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The impact of geopolitical risk on the behavior of oil prices and freight rates☆

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A B S T R A C T

The impact of geopolitical risk on energy markets has drawn attention to the need for better statistical modeling, especially of the crude oil markets and the shipping industry. In this work, the West Texas Intermediate crude oil price and the Baltic Dry Index behavior under the assumption of geopolitical risks are examined by using monthly data from January 1985 until May 2021. Using fractional integration methods, the results indicate that geopolitical risk and the Baltic Dry Index series will return to their original trends in the event of an exogenous shock, in contrast to the West Texas Intermediate behavior. These results are supported by analyzing the long-term relationship of the time series using the Fractional Cointegration Vector AutoRegressive approach. Finally, we use Bai and Perron (2003) and wavelet transform approaches to detect breaks in the prices paid for the maritime transport and for the crude oil prices caused by geopolitical risks.

1. Introduction

Oil is one of the most relevant sources of energy for every country according to the IEA [1]. The economy of many countries is based on oil production and its trading, so the price of oil may be one of the key factors determining a country's budget in terms of its revenues [2]. Also, the oil price is a key factor for the shipping industry, because oil is the main energy source for the transport of commodities by sea all over the world, and shipping markets play a role in final prices for energy, agricultural goods and metals [3]. One of the most widely used indicators to measure changes in the cost of transporting raw materials such as metals, grain and fossil fuels by sea, is the Baltic Dry Index (BDI), created by the London-based Baltic Exchange.[1] Changes in the BDI are often seen as one of the main indicators of future economic growth or contraction, because raw and pre-production materials which are shipped are typically at low levels of speculation [4]. Also, the BDI is linked to oil price fluctuations, and both are dependent on global economic and business conditions [3,4]. In fact, oil use for longer-distance freight and shipping varies according to the outlook for the global economy and international trade [1], which is also affected by geopolitical factors. In order to measure geopolitical risk, Caldara and Iacoviello [5] proposed an indicator, the geopolitical risk (GPR) index, that spikes around geopolitical events, such as the Gulf War, the aftermath of 9/11, and during the 2003 Iraq invasion, as shown in Fig. 1. Caldara and Iacoviello pointed out that the increase in GPR captures the risk of events that disrupt the normal, democratic, and peaceful course of relations across states, populations, and territories [5]. Hence, they argued that this index can be used to isolate risks related to wars and terrorist attacks,

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[1] https://www.balticexchange.com/en/index.html.

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that are more likely to be exogenous to economic developments in many countries. This fits well with the empirical results of Su et al. [6] which indicate that there existed six oil price bubbles during the period 1986–2016 when the oil price deviated from its intrinsic value based on market fundamentals, and these dates correspond to specific events in politics and the financial markets. Also, Su et al. showed that oil price and financial liquidity are related in the time domain when GPR is high [7]. Their results also support the assumed monetary equilibrium model in Saudi Arabia, which, in turn, is an indication of the fact that oil prices are dependent on GPR and that financial liquidity relies on the price of oil. Other authors, such as Bariviera et al. analyzed the informational efficiency of the oil market during the last three decades and concluded that oil prices change with geopolitical events [8].

On the other hand, Platto et al. argued that it is worth taking into account that pandemics, such as COVID-19 may reduce the demand for oil, causing prices to decrease [10], which is inconsistent with the predictions of the intertemporal capital asset pricing model [11]. For example, despite an expected annual increase of 6.2% in 2021, global oil demand is set to remain around 3% below 2019 levels [12]. Some authors have analyzed this effect from different points of view. Flynn et al. point out that onshore oil operations increase human incursions into wildlife areas, facilitating mechanisms for potential zoonotic pathogen transmission which may cause pandemics to occur [13]. Wang et al. showed the great impact COVID-19 has been having on the cross-correlation of multifractal property between oil and agricultural futures markets [14]. Sharif et al. suggest that the COVID-19 outbreak affects oil prices and it has a greater effect on US geopolitical risk, on US economic uncertainty and the stock market [15]. However, they acknowledge that their findings should be taken with caution given the small size of the sample and the statistical inference from the used tests. In a previous work, Gil-Alana and Monge analyzed the effect of the COVID-19 crisis on crude oil prices by using long memory techniques [16]. They evidenced that oil price series are mean reverting which implies that the shock would be transitory albeit with very long-lasting effects.

