Petroleum Science 21 (2024) 729–739

Contents lists available at ScienceDirect

Petroleum Science

journal homepage: www.keaipublishing.com/en/journals/petroleum-science

Original Paper

Brent vs. West Texas Intermediate in the US petro derivatives price formation

Alejandro Almeida [a], Antonio A. Golpe [b,*], Juan Manuel Martín-Alvarez [a], Jose Carlos Vides [c]

[a] Universidad Internacional de La Rioja, Department of Quantitative Methods for Economics and Business, La Rioja, Spain
[b] University of Huelva, Department of Economics and Centro de Estudios Avanzados en Fisica, Matematicas y Computacion and ICEI, Huelva, Spain
[c] Complutense University of Madrid, Department of Applied and Structural Economics and History and ICEI, Madrid, Spain

ARTICLE INFO

Article history:
Received 22 February 2023
Received in revised form
21 April 2023
Accepted 6 September 2023
Available online 9 September 2023

Edited by Jia-Jia Fei and Min Li

Keywords:
Crude oil prices
Spatial panel model
Refined products
Price formation

ABSTRACT

In this paper, we apply the spatial panel model to explore the relationship between the dynamic of two types of crude oil prices (WTI and Brent crude oil) and their refined products over time. Considering the turbulent months of 2011, when Cushing Oklahoma had reached capacity and the crude oil export ban removal in 2015 as breakpoints, we apply this method both in the full sample and the three resultant regimes. First, results suggest our results show that both WTI and Brent display very similar behaviour with the refined products. Second, when attending to each regime, results derived from the first and third regimes are quite similar to the full sample results. Therefore, during the second regime, Brent crude oil became the benchmark in the petrol market, and it influenced the distillate products. Furthermore, our model can let us determine the price-setters and price-followers in the price formation mechanism through refined products. These results possess important considerations to policymakers and the market participants and the price formation.

1. Introduction

By the end of 2019, Saudi Arabia overflows the market with crude oil, causing an international price plunge of more than 20% in a single day (Albulescu, 2020). The oil market is a spectator of unprecedented negative demand and positive supply shocks. Later, in early 2020, the COVID-19 outbreak triggered in Wuhan (China) and its rapid spread around the world caused a collapse in West Texas Intermediate (WTI, hereafter) prices in April 2020 for reasons such as the weakness of the demand and ongoing production versus storage limitations (Jefferson, 2020). Additionally, the different lockdown measures implemented by the countries to prevent and impede contagions have affected businesses, job securities and services and have brutally impacted all types of transport, either by road, rail, sea or air. As previously mentioned, the government's response faces the COVID-19 pandemic. People's behaviour has dramatically changed by the imposition of restrictions on mobility and economic activity, letting to work from home those who could and domestic and international travel severely restricted. With the application of those restrictions, people stopped driving, flying or travelling on public transport (Billio and Varotto, 2020) so the flow of people and goods has been reduced, triggering a decline in demand for energy sources (transport fuels, for instance), leading to a drop in oil prices (Ozili and Arun, 2020) or being a source of systematic risk, triggering a decline in global financial indices (Ahundjanov et al., 2020; Sharif et al., 2020).

Given this, it is not unreasonable to think that these factors have played an essential role in the shock waves of the crude oil market so, as Bakas and Triantafyllou (2020) stated, in times of higher uncertainty (as the case of a pandemic like COVID-19), supply and demand drop dramatically and gradually over time because of the rise in the price elasticity.

Similarly, in 2021, prices began to climb and recover their original pathway due to the reactivation of the economy and mobility. Otherwise, there is a blend of the planned production cuts agreed upon by OPEC and other non-OPEC producers, such as Russia. A decline in production in the United States and elsewhere due to the low prices reported per barrel the previous year translated into the explosiveness of crude oil and refined products prices

* Corresponding author.
E-mail address: antonio.golpe@dehie.uhu.es (A.A. Golpe).

https://doi.org/10.1016/j.petsci.2023.09.007

that society is experimenting nowadays. Nonetheless, and more importantly, by the beginning of 2022, the Ukraine-Russian war pushed refined product prices up to high levels. Those events provoked that in March 2022, prices first broke the record of $4.11 a gallon, which had stood since 2008. Indeed, an increasing number of gas stations nationwide are now charging more than $5 a gallon for regular, and just more than half are charging $4.75. This extreme context is bringing an undesirable situation in the economy: inflation is reaching high levels and affecting the countries in every stage of their economies (Salisu et al., 2017).

Given these facts, this paper tries to deal with the behaviour of the crude/product prices system in a novel way, capturing the sensitivity of each refined product in the face of variations in crude oil prices and, thus, assessing how different shocks could affect the price formation. Additionally, we try to dissect which crude oil, i.e., Brent or WTI, drives the relationship. Thus, as far as we know, this is the first time that a spatial model of nongeographical units (Beck et al., 2006) is applied in this topic as a nexus of union between the linkages between raw material-refined products and refined products. Methodologically, we consider the different crude oil refined products as ''locations''. The price of each product (location) has different behaviour and is influenced by the prices of other refined products. However, the structure of relationships between refined product prices may also be influenced by a common factor (crude oil prices).

Thus, different alternatives have been used in the literature to independently analyze some of these dynamics. For example, Tiwari et al. (2021) have analyzed the persistence of derivatives prices, Vides et al. (2021) have analyzed the relationship between the price of crude oil and its refined products and Martíınez et al. (2018) have analyzed the relationship between the prices of the different refined products. However, to the best of our knowledge, no work has analyzed these dynamics simultaneously in the same model. In addition, not analyzing these dynamics simultaneously can produce biased results, so a dynamic spatial panel data model with common factors is estimated for this (Vega and Elhorst, 2016), and the influence of crude oil prices is considered.

In this sense, our results show that both WTI and Brent display very similar behaviour with the refined products in terms of persistence, cross-sectional dependence and the sensitivity of each refined product to each crude oil for the full sample (2006Q2–2022Q2), being difficult to draw any conclusion about the reference role of any of these crude oils. As different events occurred in the period considered, we believe it necessary to test the existence of structural breaks by applying Bai and Perron (1998, 2003) and finding two breakpoints. Hence, we have applied our model to each regime separately, achieving interesting findings. The result derived from the first and third regimes is quite similar to the full sample results. Therefore, attending to the second regime (which matches the period between Cushing's turbulent months of 2011 and the crude oil export ban removal in 2015), Brent crude oil became the benchmark in the petrol market, and it influenced the distillate products. Furthermore, our model can let us determine the price-setters and price-followers in the price formation mechanism.

The rest of the paper is organized as follows. The following section addresses the literature regarding this topic. The methodology used for the work is described in section 3. Section 4 discusses how different dimensions of monetary policy spread through maturities and how they interact with each other. We identify the conclusions and policy implications in section 5.

2. Literature review

The economy and productive activity of the USA keep a strong dependency on fossil fuels, which represent more than 70% of its energy sources and are among the most important energy sources in the world (Martínez et al., 2018). Furthermore, crude oil and its refined products (regular gasoline, heating oil, diesel, kerosene or propane) play an important role in the global economic system and represent approximately 40% of global energy consumption. The prices of these products appear to be influenced mainly by crude oil prices and the strategies of refiners, investors, and speculators, as well as stock volumes or meteorological conditions (Tong et al., 2013; Liu and Ma, 2014). Nonetheless, crude oil and refined product prices can influence each other, so integrated and strong correlations between them are expected (Lanza et al., 2005; Zavaleta et al., 2015).

Concerning the factors that affect the behaviour of the prices of crude oil and its refined products, different drivers could be highlighted as weather conditions and seasonality, geopolitical events or changes in demand and supply of different oil components. In terms of weather conditions and seasonality (Chesnes, 2015; Oladosu, 2021), there exists a higher demand for specific refined products such as gasoline and diesel during the summer season. Otherwise, the winter season raises the demand for refined products such as diesel fuel, heating oil, or gasoline. Another factor in price formation is the effect of geopolitical matters. Throughout periods of political uncertainty and instability, there has been a drop in the oil supply (Pirog, 2005). The result is a growth in crude oil prices regarding refined products. However, the refiner's attempt to react by downsizing the supply of crude oil and refined products output plunges. Additionally, changes in foreign policy impact producers of crude oil as well as the prices of crude oil refined products (King et al., 2012).

