be linked to an OPEC meeting that took place on November 30 of that year. A break two days before the meeting reveals the expectation that economic agents had regarding the decision that would come out of the meeting. In fact, at the meeting held on November 30, 2016, a decision was made to reduce production (by around 1.8 million barrels per day) by the member countries for a period of 6 months, starting in January 2017, and then extended for a further 9 months, starting in July 2017. At the meeting on November 28, 2017, it was decided whether these production cuts would continue throughout 2018. The break in the run-up to this meeting was due to expectations about the decisions that would come out of it, with the markets anticipating the extension of the reduction agreement for another 9 months and particular concern that Russia (OPEC's largest non-member partner) might not go along with this decision. This policy of reduced oil production and the uncertainty about its continuation, combined with a strong economy, justify a break on this occasion.

The last break found in our sample is on March 5, 2021, the day after the 14th ministerial meeting between OPEC members and non-members. This meeting was particularly important because it welcomed, and above all extended, the production reductions aimed at controlling oil prices after the COVID-19 pandemic. Despite this reduction in oil supply, the economy was no longer the same fragile, shutdown economy that prompted production reductions in April 2020. March 2021 was a month of strong economic recovery after the shock of the pandemic, with a summer without major restrictions and vaccine distribution already underway. To further foster this recovery, the vote on the *American Rescue Plan Act of 2021*, a stimulus package worth 1.9 trillion USD, was also initiated on March 5, 2021, which had to be approved by the Senate on the 6th and passed into law on the 11th. The combination of a restrictive production policy and an expanding economy will have caused a structural break at the beginning of March 2021.

These results seem to point to the decisive importance of the evolution of demand and supply (and the corresponding market expectations in relation to this evolution) as determinants of the falls in the price of WTI futures contracts. Furthermore, the breaks appear to be more the result of a set of two, three or more relatively contemporaneous phenomena than the consequence of a particular statistic or isolated phenomenon and, on the other hand, there is evidence that truly unanticipated events, such as terrorist attacks, have a limited impact in the short term, i.e. in our case, they do not normally constitute structural changes.

A final comment on the conclusions we reached on the role of OPEC (and OPEC+) in setting prices, in line with much of the literature presented, in that it identifies its importance as a determinant of oil prices, but not necessarily as a direct and unique cause of breaks.

Conclusions

The overwhelming weight that fossil fuels continue to have in the world's energy supply and the reciprocal relationship between their most significant fluctuations and geoeconomic and geopolitical phenomena make it attractive and fundamental to understand the major forces behind the behavior, perhaps erratic or unexpected, of the oil price.

That's what we've tried to do in this article, not confining ourselves to presenting the main determinants of the oil price, but rather trying to identify singularities that may be associated with structural changes in the oil price, in other words, that may indicate causal relationships with them.

Based on a relatively long sample of more than five thousand daily observations between March 2004 and March 2024 of *West Texas Intermediate* oil futures prices and using the multiple break test methodology proposed by Bai & Perron (1998, 2003), we estimated possible structural changes in the sample and identified events that are contemporaneous with them.

The changes in structure identified at various times seem to be associated with macroeconomic effects, particularly in contexts characterized by larger than expected movements in demand. It is interesting to note that all the breaks were related to a macroeconomic event that would influence the demand for oil in the same direction as the price of oil after the break.

We also found that, despite the influence of the Organization of Petroleum Exporting Countries in setting oil prices, its decisions are more likely to be associated with a structural change when they coincide with a macroeconomic scenario favorable to such a movement.

Finally, we found that geopolitical events do not usually cause structural changes, especially if they are restricted to a single country and/or have a momentary impact.

From these conclusions one cannot naturally infer that the analyses that point to the existence of a wide range of factors that determine the price of oil are not valid, namely geopolitical tensions, variations in currency exchange rates, regulatory changes, the evolution of oil inventories, technological advances, speculation or market sentiment.

A different matter is considering that these factors can cause a reaction in prices strong enough to constitute a structural change: at this level, only macroeconomic events have resisted, as phenomena associated with the identified structural changes.

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