The goal of this paper is to understand the behavior of the BDI and WTI (West Texas Intermediate) crude oil prices under the assumption of geopolitical risks. To this purpose, the statistical properties of these time series are analyzed, measuring the degree of persistence by using fractional integration techniques (see Refs. [17–20], among others). This is relevant, noting that this modelization based on fractional integration is more general and flexible than the standard ones based on integer degrees of differentiation, allowing for example for nonstationary though mean reverting processes. Moreover, and to be consistent with the above approach, the long-term relationship of the time series is investigated by using the Fractional Cointegration VAR (FCVAR) approach [21,22]. Finally, the presence of structural breaks in the data is examined by using Bai and Perron's [23], Gil-Alana's [24] and wavelet transform's (Aguiar-Conraria and Soares [24]) approaches. This is also of interest since fractional methods have been sometimes questioned due to the presence of breaks in the data that have not been taken into account.

To be more precise, the paper deals with the following questions: first, are Geopolitical Risk (GPR), Baltic Dry Index (BDI) and West Texas Intermediate (WTI) oil prices mean reverting or not? This is important since in the former case there is no need of strong policy actions since shocks return by themselves to the long term projection of the series. Second, in a multivariate context, do GPR and BDI, and GPR and WTI display a long run equilibrium relationship, and if so, is it of a fractional nature? This is also of relevance to determine the dynamics of their long run relationships. Finally, are these previous questions related to potential breaks in the data? If that is the case, the break dates are investigated to find any explanation for them along the analysis of each subsample separately.

To the best of our knowledge, this is the first paper that analyzes the statistical properties of geopolitical risks and the Baltic Dry Index and WTI crude oil prices using the methodologies mentioned above. It is important to examine whether the impact of geopolitical risks on the BDI and WTI crude oil prices is temporary or permanent. This knowledge is extremely relevant to analyze what the effects of geopolitical risks may be for oil prices and for the prices paid for the maritime transport of raw materials. The study is both crucial and timely as, despite the importance of oil prices and maritime transport in the literature in economics, political science and international relations, there is surprisingly not too much scholarly discussion.

Our results can be summarized as follows: Using fractional integration methods, the results indicate that geopolitical risk (GPR) and the Baltic Dry Index (BDI) series will return to their original trends in the event of an exogenous shock, in contrast to the West Texas Intermediate (WTI) behavior. Analyzing the long-term relationship of the time series using the Fractional Cointegration Vector AutoRegressive approach, we conclude that the relationships between GPR-BDI and GPR-WTI, respectively, have the same behavior. In these two cases the results imply I(0) behavior and the shock duration is short-lived. Finally, we use several approaches to detect breaks in the geopolitical risk data and we use Continuous Wavelet Transform to analyze how this affects the behavior of the Baltic Dry Index and crude oil prices. We conclude that the geopolitical risk has had a very small and short-lived impact on oil prices during the identified structural changes.

The rest of the paper is organized as follows. Section 2 reviews the literature on the relationship between BDI, oil price and geopolitical conflicts from different points of view and by using different methodologies. In the following two sections the data source and the methodology applied in the paper are shown. Section 5 presents the main empirical results, while the final section shows the main conclusions of