Likewise, macroeconomic and financial decisions enclose some implications for price behaviour. Perifanis and Dagoumas (2021) have also addressed this topic by providing a review of crude oil price dynamics, summarising the factors that determine oil prices and their impact on the macroeconomy and the stock market. Thus, crude oil and currencies are linked because any change in the power of a currency can influence crude oil prices, i.e., when the value of a currency decays, crude oil prices rise. Also, a gain in the value of crude oil could suggest that the profit margins of producers using crude oil components are decreased. These cases hold implications for refiners and refineries. Whether they wish to receive a considerable differential, the price of crude oil must be significantly lower than the price of refined products. Furthermore, as Miao et al. (2017) or Lu et al. (2020) suggest, there are various factors that underlie crude oil price movements, such as supply, demand, financial market, commodities market, speculative, and political factors.

On the other hand, investors can adjust their investment strategies to benefit from the changes in the behaviour of the refined products price depending on the price and the supply of and demand for refined products. Also, central banks are worried about the price of refined products (such as gasoline) on inflation expectations and consumer spending (Yellen, 2011). Refined product prices can also help predict the income from taxes, the behaviour of the automobile market or environmental policies (Baumeister et al., 2017). Further, oil refiners and speculators launch hedging strategies not exposed to adverse price movements (Girma and Mougoue, 2002). Thus, this issue also contains important concerns for regulating and organising markets and policies. Therefore, exploring the connection between the prices of crude oil and each refined product is also important to know the margins between the output prices of the products for the petroleum industry and crude oil costs (Martínez et al., 2018). In this respect, the relationships between changes in crude oil price and each refined product price have been evaluated to understand the prevailing channel for price formation (Lahiani et al., 2017; Ederington et al., 2019b).

The empirical literature on the relationship between oil prices and refined product prices evidence that gasoline, heating oil or other refined products prices and crude oil prices move together (Ederington et al., 2019b). In this sense, Borenstein et al. (1997) influenced succeeding papers by the publication of their seminal paper and helped as a reference point to this day. The authors employ a threshold cointegration analysis and find that U.S. retail motor gasoline prices react more quickly to crude oil price increases than decreases. Nevertheless, most of the literature has focused on how the behaviour of refined product prices is due to shifts in oil prices by using the error correction model (ECM), different types of cointegration (VAR, CVAR or FCVAR model), copulas or causality tests. In this vein, a large body of literature examines how refined product prices respond to oil price increases and decreases, i.e., how refined product prices are sensitive to oil price changes (Ederington et al., 2019a). Many studies have recognized a link and sensitivity between crude oil and its refined products prices by performing different econometric techniques (Gjolberg and Johnsen, 1999; Asche et al., 2003; Hammoudeh et al., 2003; Galeotti et al., 2003; Kaufmann and Laskowski, 2005; Al-Gudhea et al., 2007; Grasso and Manera, 2007; Oladunjoye, 2008; Kaufmann et al., 2009; Douglas, 2010; Zhang et al., 2015; Kristoufek and Lunackova, 2015; Lahiani et al., 2017; Fousekis and Grigoriadis, 2017; Bagnai and Ospina, 2018; Ederington et al., 2021; Vides et al., 2021), or machine learning/AI techniques for prediction, such as the Least Absolute Shrinkage and Selection Operator (LASSO) regression method (Miao et al., 2017), Random sparse Bayesian learning joint to Variational mode decomposition (Li et al., 2021), or the combination of Bayesian models like the dynamic Bayesian structural time series model (DBSTS) with Bayesian model average (BMA), by using historical prices and google trends data (Lu et al., 2020).

The body of literature applies the spatial models by attending to geographical assumptions, following Tobler's First Law (1970), i.e., "*everything is related to everything else, but near things are more related than distant things*". To the best of our knowledge, in this paper, we apply a new methodology in the literature. The present paper uses a spatial model for non-geographical units (Beck et al., 2006) by considering the different crude oil refined products as "locations" with distances between them, measuring how the policies or any shock may spread and how the spillover behaviour between crude oil refined products and bringing important consideration to market participants regarding the behaviour of the prices of crude oil and refined products. Furthermore, our model allows us to estimate the impact of the crude oil on each refined product. Following Ederington et al. (2021), crude oil is the main input in refined product production at a more fundamental level. Consequently, oil supply disruptions can affect the price of oil and potentially the prices of the products refined from oil being the crude oil treated as a common factor. Similarly, changes in the demand for refined products, as well as changes in the capability or capacity of refiners to process crude oil, thus influencing the supply of these products, can influence the prices of these products independent of oil price changes and, consequently, the price of oil via the oil demand. We aim to explore how the relationship between the prices of two types of crude oil (WTI and Brent crude oil) and their refined products has evolved over time, i.e., by capturing the dynamics of these relationships over time.

The following Table 1 summarizes the research methods and research goals of previous studies.

3. Methodology

3.1. Data description

According to Población and Serna (2016), the refining process depends mainly on the refinery configuration, but, usually, this process converts 47% of crude oil barrels into gasoline, 24% into heating oil and diesel, 13% into jet fuel oil, 4% into heavy fuel oil and the rest into other products. Thus, as one can suppose, the prices of refined products are indistinguishably connected to the crude oil price by the technology and economics of refining. Otherwise, propane is a byproduct of the refining process, and its elaboration is shared with natural gas or oil wellhead gas at processing plants (Ederington et al., 2019b).

The data used in this article is available in three periodicities: monthly, quarterly, and annual. A great and balanced N and T are desirable for estimating panel data models. In our case study, we have 9 "locations" (N) and the possibility of using three different periodicities. Finally, we select the quarterly data that allow us to obtain an optimal number of periods for the estimates (similar to the one used by Vega and Elhorst (2016)). Additionally, selecting monthly data could limit the ability of the model to find the influences between prices since these influences may take more than a month to be reflected (Bakhat et al., 2022). The model is estimated by a quasy-maximun likelihood (QML) estimator where T cannot be too small relative to N (Elhorst, 2014). In addition, from an empirical point of view, the spillovers between crude oil prices and refined prices can take more than a month to be reflected. At the same time, a year may be a very long period to collect these relationships.

Furthermore, the US time series of prices selected correspond to WTI and Brent crude oil, conventional gasoline (NY and Gulf), RBOB regular gasoline, heating oil, ultra-low-sulphur diesel fuel (NY and Gulf), kerosene and propane. WTI and Brent indicate different segments of the crude oil market. The WTI crude oil price is mainly formed in the US domestic market, and conversely, Brent crude oil is a global price and representative of European markets. Over the last decade, WTI and Brent prices have followed large divergences. Therefore, after the removal of the US crude oil export ban, both types of crude oil are converging, narrowing the gap between them (Afkhami et al., 2017). According to Ghoddusi et al. (2021), the difference between Gulf and NY refined products is that New York harbour receives shipments of refined products from the European Union, so the price of New York harbour is linked to prices globally. In contrast, US refiners in the Midwest mostly use WTI for the refining process. Series are collected from the US Energy Information Administration (EIA). Our dataset spans the period from 2006Q2 to 2022Q2. Our sample starts in 2006 due to the availability of the data, being this point the year when we have observations for all the variables. All prices are expressed in dollars. Based on US production, prices are shown per gallon, which are converted to dollars per barrel by the equality 1 barrel = 42 US gallons to the Energy Information Administration (EIA).

In Fig. 1, we can observe the behaviour of both crude oils and refined products. In this regard, we can see that, except for propane, all the refined products follow a similar pattern to WTI and Brent crude oils.

Table 2 shows the main statistics that help us to get a global idea of the properties of each variable. Table 2 shows descriptive statistics associated with each petroleum product. We can see the similar behaviour of WTI and Brent and the wide range between the prices for the whole period.

This similar behaviour in prices reveals that they have a specific relationship. This relationship may be because the prices of each product individually influence each other (commonly known as weak cross-sectional dependence) or because there is a common factor that affects all of them (known as strong cross-sectional dependence). To statistically test the presence and type of cross-sectional dependence present in our data panel, we used the CD-test developed by Frees (1995) and Pesaran (2015). The first one

Table 1
Summary of the literature review.

Author	Data sample	Country	Technique	Results
Borenstein et al. (1997)	March 1986 –December 1992	USA	Cointegration	When crude oil prices fluctuate, i.e., increase or decrease, the response of the gasoline prices is asymmetric.
Gjolberg and Johnsen (1999)	January 1992 –August 1998	USA	ECM	All refined products, possibly excluding heavy fuel oil, prices are co-integrated with the crude price. Having estimated two simple error correction models, we find that the current product-crude margin deviations from a long-run equilibrium may contain significant information about the future changes in product prices and margins.
Girma and Mougoue (2002)	December 1984 –November 1999	USA	GARCH	They find that the contemporaneous weighted average of volume and open interest have significant explanatory power for futures spreads volatility when entered separately. They also show that the lagged weighted average volume and lagged open interest provide a significant explanation for futures spread volatility, suggesting a degree of market inefficiency in petroleum futures spreads.
Asche et al. (2003)	January 1992 –November 2000	USA	Cointegration	In the long run, changes in crude oil prices feed through to these refined product prices, while the reverse is not true. Given that the crude oil price seems to determine these prices, this also provides an example of supply-driven market integration.
Hammoudeh et al. (2003)		USA	Cointegration, Vector ECM and ARCH/GARCH	They suggest a bidirectional causal relationship between daily crude oil and gasoline prices. He also evidences a unidirectional causality from crude oil price to heating oil.
Galeotti et al. (2003)	January 1985 –June 2000	Germany, France, the UK, Italy and Spain	ECM	The results of the estimated parameters generally point to widespread differences both in adjustment speeds and short-run elasticities when input prices rise or fall. This appears to confirm the common perception amply echoed by newspapers in periods of increasing international oil prices of more rapid price increases relative to price reductions.
Kaufmann and Laskowski (2005)	January 1986 –December 2002	USA	ECM	An asymmetric relation between crude oil and motor gasoline is explained by refinery utilization rates and inventory behaviour. Additionally, the asymmetric relation between crude oil and heating oil may be produced by contractual arrangements between retailers and consumers. Indeed, these results would suggest that price asymmetries might be caused by efficient markets.
Lanza et al. (2005)	1994–2002	Europe and Americas	ECM	They find, by using ten series of crude oil prices and fourteen series of refined product prices, that the long-run relationship between the crude oil and refined product prices is specific to each product area and that the market price is the driving variable of the crude price in the short run, regardless of the specific area. Nonetheless, crude oil and refined product prices can influence each other, so integrated and strong correlations between them are expected.
Grasso and Manera (2007)	1985–2003	France, Germany, Italy, Spain and the UK	Symmetric ECM, threshold ECM, and ECM with threshold cointegration	The type of stages and the number of countries that are characterized by asymmetric oil–gasoline price relations vary across models.
Al-Gudhea et al. (2007)	December 1998–January 2004	USA	Asetof cointegration and error correction methods with nonlinear adjustment	They show that, in a vector error correction framework, above-threshold shocks may be corrected in a fundamentally different way than below-threshold shocks. Instead of tracing the response of the retail gasoline price to a $1 crude oil price shock, they contrast the response of the retail price to a "typical" crude oil price shock of historical size and an "unusually large" crude oil price shock.
Oladunjoye (2008)	1 June 1987 –30 December 2004	USA	ECM	He shows that market concentration has an insignificant asymmetric effect on the speed of price adjustment but a significant asymmetric effect on short-run price adjustments in the response of wholesale gasoline prices to crude price shocks in three U.S. wholesale markets. Additionally, the signs on the coefficients of market concentration effects on price dynamics in the models support the assertion that increased market concentration leads to downward price stickiness in only one of the three markets examined. In sum, the results indicate that market structure does not have a strong effect on the dynamics of price adjustment.
Kaufmann et al. (2009)	25 February 1994–15 September 2006	USA	ECM	They show that shifts in prices of refined products do not affect crude oil prices. Hence, changes in the demand for a given refined product have effects on the product mix of refined products and, thus, the demand for crude oil, creating a situation in which excess demand may result in rising prices.
Douglas (2010)	August 1990 –May 2008	USA	Threshold autoregressive model for the error-correction term	He evidences that retail gasoline prices exhibit asymmetric price adjustment.
King et al. (2012)	Daily 2007 –2008	USA	Granger causality	They find that fundamental supply and demand factors, including OPEC decisions and the multiple factors reflected in inventory levels, influenced oil prices. Furthermore, they show that political events, including violence and threats of violence in oil-producing regions, were associated with the largest share of day-to-day oil price changes during the 2007–2008 price run-up period. Finally, they cannot provide evidence that changes in aggregate positions of managed money traders or commodity swap dealers (categories often labelled

Table 1 (*continued*)

Author	Data sample	Country	Technique	Results
				"speculators") caused changes in oil prices during the "price run-up" period from mid-2007 to mid-2008.
Zhang et al. (2015)	19 April 1996 –4 March 2011	USA	Threshold VECM	They show that nonlinear correlations are stronger in the long term than in the short term. Crude oil and product prices are cointegrated, and the financial crisis in 2007–2008 caused a structural break in the cointegrating relationship. Additionally, they reveal that the relationships are almost symmetric based on a threshold ECM. Most of the time, crude oil prices play a major role in the adjustment process of the long-term equilibrium. However, refined product prices dominated crude oil prices during the period of the financial crisis.
Zavaleta et al. (2015)	May 1987 –September 2010	USA and Europe	Cointegration	Econometric evidence supports the hypothesis that the US and European markets for oil and refined products are integrated. The evidence that a structural break during the financial crisis of 2008 changed the long-run equilibrium price relationships and the short-run price dynamics.
Kristoufek and Lunackova (2015)	8 January 1996 –19 May 2014	Belgium, France, Germany, Italy, the Netherlands, the UK and the USA	Cointegration and fractional integration	They find that the gasoline markets are cointegrated with crude oil. However, they also evidence that gasoline prices return to their long-run equilibrium very slowly. Specifically, they show that such dynamics can be attributed to long-term correlations and, hence, the Joseph effect rather than to the rapidly adjusting error correction model.
Miao et al. (2017)	4 January 2002 –25 September 2015	USA	Least Absolute Shrinkage and Selection Operator (LASSO)	They employ weekly data and classify variables along six wide factor dimensions: supply, demand, financial market, commodities market, speculative, and political factors. Purposely, they apply the LASSO method to generate out-of-sample forecasts. Their findings suggest that the LASSO method yields superior forecasts, as observed by reductions in the mean squared prediction error relative to various benchmark models such as the no-change forecast, EIA projections and futures market predictions. Furthermore, they specify insights into the temporal relationship between various influential factors and crude oil prices.
Baumeister et al. (2017)	1996–2016	USA	Mean-squared prediction error (MSPE), VAR model, factor augmented VAR	When using a MSPE model, they show that as much as 39% of the widely discussed decline in the retail price of gasoline after June 2014 was predictable, but only when using a VAR model of the global market for crude oil augmented with the US price of gasoline
Lahiani et al. (2017)	January 1997 –October 2015	USA	Quantile Autoregressive Distributed Lags (QARDL) model	Two key findings emerge from this paper. First, all considered energy prices are shown to be cointegrated with oil prices across quantiles, meaning that a stationary equilibrium relationship exists between a single energy price and oil price. Second, they evidence that oil price is a significant predictor of individual petroleum products prices and natural gas in the short run.
Fousekis and Grigoriadis (2017)	3 January 2006 –31 March 2017	USA	ARMA-GARCH models	They find that future prices of crude oil and of reformulated gasoline tended to go up or down together, and the futures prices of crude oil and heating oil tended to go up or down together. In the long run, price co-movement for both the crude oil and re-formulated gasoline and the crude oil and heating oil pairs becomes perfect in the sense that a 1% shock in a given market is associated with a 1% shock in the other, and co-movement with respect to the sign of price shocks is symmetric.
Martínez et al. (2018)	14 June 2006 –16 February 2017	USA	Wavelet local multiple correlation	They find that the wavelet correlations are strong throughout the period studied and show a strong decline in correlation values from 2013 to 2015 (due to the overproduction of tight oil in the U.S. and a slowdown in global demand for oil) when seven commodities (crude oil -WTI- and six refined products-conventional gasoline, RBOB regular gasoline, heating oil, ultra-low-sulphur diesel fuel, kerosene and propane) are analyzed.
Bagnai and Ospina (2018)	January 1983 –December 2015	USA	Threshold auto-regressive distributed-lag (ARDL) model	Their results confirm the persistent presence of asymmetries and the importance of the structural break that occurred in the second half of 2008. The evidence is that while the adjustment process was characterized by short-run negative asymmetry and long-run symmetry before 2008:10, after the structural break, the nature of asymmetry changed: short-run adjustments somehow became symmetric, while in the long run, mild changes show negative asymmetry and extreme regimes show positive asymmetry.
Lu et al. (2020)	January 2004 –December 2017	USA	Dynamic Bayesian structural time series model (DB-STS) and the Bayesian model average (BMA)	They provide some contributions to the oil prices field of study and further analyze the current oil market and the changes of various influence forces on the oil price. They also use Google trend data as one of the influencing factors and optimize the existing economic indicators for building a new forecast system.
Ederington et al. (2021)	24 June 1988 –26 April 2019	USA	Granger causality	They cannot evidence Granger causality from product prices to oil prices is found for the full sample period nor the period up to the end of 2005, but evidence that gasoline prices Granger-caused oil prices are found for post-2005. Similar results are found for an extended