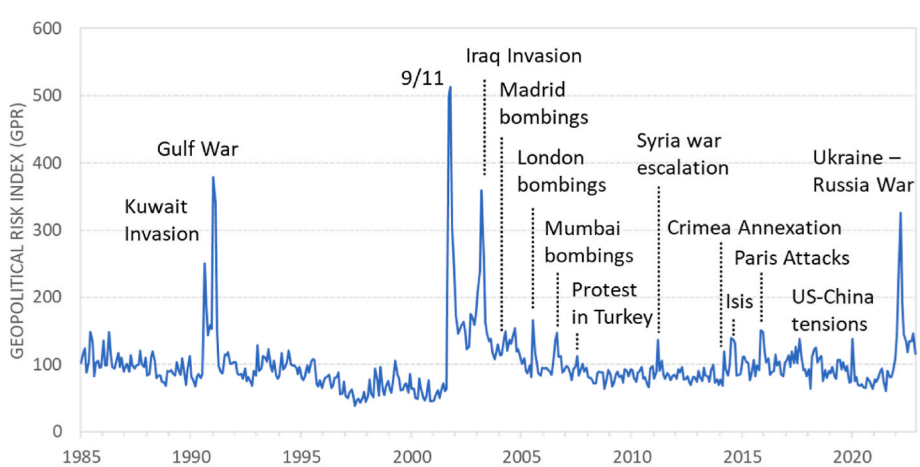

Fig. 1. The geopolitical risk index (from 1985 to 2022). Source: Reference [9].

this work.

2. Literature review

Economic development depends heavily on global trade, which has been identified as an instrument and driver of economic growth [25], leading to several advantages, such as, specialization, increase in resource productivity, large total output, creation of employment, generation of income and the relaxation of foreign exchange restraints, among others. However, international trade requires effective transportation to connect countries in different regions. In particular, seaborne transportation, which accounts for about 80% of international merchandise [26], is the pillar of globalization [27]. Moreover, the shipping industry promotes industrial development by supporting manufacturing growth as well as encouraging regional economic and trade integration [26].

In order to provide a benchmark for the price of moving the major raw materials by sea, the Baltic Dry Index (BDI) is used [28]. This is reported monthly by the Baltic Exchange in London, as shown in Fig. 2, and is a composite of three sub-indices that measure different sizes of dry bulk carriers: Capesize, which typically transport iron ore or coal cargoes of about 150,000 tonnes; Panamax, which usually carry coal or grain cargoes of about 60,000 to 70,000 tonnes; and Supramax, with a carrying capacity of between 48,000 and 60,000 tonnes.[2] The BDI takes into account 23 different shipping routes carrying coal, iron ore, grain and many other commodities.

It is worth taking into account that the BDI depends heavily on changes in oil prices because oil is the shipping industry's highest fuel cost [3]. The relationship between the BDI and oil prices has been analyzed from different points of view and by using different methodologies. Beenstock recounts the mutual relationship between freight rate, global seaborne trade, and fuel cost [30]. He described a theoretical model in which freight markets and ship markets are interdependent and in which second-hand ships are treated as capital assets. The results suggest that the BDI is more volatile around higher oil prices and geopolitical uncertainty. Alizadeh and Nomikos investigated the dynamic relationship between oil futures and spot markets and tanker freight rates across two major tanker routes [31]. The most prominent crude oil grade in the United States and the primary pricing marker for North American crude is West Texas International (WTI). Thus, they examine the validity of the cost of carry relationship in the WTI futures market, which suggests that the difference between physical and future crude oil prices should reflect the transportation costs. They found that oil prices and the BDI have a long term correlation. Shi et al. investigated the relationship between fluctuations in oil prices and the freight market by using a structural vector autoregressive (SVAR) model [32]. In addition, the response of the tanker market to different shocks was examined using impulse response analysis. The results showed that the impact of crude oil supply shocks on the oil tanker market in the same period is significant, while the impact of non-supply shock is weak. Ruan et al. displayed the short-run multifractal significant association between oil prices and the BDI [4]. Said and Giouvris found that oil is one of the most vital indicators for the BDI and illustrated bidirectional causality between the two [33]. Choi and Yoon investigated and compared the linkage between oil prices and all main sectors of maritime freight rates: the Baltic Dry Index (BDI), the Baltic Dirty Tanker Index (BDTI), and the Baltic Clean Tanker Index (BCTI) [34]. They also analyzed the dependence between crude oil and freight rates of time-series components. They used the decomposition method and the copula approach, showing that the decomposed components display different conditional dependence patterns, and asymmetry was revealed in the upper and lower tail dependence. In the long-run, they found more dependence in extreme periods such as the financial crises. In short-run fluctuations, they found that dependence increases in an economic boom.