(*continued on next page*)

Table 1 (*continued*)

Author	Data sample	Country	Technique	Results
				model that also includes potentially endogenous real market variables related to supply and demand in the oil, heating oil and gasoline markets.
Vides et al. (2021)	16 June 2006 –29 January 2021	USA	FCVAR model	The evidence that the order of integration of the crack spread displays a long memory process. Finally, by attending to the coefficient adjustments, supply-driven market integration is given. Additionally, the Ver-leger hypothesis is rejected for all refined products, corroborated by the component share.

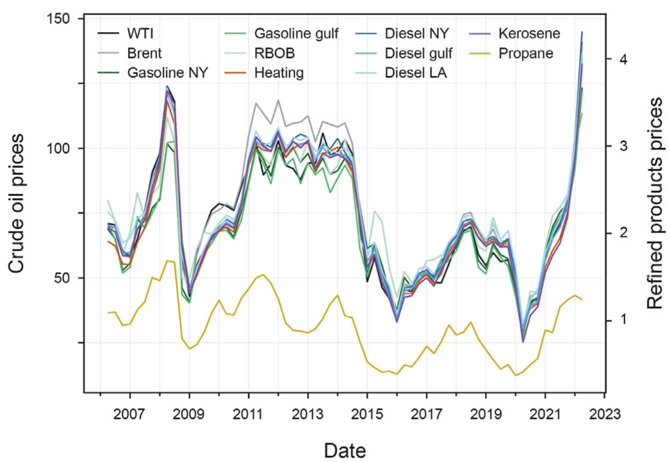

Fig. 1. Dynamics of the US petroleum market.

Table 2
Descriptive statistics for the data.

Product	Mean	Median	S.D.	Min	Max
WTI	71.758	69.757	22.538	27.807	123.953
Brent	76.420	69.620	25.263	29.343	121.397
Gasoline NY	2.096	2.047	0.611	0.863	3.701
Gasoline Gulf	2.042	1.950	0.607	0.823	3.660
RBOB	2.243	2.176	0.611	0.934	3.904
Heating	2.147	1.959	0.698	0.923	4.232
Diesel NY	2.236	2.087	0.707	0.964	4.350
Diesel Gulf	2.183	2.077	0.691	0.908	4.058
Diesel LA	2.257	2.151	0.680	0.972	4.106
Kerosene	2.149	2.032	0.711	0.758	3.979
Propane	0.935	0.911	0.348	0.373	1.701

Notes: The data spans from 2006Q2 to 2022Q2.

follows a chi-square distribution with T-1 degrees of freedom and measures whether the degree of cross-sectional dependence is zero or positive. On the other hand, Pesaran's CD statistic follows a standard normal distribution and measures whether the degree is weak (null hypothesis) or strong (alternative hypothesis). Both tests are independent of the weight matrix specified in the next section.

The results of the tests applied to the complete panel show a value of 539.71 for Frees' CD-test and 13.35 for Pesaran's CD-test, with p-values being 0.00 in both cases. These results suggest a strong cross-sectional dependence justifying the estimation of a model that considers the relationships between prices and the common factor that affects all prices. A dynamic spatial panel data model with common factors.

3.2. Model

As previously mentioned in the literature review section, several studies have explored how crude oil price influences the prices of refined products. This generates a cross-sectional correlation, which implies that part of the variations we observe in their prices are due to variations in the prices of other derivatives. In addition, many works also find that the prices are persistent over time, that is, part of their variations are explained by the prices of previous periods. Furthermore, as explained before, refined product prices are related to oil prices. In this sense, any model that attempts to model variations in price formation of refined products must take into account the cross-sectional dependence and persistence.

In our case, we add the WTI and Brent to the model to find out its influence on its refined products. To do so, these products must be modelled as a variable that varies in each period but is the same for the different prices of each refined product; that is, it can influence all of them. To model the dynamics found in this relation, as well as the influence of the WTI or Brent on different refined products, we use a recent model developed by Vega and Elhorst (2016).

This model comes from the spatial econometrics literature and, to the best of our knowledge, is the first to consider simultaneously the cross-sectional dependence and persistence of a variable (each refined product) observed in different places (type of refined product, in our case) at different points of time, in addition to including common factors, variables that affect all places where the analyzed variable is measured (the WTI and Brent in our case study). The Vega and Elhorst (2016) model, which simultaneously accounts for serial dynamics, cross-sectional dependence, and common factors, is an extension of the Bailey et al. (2016) two-stage method that outperforms analyses done independently or sequentially. The model read as follows:

$$RP_t = \tau\, RP_{t-1} + \delta\, WRP_t + \eta\, WRP_{t-1} + \Gamma_1\, \mathrm{CO}_t + \mu + \varepsilon_t \quad (1)$$

where RP_t is a column vector with one observation of the dependent variable (RP) for each refined product (i) at every point at a time. RP_{t-1}, WRP_t and WRP_{t-1} are vectors of temporal, cross-sectional and cross-sectional temporal lags, respectively, with τ, δ and η autoregressive coefficients.

W is the row-normalized connectivity matrix setting the relation structure of the different refined product prices, which will be explained later. CO_t is the crude oil (WTI or Brent in our specific analysis) and Γ_1 column vector with unit-specified coefficients of response to the common factor, that is, an individual coefficient for every refined product price of response to the WTI or Brent.

μ represents the cross-sectional fixed effect added to the model, and ε_t is the Nx1 vector independently and identically distributed error term with zero mean and constant variance σ^2.

The parameter of the sensitivity of each maturity rate to the WTI or Brent (γ) can be estimated by dividing the elements of Γ_1 by $1-\delta$.

This model allows us to simultaneously estimate the persistence of the RP, the influence between the different refined products and, finally, how changes in the WTI or Brent affect each refined product. Other alternative models have been estimated, producing similar results in the parameters, however, to the best of our knowledge, the selected model is the only one that allows the simultaneous estimation of the three mentioned dynamics.

3.2.1. Cross-sectional dependence and weight matrices

A significant cross-sectional dependence parameter implies that the price of each refined product can be explained by the other refined products with which it is related. If this parameter is positive, it reflects a positive cross-sectional dependence, which implies that if the price of a given refined product that influences a certain price grows, it will also grow. On the contrary, if this influence is negative, it implies that if the price of the refined product that influences a certain maturity grows, it will do the opposite. In general terms, a positive cross-sectional dependence would imply that all prices have similar behaviour and are aligned. Otherwise, a negative cross-sectional dependence would imply that the different prices have an antagonistic behaviour.

As stated above, the cross-sectional dependence will be influenced by the relationship established between the different refined products. This relationship determined in the weight matrix ($\boldsymbol{W}$), as established in the literature, must be pre-specified and symmetrical (Dahlhaus et al., 2021). In the spatial econometrics literature, the weight matrix can be defined by economic or geographic distance. However, in our case, we must define the relationship between different prices of the crude oil's refined products.