These results highlight that the oil price and hence the BDI is affected by geopolitical destabilization. Baracuhy states that geopolitical risks, such as interstate tensions and conflicts, terrorism, piracy, and cyber-attacks have immediate impacts on the global supply chain business and trade [35]. Likewise, geopolitical conflicts threaten tariffs, change the volume and direction of trade flows, or cause fuel prices to rise rapidly and in the end destabilize transportation. The Geopolitical Risk (GPR) index shown in Fig. 1, highlights geopolitical events that affect oil prices and hence the BDI. For example, the terrorist attacks in 2001 pushed GPR to a high level and oil prices were reduced in the short run. Also, the slowdown in economic growth reduced the demand for shipping services, leading to lower values in the BDI (see Fig. 2). Similarly, during the 2003 Iraq war, the highest level of GPR was observed, and the outbreak of war caused supply interruptions and reduced production, leading to an increase in oil prices [36]. Therefore, the BDI fell, as shown in Fig. 2. In 2011, the Arab Spring thoroughly destabilized the Middle East, leading to an increase in GPR. Oil prices were very unstable due to concerns about supply interruptions in Libya, Iran, Russia, and Iraq [27], and this instability is also observed in the BDI behavior. Since 2013, GPR increased again due to the Russia-Ukraine conflict, the Paris terrorist attacks, and tension in North Korea. The price of oil decreased rapidly in 2015 due to the decline in the global economy as did the BDI in 2016. In addition, the trade war between China and the U.S. in recent years led to global trade uncertainty which extended to the oil market, which remained volatile due to low demand and GPR. Several studies about the connection between GPR and oil prices are found in the literature, among which can be found the following: Salameh revealed that whenever a conflict occurs in an oil-producing country, oil prices rise [37]. He observed that in the short term, two major geopolitical developments could impact immediately and very adversely on the oil price: one is a deterioration of the situation in Iraq affecting its oil infrastructure and production and the second is an escalation of the Russia-Ukraine conflict causing a disruption in Russian oil and gas supplies to the European Union (EU). He argued that a disruption of Iraq's oil production could push oil prices to more than $140/barrel whilst any disruption of Russian oil supplies to the EU could easily add $20-$30 to the price of oil. Chen et al. using the International Country Risk Guide (ICRG) index as a proxy for countries' political risk situation, empirically investigated the impacts of OPEC's political risk on Brent crude oil prices, based on several Structural Vector Autoregression (SVAR) models [38]. They explained that regional geopolitical destabilization has a positive but weak impact on oil prices. Bariviera et al. analyzed the informational efficiency of the oil market during the last three decades, and they examined changes in informational efficiency with major geopolitical events, such as terrorist attacks, financial crisis and other important events [8]. They found that some geopolitical events impact on the underlying dynamic structure of the crude oil market. Caldara and Iacoviello point out that high GPR leads to a decline in real activity, lower stock returns, and movements in capital flows away from emerging economies and towards advanced economies [5]. They also analyzed the evolution of the GPR index since 1900, showing that it rose dramatically during World War I and World War II, it was elevated in the early 1980s, and has drifted upward since the beginning of the 21st century. Uddin et al. used a time–frequency decomposition approach based on wavelet analysis to explore the inherent dynamics and the causal interrelationships between various types of geopolitical, economic and financial uncertainty indices and oil markets [39]. They described a strong relationship between GPR and oil prices. Abdel-Latif and El-Gamal used the simple VAR-based Granger-causality test and confirmed that the triad of oil prices, geopolitical risk, and financial liquidity are closely linked in a self-perpetuating cycle [40]. They confirmed the perpetuation of the cycle of low oil prices (e.g. in the late 1980s) leading to geopolitical strife (e.g. first Iraq War), which, in turn, leads to higher oil prices. Therefore, they concluded that a low oil price

[2] https://www.balticexchange.com/en/index.html.

Fig. 2. Bdi from 1985 to 2022. Source: Reference [29].

is mainly responsible for causing higher GPR. Su et al. evidenced that OP and GPR are moving in the same direction [27]. Khan et al. investigated oil response to geopolitical instability and concluded that GPR led oil prices in the medium term [41]. Su et al. assessed the causality of GPR, oil prices and financial liquidity by means of wavelet analysis, in order to investigate whether such relationships support the monetary equilibrium model in Saudi Arabia [7]. Their findings indicate that oil price and financial liquidity are related in the time domain when GPR is high. Li et al. investigated the frequency- and time-varying co-movement and causal relationship between crude oil prices and geopolitical risks based on wavelet analysis over the period of 1985–2016 [42]. They found a high degree of co-movement between geopolitical risks and oil prices at high frequencies (in the short run) for the entire sample period. However, such a correlation was not observed at low frequencies (in the long run) for most of the sample period. Li et al. examined the dynamic correlation and causal link between geopolitical factors and crude oil prices based on data from June 1987 to February 2020 [43]. By using a time-varying copula approach, they showed that the correlation between geopolitical factors and crude oil prices was strong during periods of political tensions. Moreover, the dynamic correlation between geopolitical factors and crude oil prices showed strong volatility over time during periods of political tensions.

Most recently, the global spread of the COVID-19 virus in 2020 led to a severe recession. The restrictions imposed to stem the pandemic and the global recession triggered by the outbreak of the COVID-19 pandemic have been accompanied by an unprecedented collapse in oil demand and prices [44]. This pushed uncertainty to the highest level and global trade declined rapidly, the decline being reflected in the BDI, as shown in Fig. 2. In addition, a rapid increase of the GPR is observed in 2022 due to the Russian invasion of Ukraine, however, this data is beyond the scope of this study.

3. Data and methodology

3.1. Dataset

The data examined in this research paper are:

- Geopolitical Risk (GPR) index, obtained from Caldara and Iacoviello [5], which is the result of war, terrorist attacks, and interstate conflicts that interrupt the routine of national strategies and international dealings. The GPR index dataset was obtained from Iacoviello's website [9].
- Baltic Dry Index (BDI). These are the prices paid for the maritime transport of raw materials on the 26 routes around the world that are covered by the Baltic Exchange. The BDI dataset was obtained from Thomson Reuters Eikon [29].
- Finally, to analyze the crude oil prices, the West Texas Intermediate (WTI) is used. The WTI dataset was obtained from the Federal Reserve Bank of St. Louis [45].

Data are monthly from January 1985 until May 2021.

3.2. Unit roots

Unit roots can be tested in many different ways. ADF tests based on Fuller [46] and Dickey and Fuller [47] are used in this work. There are many other tests available to calculate unit roots that have greater power such as Phillips [48] and Phillips and Perron [49] in which a non-parametric estimate of the spectral density of u_t at the zero frequency is used. Also, considering deterministic trends, the methodology based on Kwiatkowski et al. [50], Elliot et al. [51] and Ng and Perron [52] are also employed, producing all essentially the same results.

3.3. ARFIMA (p, d, q) model

To carry out this research, fractionally integrated methods are used with the purpose of getting the time series to be stationary I(0). We achieve this objective by differentiating the time series with a fractional number.

Following a mathematical notation, a time series $x_t, t = 1, 2, \ldots$ follows an integrated order process d (and denoted as $x_t \approx I(d)$) if:

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

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

Although fractional integration can also occur at other frequencies away from zero, as in the case of seasonal and cyclical fractional models, the series used for our analysis do not present these features and hence standard I(d) models as in (1) are used in this paper. The idea of fractional integration was introduced by Granger and Joyeux [53], Granger [54,55] and Hosking [56], though Adenstedt [57] had already showed awareness of its representation. The polynomial $(1 - L)^d$ in equation (1) can be expressed in terms of its Binomial expansion, such that, for all real d, x_t depends not only on a finite number of past observations but on the whole of its past history. In this context, d plays a crucial role since it indicates the degree of dependence of the series: the higher the value of d is, the higher the level of association between the observations will be.

Given the parameterization in (1) one can distinguish between several cases depending on the value of the parameter d, and several specifications based on (1) can be observed. Thus, if $d < 0$, x_t is said to be anti-persistent, with the series exhibiting zero spectral density at the origin [58] and switching signs more frequently than a random process. The process is short memory or I(0) when $d = 0$ in (1). This occurs because $x_t = u_t$. Long memory process ($d > 0$) is the name given when there is a high degree of association over a long time. With this last assumption, the process is still covariance stationary if $d < 0.5$ because the infinite sum of the autocovariances is still finite. Our interpretation of this can also be related to the issue of mean reversion. If the series reverts to the mean, shocks will be transitory and this happens when d is smaller than 1. In contrast to the above, shocks are expected to be permanent when $d \geq 1$.