To determine the weight matrix in our model, we follow the approach of Fernandez (2011) that states that the element *(i, j)* of the distance matrix is given by the Euclidean distance d_{ij}, between the elements. This distance is calculated by Eq. (2):

$$d_{ij} = \sqrt{2(1-\rho_{ij})} \tag{2}$$

where ρ_{ij} is the Spearman's correlation coefficient. Given that, the weight matrix that we use in our model ($\boldsymbol{W}_1$) is defined as

$$\boldsymbol{W}_1 = \exp(-d_{ij}) \tag{3}$$

and it is row-standardized, as usual in the literature of spatial econometrics. In this matrix, more distant prices receive smaller weights.

3.2.2. Persistence

The habit of persistence is added to the model through the inclusion of temporal lag RP_{t-1}, and cross-sectional temporal lag WRP_{t-1}. This makes our model dynamic, that is, it takes into account the persistent habit of petroleum products.

The τ parameter represents what Korniotis (2010) interprets as the coefficient of external habit persistence, which reflects the time that a given price of the refined product takes to pick up information from other maturities. Elhorst (2010) shows that imposing $\eta = -\tau\delta$, an empirical regularity in this model (Parent and LeSage, 2010, 2011), the impact of a change will gradually diminish over space (refined products) and time, which is expected in our case study.

3.2.3. Common factors

One of the main benefits of using this model in our case study is that it allows us to estimate the sensitivity parameter of each refined product to changes in the WTI or Brent, which can be a measure of the price formation of these commodities.

This parameter can be estimated by including the WTI or Brent in the model for each period analyzed, modelled as a common factor. In our model, we include the WTI or Brent from the same time CO_t. To obtain this sensitivity parameter, it is necessary to apply a transformation to the estimated parameters in Γ_1 (Vega and Elhorst, 2016):

$$\gamma_1 = \Gamma_1/(1-\delta) \tag{4}$$

The parameter γ can be interpreted as the sensitivity of each refined product to changes in the crude oil. Finally, following Vega and Elhorst (2016), a given refined product turns out to be price-setters if $\gamma < 1$, and price-followers if $\gamma > 1$.

4. Empirical results

This section shows the results of applying the spatial panel model to assess the price formation of crude oil's refined products to changes in the WTI or Brent by accounting for persistence, cross-sectional dependence, and common factors. The model with one and two common factors (one of them lagged one period) has been estimated, however, based on the log-likelihood, the model finally selected is the one with a single common factor in the same period of time (t). The application of the spatial panel model, which is a new procedure in this literature, is summarised in Table 3.

Table 4 shows the general information on the behaviour of the crude oils selected, i.e., WTI and Brent, for the full sample (2006Q2–2022Q2). First, the estimated results with both crude oils are very similar. Concerning the persistence parameter τ, it shows a high persistence for both products with $\tau > 0.500$ in both estimated results. In the same way, the cross-sectional dependence parameter measures the spillovers that occur between different refined products on average. The results show a high cross-sectional dependence $\delta > 0.70$, which reflects that the different refined products influence each other, that is, they follow a similar dynamic. The cross-sectional persistence parameter η is interpreted as the external habit of persistence (Elhorst, 2021) for an extensive review of this parameter. In our model, this parameter follows an empirical regularity of $\eta = -\tau\delta$ that Parent and LeSage (2010, 2011) show that imposing this parameter constraint might avoid over-identification problems. Thus, it is difficult to identify which of both crude oils is the benchmark in the market. Furthermore, attending to the sensitivity to common factors, as we explained in the methodology section, we can differentiate price-setters and price-followers depending on the value of γ. In the case at hand, both types of gasoline (NY and Gulf, respectively) and RBOB would be the price-setters and, on the other hand, the rest of refined products as price-followers, which makes sense attending to the refining mix and the crack spread (EIA, 2014b).

This similarity shown in the previous table looking at both crude oils may be explained by the behaviour of both crude oils has been similar over time. However, the existence of different shocks during the time that elapses in our sample brings us to explore the existence of structural breaks to account for which of both crude oil has acted as a benchmark (see Fig. 2). Thus, we now apply the test for structural breaks proposed by Bai and Perron (2003) with a 20% trimming, which limits the maximum number of breaks allowed under the alternative hypothesis to 3. Among the breaks identified, the first breakpoint (2010:4) could be identified as the beginning of the turbulent months of 2011, when Cushing Oklahoma had reached capacity due to US crude oil production exceeding and surplus of its regular production (780,000 barrels per day) joint to the difficulties in transporting WTI-priced oils from Cushing to Gulf Coast (Afkhami et al., 2017) for a deep discussion of the issue. This implied that when WTI prices first moved to a significant discount to Brent prices, it offered a useful breakpoint for testing crude oil-gasoline price relationships. EIA (2014b) also justified the statistical significance of establishing January 2011 as a breakpoint for the data series. The second breakpoint (2014:3) may be explained by the crude oil export ban removal in 2015 (Ghoddusi et al., 2021). These results confirm those that can be seen in the behaviour of the

Table 3
Strategy of empirical research.

Procedure	Parameter	Hypotheses
Persistence	τ	Are the crude oil prices persistent over time?
Cross-sectional dependence	δ	Does each refined product influence the others?
Model stability	η	Is the estimated model stable?
Sensitivity to common factor	γ	How do changes in crude oil prices affect refined product price formation?

Table 4
Full sample.

	Crude oil benchmark	
	WTI	Brent
τ	0.567	0.531
	(0.000)	(0.000)
δ	0.757	0.768
	(0.000)	(0.000)
η	−0.524	−0.489
	(0.000)	(0.000)
Sensitivity to common factors		
Gasoline NY	0.834	0.823
	(0.000)	(0.000)
Gasoline Gulf	0.839	0.806
	(0.000)	(0.000)
RBOB	0.794	0.786
	(0.000)	(0.000)
Heating	1.253	1.208
	(0.000)	(0.000)
Diesel NY	1.299	1.245
	(0.000)	(0.000)
Diesel Gulf	1.240	1.194
	(0.000)	(0.000)
Diesel LA	1.191	1.151
	(0.000)	(0.000)
Kerosene	1.379	1.323
	(0.000)	(0.000)
Propane	−0.586	−0.69
	(0.000)	(0.005)

Notes: The *p*-values are reported in parentheses.

variables shown in Fig. 2 and they are in line with those obtained by Caporin et al. (2019).

As can be observed in Table 6, in general terms, the results obtained are quite similar to those obtained in the full sample. Regarding the persistence parameter, we can see how it increases over time, which holds important considerations for investors, refiners and policymakers. Therefore, attending to each period, we can find a significantly different behaviour. In this sense, period 1 and period 3 display a similar pattern compared to the findings achieved in the full sample (see Table 4). Focusing on the second period (2011Q1–2014Q3), as mentioned, this is characterized by a divergent period concerning the behaviour of both crude oil prices. Following Caporin et al. (2019), the price trend reversed, and Brent started to be the leader in the relationship at a global level, indicating that the two crude oils are not fully integrated in this period.

Table 6
Sensitivity along periods.

	Crude oil benchmark					
	2006Q2–2010Q4		2011Q1–2014Q3		2014Q4–2022Q2	
	WTI	Brent	WTI	Brent	WTI	Brent
τ	0.352	0.374	0.562	0.648	0.649	0.630
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
δ	0.719	0.676	0.681	**0.200**	0.670	0.786
	(0.000)	(0.000)	(0.000)	**(0.145)**	(0.000)	(0.000)
η	−0.338	−0.343	−0.633	−0.658	−0.566	0.825
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sensitivity to common factors						
Gasoline NY	0.664	0.743	**0.898**	1.052	1.020	0.815
	(0.004)	(0.001)	**(0.271)**	(0.002)	(0.000)	(0.001)
Gasoline Gulf	0.847	0.913	1.377	1.132	1.008	0.815
	(0.000)	(0.000)	(0.058)	(0.001)	(0.000)	(0.000)
RBOB	0.544	0.644	**0.981**	1.109	1.171	1.127
	(0.000)	(0.004)	**(0.169)**	(0.002)	(0.000)	(0.000)
Heating	1.374	1.331	**−0.472**	0.946	1.597	1.702
	(0.000)	(0.000)	**(0.440)**	(0.003)	(0.000)	(0.000)
Diesel NY	1.439	1.393	**−0.683**	0.739	1.631	1.749
	(0.000)	(0.000)	**(0.278)**	(0.020)	(0.000)	(0.000)
Diesel Gulf	1.411	1.373	**−0.245**	0.811	1.395	1.423
	(0.000)	(0.000)	**(0.642)**	(0.011)	(0.000)	(0.000)
Diesel LA	1.333	1.311	**0.216**	0.809	1.396	1.437
	(0.000)	(0.000)	**(0.819)**	(0.010)	(0.000)	(0.000)
Kerosene	1.600	1.540	**0.035**	0.980	1.433	1.480
	(0.000)	(0.000)	**(0.899)**	(0.002)	(0.000)	(0.000)
Propane	−0.407	**−0.259**	**−1.029**	**−0.058**	−0.836	−1.873
	(0.067)	**(0.214)**	**(0.258)**	**(0.635)**	(0.000)	(0.001)

Notes: The p-values are reported in parentheses. Bold indicates no significance.

So, WTI can no longer be considered a crude oil price benchmark in the USA (see Kao and Wan (2012) or Fattouh (2011), for instance).

Furthermore, according to our results, we can highlight that each type of refined product has lost its sensitivity to WTI, except the gasoline Gulf. This behaviour can be explained because of the proximity of this type of gasoline to the refining plant, as well as the competitive advantage of Gulf coast refineries in the dynamics of gasoline pricing. As we can see, recalling that this is a divergent period, every refined product price is statistically significant concerning Brent crude oil. This could be a signal that Brent has become the benchmark in the US crude oil refined product price formation mechanism. As we can see in Fig. 2, it can be observed some episodes of divergence in the behaviour of both crude oils. In this Fig. 2, we can see a vertical dashed line, which corresponds to the second regime determined in Table 5.

Table 5
Bai-Perron tests of multiple structural changes in the crude oil market.

Statistics						
UDmax	WDmax	$SupF_t$ (1)	$SupF_t$ (2)	$SupF_t$ (3)	$SupF_t$ (2/1)	$SupF_t$ (3/2)
98.455***	178.656***	46.940***	81.815***	98.455***	300.601***	6.123
Break dates estimates						
T_1		2010:4			[2010:1–2012:1]	
T_2		2014:3			[2013:4–2016:1]	

*, **, and *** denote significance at the 10, 5 and 1% levels, respectively. The critical values are taken from Bai and Perron (1998), Tables 1 and 2, and from Bai and Perron (2003), Tables 1 and 2 The number of breaks has been determined according to the sequential procedure of Bai and Perron (1998) at the 1% size for the sequential test. 90% confidence intervals for T_1 in square brackets.

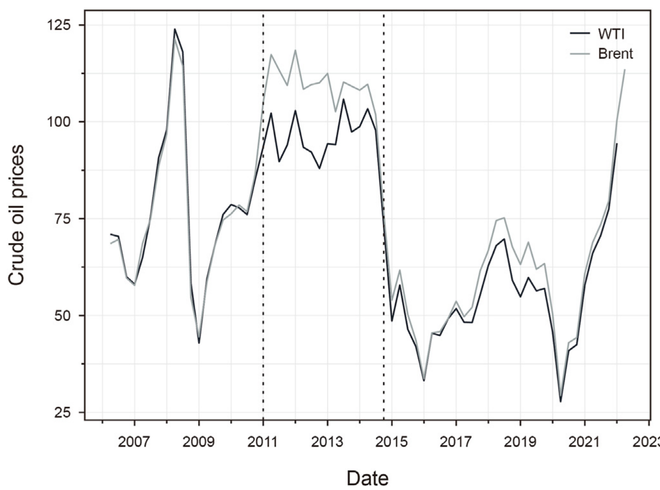

Fig. 2. Dynamics of WTI and Brent crude oil.

These results are in line with Caro et al. (2020) and EIA (2014a), that is, Brent crude oil price possesses more explanatory power than WTI crude oil price for the 2011–2014 period. Therefore, the WTI price loses considerable explanatory power from the period 2000–2010 to the period 2011–2014. Conversely, WTI crude oil prices have more explanatory power for the period 2000–2010. Prior to 2010, there were not enough reasons to suggest which crude oil price was more important concerning effects on domestic gasoline prices, as the two benchmarks traded at similar prices (EIA, 2014b).

Finally, Table 7 provides a summary of the findings obtained throughout the empirical results section. In this table, we also present data that are valuable to highlight.

5. Conclusion and policy implications

This paper examines the behaviour of crude oil and its refined product prices by employing the spatial panel model that accounts for serial dynamics, cross-sectional dependence, and common factors simultaneously (Vega and Elhorst, 2016). This procedure aims to analyze the sensitivity of each refined product in the face of variations in crude oil prices and, thus, assess how different shocks could affect the price formation. As we know, during the time period considered in our analysis, some production and logistics troubles emerged in the US crude oil market, such as the turbulent months of 2011, when Cushing Oklahoma had reached capacity and the difficulties in transporting WTI oils from Cushing to Gulf Coast (Afkhami et al., 2017). These events finished when the crude oil export ban was removed in 2015 and let us explore the existence of structural breaks in our dataset and execute the same exercise for each resulting regime. Hence, the aim of this paper is to explore the relationship between the dynamic of two types of crude oil prices (WTI and Brent crude oil) and their refined products over time and, subsequently, check which crude oil is the benchmark in price formation.

Indeed, attending to the obtained results, we find persistence in the relations amongst both types of crude oil and refined products and, hence, in the application of measures by refiners and, subsequently, by the monetary authorities. From an economic point of view, when a shock is spread over a given variable, the concept of persistence would imply a more prolonged effect on the variable in question, that is, an eventual shock tends to disappear slower because there is more time to respond to changes in the price behaviour. Therefore, in our case, when structural breaks are examined, we find more persistence over time, which seems that there would be created more inefficiencies in the crude oil market (Gil-Alana and Monge, 2021). This persistence would have an impact on economic activity, and such shocks could be transmitted to other sectors of the economy, affecting in different ways, such as a negative effect on economic growth or prices. In this sense, strong policy measures are required to recover the original trends of the series (Barros et al., 2011). Furthermore, as indicated in the Introduction section, the price of energy products such as crude oil and refined products affects inflation. Thus, attending to this nexus, the monetary authority would find it difficult to diminish high inflation levels because this persistence could send erroneous signals to the monetary policy authority, which could feel the necessity to influence interest rates to alleviate the impact of oil prices on the economy (Gil-Alana and Gupta, 2014).

For the above, it seems necessary to monitor the Brent crude oil for a few reasons. First, as we have demonstrated, since Cushing's turbulent months, Brent crude oil became the benchmark in the price formation of petrol products. In this sense, investors should guide their hedging strategies, and banks should incorporate them into their forecasts (Caro et al., 2020). Second, it seems clear that the Brent price affects the price formation of refined products, so refiners must take into account the behaviour of this crude oil to establish an optimal refining mix, which is important to contemplate the differences or margins (or crack spread) between the prices of distilled products for petroleum industry refiners and crude oil costs (Martínez et al., 2018). Finally, in line with the prior, we have shown two types of patterns in the sensitivity of each refined product to each crude oil, i.e., the price-setters (gasoline NY and Gulf) and the price-followers (the rest of refined products). Given this result, one could suggest that demand and supply may force alter the price formation mechanism so that when there are high peaks of demand for gasoline (such as during the post-COVID-19 lockdown period), rocketing the prices, affecting the rest of the products and, as abovementioned, altering the whole economy.

Conflict of interest and authorship conformation form

All authors have participated in (a) conception and design, or analysis and interpretation of the data; (b) drafting the article or revising it critically for important intellectual content; and (c) approval of the final version. This manuscript has not been submitted to, nor is under review at, another journal or other publishing venue. The authors have no affiliation with any organization with a direct or indirect financial interest in the subject matter discussed in the manuscript.

Table 7
Summary of empirical results.