Although there are several procedures for estimating the degree of long-memory and fractional integration [59–65], among others, the approach of Sowell [62] and his likelihood ARFIMA approach is used, employing the Akaike information criterion (AIC) [66] and the Bayesian information criterion (BIC) [67] to select the most appropriate ARMA approach for the short run dynamics.

3.4. FCVAR model

A method called Fractionally Cointegrated Vector AutoRegressive (FCVAR) was introduced by Johansen to check for a multivariate fractional cointegration model [68]. It was further expanded by Johansen and Nielsen [21,22]. It is one step ahead of the Cointegrated Vector AutoRegressive model [69], which is named CVAR, and it allows for series integrated of order d and that cointegrate with order d - b, with b > 0. To introduce the FCVAR model, the non-fractional CVAR model is first presented.

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

$$\Delta Y_t = \alpha\beta^{'} Y_{t-1} + \sum_{i=1}^{k} \Gamma_i \Delta Y_{t-i} + \varepsilon_t = \alpha\beta^{'} L Y_t + \sum_{i=1}^{k} \Gamma_i \Delta L^i Y_t + \varepsilon_t \tag{2}$$

Δ^b and $L_b = 1 - \Delta^b$, representing the difference and the lag operator. We then obtain:

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

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

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

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

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

Johansen and Nielsen [22] and Nielsen and Morin [70] discuss estimation and inference of this model.

It is noteworthy that fractional differencing is defined in terms of an infinite series but any actual sample will include only a finite number of observations. In order to calculate the fractional differences one can assume that X_t was zero before the start of the sample. (This is related with the type I and type II definitions of fractional integration, see Davidson and Hashimzade [71], and Gil-Alana and Hualde [72] among others). The bias introduced by this assumption is analyzed by Jones and Nielsen [73] using higher-order expansions. They showed that it can be completely avoided by including a level parameter μ that shifts each of the series by a constant.

The estimated empirical model is the following:

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

The asymptotic analysis in Johansen and Nielsen [22] shows that the maximum likelihood estimators of $(d, \alpha, \Gamma, \ldots, \Gamma_2)$ are asymptotically normal, while the maximum likelihood estimator of (β, ρ) is asymptotically mixed normal when $d_0 < 1/2$ and asymptotically normal when $d_0 > 1/2$. FCVAR models have recently been estimated in numerous empirical papers, such as [73–79]. Nielsen and Popiel provide Matlab computer programs for the calculation of estimators and test statistics [80].

4. Empirical results

4.1. Unit roots

Three standard unit root/stationarity tests (the Augmented Dickey-Fuller (ADF) test, the Phillips Perron (PP) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test) are considered to analyze the statistical properties of geopolitical risk (GPR), the Baltic Dry Index (BDI) and West Texas Intermediate (WTI) crude oil prices. The results, displayed in Table 1 suggest that GPR and the BDI are stationary I(0). On the other hand, crude oil prices are non-stationary I(1), therefore performing the analysis on the first differences we observe that the latter series is then stationary I(0).

4.2. Fractional integration

Following the results obtained using unit root methods in the three time series and due to the low power of the unit root methods under fractional alternatives,[3] fractional methods are also employed, using ARFIMA (p, d, q) models to study the persistence of the geopolitical risk (GPR), Baltic Dry Index (BDI) and West Texas Intermediate (WTI) crude oil prices. The Akaike information criterion (AIC) [66] and the Bayesian information criterion (BIC) [67] were used to select the appropriate AR and MA orders in the models.[4]

Table 2 Displays the fractional parameter d and the AR and MA terms obtained using Sowell's maximum likelihood estimator [62] of various ARFIMA (p, d, q) specifications with all combinations of p, q ≤ 2, for each time series.