Procedure	Parameter	Hypotheses
Persistence	τ	Crude oil price persistence has increased over time.
Cross-sectional dependence	δ	Each refined product influences each other's in the full sample and in each regime.
Model stability	η	The estimated model is stable over space and time.
Sensitivity to common factor	γ	There is no crude oil benchmark when analyzing the full sample.
		Attending to the breakpoints, Brent crude oil became the benchmark.

References

Afkhami, M., Kunst, R.M., Ghoddusi, H., 2017. A dynamic relationship between crude oil and refined products prices. SSRN Elecronic J. Available at SSRN 2991633. https://doi.org/10.2139/ssrn.2991633.

Ahundjanov, B.B., Akhundjanov, S.B., Okhunjanov, B.B., 2020. Information search and financial markets under COVID-19. Entropy 22 (7), 791. https://doi.org/10.3390/e22070791.

Al-Gudhea, S., Kenc, T., Dibooglu, S., 2007. Do retail gasoline prices rise more readily than they fall?: a threshold cointegration approach. J. Econ. Bus. 59 (6), 560–574. https://doi.org/10.1016/j.jeconbus.2006.10.002.

Albulescu, C., 2020. Coronavirus and oil price crash. SSRN Elecronic J. https://doi.org/10.2139/ssrn.3553452.

Asche, F., Gjølberg, O., Völker, T., 2003. Price relationships in the petroleum market: an analysis of crude oil and refined product prices. Energy Econ. 25 (3), 289–301. https://doi.org/10.1016/S0140-9883(02)00110-X.

Bagnai, A., Ospina, C.A.M., 2018. Asymmetries, outliers and structural stability in the US gasoline market. Energy Econ. 69, 250–260. https://doi.org/10.1016/j.eneco.2017.11.014.

Bai, J., Perron, P., 1998. Estimating and testing linear models with multiple structural changes. Econometrica 66 (1), 47–78. https://doi.org/10.2307/2998540.

Bai, J., Perron, P., 2003. Computation and analysis of multiple structural change models. J. Appl. Econom. 18 (1), 1–22. https://doi.org/10.1002/jae.659.

Bailey, N., Holly, S., Pesaran, M.H., 2016. A two-stage approach to spatitemporal analysis with strong and weak cross-sectional dependence. J. Appl. Econom. 31 (1), 249–280. https://doi.org/10.1002/jae.2468.

Bakas, D., Triantafyllou, A., 2020. Commodity price volatility and the economic uncertainty of pandemics. Econ. Lett. 193, 109283. https://doi.org/10.1016/j.econlet.2020.109283.

Bakhat, M., Rosselló, J., Sansó, A., 2022. Price transmission between oil and gasoline and diesel: a new measure for evaluating time asymmetries. Energy Econ. 106, 105766. https://doi.org/10.1016/j.eneco.2021.105766.

Barros, C.P., Gil-Alana, L.A., Payne, J.E., 2011. An analysis of oil production by opec countries: persistence, breaks, and outliers. Energy Pol. 39 (1), 442–453. https://doi.org/10.1016/j.enpol.2010.10.024.

Baumeister, C., Kilian, L., Lee, T.K., 2017. Inside the crystal ball: new approaches to predicting the gasoline price at the pump. J. Appl. Econom. 32 (2), 275–295. https://doi.org/10.1002/jae.2510.

Beck, N., Gleditsch, K.S., Beardsley, K., 2006. Space is more than geography: using spatial econometrics in the study of political economy. Int. Stud. Q. 50 (1), 27–44. https://doi.org/10.1111/j.1468-2478.2006.00391.x.

Billio, M., Varotto, S., 2020. A New World Post COVID-19: Lessons for Business, the Finance Industry and Policy Makers. Venezia Edizioni Ca'Foscari-Digital Publishing. https://doi.org/10.2139/ssrn.3665230.

Borenstein, S., Cameron, A.C., Gilbert, R., 1997. Do gasoline prices respond asymmetrically to crude oil price changes? Q. J. Econ. 112 (1), 305–339. https://doi.org/10.1162/003355397555118.

Caporin, M., Fontini, F., Talebbeydokhti, E., 2019. Testing persistence of wti and brent long-run relationship after the shale oil supply shock. Energy Econ. 79, 21–31. https://doi.org/10.1016/j.eneco.2018.08.022.

Caro, J.M.B., Golpe, A.A., Iglesias, J., Vides, J.C., 2020. A new way of measuring the wti–brent spread. globalization, shock persistence and common trends. Energy Econ. 85, 104546. https://doi.org/10.1016/j.eneco.2019.104546.

Chesnes, M., 2015. The impact of outages on prices and investment in the US oil refining industry. Energy Econ. 50, 324–336. https://doi.org/10.1016/j.eneco.2015.05.008.

Dahlhaus, T., Schaumburg, J., Sekhposyan, T., 2021. Networking the Yield Curve: Implications for Monetary Policy. Bank of Canada. Technical report. https://doi.org/10.2139/ssrn.3807229.

Douglas, C.C., 2010. Do gasoline prices exhibit asymmetry? not usually. Energy Econ. 32 (4), 918–925. https://doi.org/10.1016/j.eneco.2009.12.002.

Ederington, L.H., Fernando, C.S., Hoelscher, S.A., Lee, T.K., Linn, S.C., 2019a. Characteristics of petroleum product prices: a survey. J. Commod. Mark. 14, 1–15. https://doi.org/10.1016/j.jcomm.2018.09.002.

Ederington, L.H., Fernando, C.S., Hoelscher, S.A., Lee, T.K., Linn, S.C., 2019b. A review of the evidence on the relation between crude oil prices and petroleum product prices. J. Commod. Mark. 13, 1–15. https://doi.org/10.1016/j.jcomm.2018.09.002.

Ederington, L.H., Fernando, C.S., Lee, T.K., Linn, S.C., Zhang, H., 2021. The relation between petroleum product prices and crude oil prices. Energy Econ. 94, 105079. https://doi.org/10.1016/j.eneco.2020.105079.

EIA, 2014a. U.S. Gasoline Prices Move with Brent rather than WTI Crude Oil.

EIA, 2014b. What Drives U.S. Gasoline Prices.

Elhorst, J.P., 2010. Applied spatial econometrics: raising the bar. Spatial Econ. Anal. 5 (1), 9–28. https://doi.org/10.1080/17421770903541772.

Elhorst, J.P., 2014. Spatial Panel Data Models. Spatial Econometrics. Springer, pp. 37–93. https://doi.org/10.1007/978-3-642-40340-8_3.

Elhorst, J.P., 2021. The dynamic general nesting spatial econometric model for spatial panels with common factors: further raising the bar. Rev. Reg. Res. 1–19. https://doi.org/10.1007/s10037-021-00163-w.

Fattouh, B., 2011. An Anatomy of the Crude Oil Pricing System. Oxford institute for energy studies. Working Paper.

Fernandez, V., 2011. Spatial linkages in international financial markets. Quant. Finance 11 (2), 237–245. https://doi.org/10.1080/14697680903127403.

Fousekis, P., Grigoriadis, V., 2017. Price co-movement and the crack spread in the US futures markets. J. Commod. Mark. 7, 57–71. https://doi.org/10.1016/j.jcomm.2017.08.003.

Frees, E.W., 1995. Assessing cross-sectional correlation in panel data. J. Econom. 69 (2), 393–414. https://doi.org/10.1016/0304-4076(94)01658-M.

Galeotti, M., Lanza, A., Manera, M., 2003. Rockets and feathers revisited: an international comparison on European gasoline markets. Energy Econ. 25 (2), 175–190. https://doi.org/10.1016/S0140-9883(02)00102-0.

Ghoddusi, H., Titman, S., Tompaidis, S., 2021. Crack Spreads and Capacity Utilization in the US Refinery. https://doi.org/10.2139/ssrn.3951918.

Gil-Alana, L., Monge, M., 2021. Crude oil prices and COVID-19 persistence of the shock. Energy Research Letters 1 (1), 1–4. https://doi.org/10.46557/001c.13200.

Gil-Alana, L.A., Gupta, R., 2014. Persistence and cycles in historical oil price data. Energy Econ. 45, 511–516. https://doi.org/10.1016/j.eneco.2014.08.018.

Girma, P.B., Mougoue, M., 2002. An empirical examination of the relation between futures spreads volatility, volume, and open interest. J. Futures Mark.: Futures, Options, Other Deriv. Prod. 22 (11), 1083–1102. https://doi.org/10.1002/fut.10047.

Gjolberg, O., Johnsen, T., 1999. Risk management in the oil industry: can information on long-run equilibrium prices be utilized? Energy Econ. 21 (6), 517–527. https://doi.org/10.1016/S0140-9883(99)00023-7.

Grasso, M., Manera, M., 2007. Asymmetric error correction models for the oil–gasoline price relationship. Energy Pol. 35 (1), 156–177. https://doi.org/10.1016/j.enpol.2005.10.016.

Hammoudeh, S., Li, H., Jeon, B., 2003. Causality and volatility spillovers among petroleum prices of WTI, gasoline and heating oil in different locations. N. Am. J. Econ. Finance 14 (1), 89–114. https://doi.org/10.1016/S1062-9408(02)00112-2.

Jefferson, M., 2020. A crude future? COVID-19's challenges for oil demand, supply and prices. Energy Res. Social Sci. 68, 101669. https://doi.org/10.1016/j.erss.2020.101669.

Kao, C.W., Wan, J.Y., 2012. Price discount, inventories and the distortion of wti benchmark. Energy Econ. 34 (1), 117–124. https://doi.org/10.1016/j.eneco.2011.03.004.

Kaufmann, R.K., Dees, S., Mann, M., 2009. Horizontal and vertical transmissions in the US oil supply chain. Energy Pol. 37 (2), 644–650. https://doi.org/10.1016/j.enpol.2008.09.052.

Kaufmann, R.K., Laskowski, C., 2005. Causes for an asymmetric relation between the price of crude oil and refined petroleum products. Energy Pol. 33 (12), 1587–1596. https://doi.org/10.1016/j.enpol.2004.01.013.

King, K., Deng, A., Metz, D., 2012. An econometric analysis of oil price movements: the role of political events and economic news, financial trading, and market fundamentals. Bates White Econ. Consult. 1, 53.

Korniotis, G.M., 2010. Estimating panel models with internal and external habit formation. J. Bus. Econ. Stat. 28 (1), 145–158. https://doi.org/10.1198/jbes.2009.08041.

Kristoufek, L., Lunackova, P., 2015. Rockets and feathers meet Joseph: reinvestigating the oil–gasoline asymmetry on the international markets. Energy Econ. 49, 1–8. https://doi.org/10.1016/j.eneco.2015.01.013.

Lahiani, A., Miloudi, A., Benkraiem, R., Shahbaz, M., 2017. Another look on the relationships between oil prices and energy prices. Energy Pol. 102, 318–331. https://doi.org/10.1016/j.enpol.2016.12.031.

Lanza, A., Manera, M., Giovannini, M., 2005. Modeling and forecasting cointegrated relationships among heavy oil and product prices. Energy Econ. 27 (6), 831–848. https://doi.org/10.1016/j.eneco.2005.07.001.

Li, T., Qian, Z., Deng, W., Zhang, D., Lu, H., Wang, S., 2021. Forecasting crude oil prices based on variational mode decomposition and random sparse bayesian learning. Appl. Soft Comput. 113, 108032. https://doi.org/10.1016/j.asoc.2021.108032.

Liu, L., Ma, G., 2014. Cross-correlation between crude oil and refined product prices. Phys. Stat. Mech. Appl. 413, 284–293. https://doi.org/10.1016/j.physa.2014.07.007.

Lu, Q., Li, Y., Chai, J., Wang, S., 2020. Crude oil price analysis and forecasting: a perspective of "new triangle.". Energy Econ. 87, 104721. https://doi.org/10.1016/j.eneco.2020.104721.

Martínez, J.M.P., Abadie, L.M., Fernández-Macho, J., 2018. A multi-resolution and multivariate analysis of the dynamic relationships between crude oil and petroleum-product prices. Appl. Energy 228, 1550–1560. https://doi.org/10.1016/j.apenergy.2018.07.021.

Miao, H., Ramchander, S., Wang, T., Yang, D., 2017. Influential factors in crude oil price forecasting. Energy Econ. 68, 77–88. https://doi.org/10.1016/j.eneco.2017.09.010.

Oladosu, G., 2021. Bubbles in US gasoline prices: assessing the role of hurricanes and anti–price gouging laws. J. Commod. Mark., 100219 https://doi.org/10.1016/j.jcomm.2021.100219.

Oladunjoye, O., 2008. Market structure and price adjustment in the US wholesale gasoline markets. Energy Econ. 30 (3), 937–961. https://doi.org/10.1016/j.eneco.2007.09.009.

Ozili, P.K., Arun, T., 2020. Spillover of COVID-19: Impact on the Global Economy. https://doi.org/10.2139/ssrn.3562570.

Parent, O., LeSage, J.P., 2010. A spatial dynamic panel model with random effects applied to commuting times. Transp. Res. Part B Methodol. 44 (5), 633–645. https://doi.org/10.1016/j.trb.2010.01.004.

Parent, O., LeSage, J.P., 2011. A space–time filter for panel data models containing random effects. Comput. Stat. Data Anal. 55 (1), 475–490. https://doi.org/10.1016/j.csda.2010.05.016.

Perifanis, T., Dagoumas, A., 2021. Crude oil price determinants and multi-sectoral

effects: a review. Energy Sources B Energy Econ. Plann. 16 (9), 787–860. https://doi.org/10.1080/15567249.2021.1922956.
Pesaran, M.H., 2015. Testing weak cross-sectional dependence in large panels. Econom. Rev. 34 (6–10), 1089–1117. https://doi.org/10.1080/07474938.2014.956623.
Pirog, R., 2005. World Oil Demand and its Effect on Oil Prices, CRS Report for Congress. Impact of High Oil Prices on African Economies.
Población, J., Serna, G., 2016. Is the refining margin stationary? Int. Rev. Econ. Finance 44, 169–186. https://doi.org/10.1016/j.iref.2016.04.011.
Salisu, A.A., Isah, K.O., Oyewole, O.J., Akanni, L.O., 2017. Modelling oil price-inflation nexus: the role of asymmetries. Energy 125, 97–106. https://doi.org/10.1016/j.energy.2017.02.128.
Sharif, A., Aloui, C., Yarovaya, L., 2020. COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: fresh evidence from the wavelet-based approach. Int. Rev. Financ. Anal. 70, 101496. https://doi.org/10.1016/j.irfa.2020.101496.
Tiwari, A.K., Umar, Z., Alqahtani, F., 2021. Existence of long memory in crude oil and petroleum products: generalised hurst exponent approach. Res. Int. Bus. Finance 57, 101403. https://doi.org/10.1016/j.ribaf.2021.101403.
Tobler, W.R., 1970. A computer movie simulating urban growth in the Detroit region. Econ. Geogr. 46 (Suppl. 1), 234–240. https://doi.org/10.2307/143141.
Tong, B., Wu, C., Zhou, C., 2013. Modeling the co-movements between crude oil and refined petroleum markets. Energy Econ. 40, 882–897. https://doi.org/10.1016/j.eneco.2013.10.008.
Vega, S.H., Elhorst, J.P., 2016. A regional unemployment model simultaneously accounting for serial dynamics, spatial dependence and common factors. Reg. Sci. Urban Econ. 60, 85–95. https://doi.org/10.1016/j.regsciurbeco.2016.07.002.
Vides, J.C., Carmona, M., Feria, J., Golpe, A.A., 2021. Modeling the United States crack spread: market efficiency, persistence and the Verleger hypothesis. Energy Sources B Energy Econ. Plann. 16 (10), 951–970. https://doi.org/10.1080/15567249.2021.1986172.
Yellen, J.L., 2011. Commodity Prices, the Economic Outlook, and Monetary Policy: a Speech at the Economic Club of New York. New York.
Zavaleta, A., Walls, W., Rusco, F.W., 2015. Refining for export and the convergence of petroleum product prices. Energy Econ. 47, 206–214. https://doi.org/10.1016/j.eneco.2014.11.007.
Zhang, T., Ma, G., Liu, G., 2015. Nonlinear joint dynamics between prices of crude oil and refined products. Phys. Stat. Mech. Appl. 419, 444–456. https://doi.org/10.1016/j.physa.2014.10.061.