Table 2 indicates that the estimates of d in GPR and BDI are equally I (d), where the values of d are in the range (0, 1), implying fractional integration. The value of d are below 1 for these two time series, therefore supporting mean reversion which implies transitory shocks and thus, in the event of exogenous shocks the series will return to its original trend in the future. In the case of crude oil prices, a different

[3] See references of Diebold and Rudebusch [88], Hassler and Wolters [89] and Lee and Schmidt [90].

[4] A point of caution should be adopted here since the AIC and BIC may not necessarily be the best criteria for applications involving fractional models ([56, 91]).

Table 1
Unit root tests.

	ADF			PP		KPSS	
	(i)	(ii)	(iii)	(ii)	(iii)	(ii)	(iii)
GPR	−3.9967*	−7.3646*	−7.9679*	−7.5755*	−8.2076*	1.3851*	0.1986*
BDI	−2.5025*	−3.9726*	−3.9912*	−3.4254*	−3.4454*	0.7311*	0.5858*
WTI	−1.0791	−2.4265	−3.4939	−2.1146	−2.9973	4.4845	0.5982

(i) Refers to the model with no deterministic components; (ii) with an intercept, and (iii) with a linear time trend. * Denotes a statistic significant at the 5% level. For ADF and PP, the 5% critical value with T = 310 is −1.9418 for no deterministic components; −2.8707 with an intercept; −3.4245 with a linear time trend. For KPSS, the 5% critical value with T = 310 is 0.4630 with an intercept component; 0.1460 with a linear time trend.

Table 2
Results of long memory tests.

Long memory test						
Data analyzed	Sample size (months)	Model Selected	d	Std. Error	Interval	I (d)
GPR	437	ARFIMA (2, d, 2)	0.45	0.1394	[0.22, 0.68]	I (d)
BDI	437	ARFIMA (0, d, 1)	0.49	0.0000	[0.24, 0.49]	I (d)
WTI	437	ARFIMA (0, d, 0)	1.30	0.0505	[1.22, 1.38]	I (1)

behavior and a higher level of persistence is observed. In fact, the estimate of d is much higher than 1 clearly rejecting the I(1) hypothesis and implying permanency of shocks.

4.3. FCVAR model ($d \neq b$)

Next, the FCVAR model proposed by Johansen and Nielsen [22], where the fractional integration and the classical CVAR model join is used to contrast the possible existence of persistence in the long run co-movements of the series. Table 3 summarizes the results of the FCVAR model.

Following the indications suggested by Jones, Nielsen and Popiel [73] the lag value k determined to be equal to 3. Also, we consider deterministic components and cointegration rank (r) to get our results. We observe from Panel I and Panel II (cointegrating the geopolitical risks with the Baltic Dry Index and crude oil prices) in Table 3 that the orders of integration of the individual series are about 0.598 and 0.669, respectively while the reduction in the degree of integration in the cointegrating regression is exactly the same magnitude, implying that the order of integration $(d - b) = 0$, which in turn implies I(0) cointegration errors. Thus, the hypothesis in which the error correction term shows short-run stationary behavior and where the shock duration is short-lived cannot be rejected. These results are in line with those obtained using fractional integration.

4.4. Structural breaks and Continuous Wavelet Transform

Perron and Vogelsan's [81], Bai and Perron's [23] and Gil-Alana's [24] approaches are used for detecting breaks in the data. The break dates, for the monthly case are reported in Table 4.

Following the BIC criterion to choose the number of structural breaks, we see that the most relevant ones in the GPR series are 4. The Gulf War in January 1991, the 9/11 terrorist attacks in the U.S. in 2001, the protest in Turkey over concerns about war and terrorism in May 2007 and the invasion of Crimea by Russia in March 2014.

Table 3
Results of the FCVAR model.

	d	B
Panel I: GPR and BDI	$d = 0.598$ (0.159)	$b = 0.598$ (0.279)
Panel II: GPR and WTI	$d = 0.669$ (0.000)	$b = 0.669$ (0.000)

Table 4
Structural breaks.

Time Series	Number of breaks chosen by BIC	Structural break dates
GPR	4	January 1991 September 2001 May 2007 March 2014

Fig. 3 displays the wavelet coherency and the phase difference for the monthly data of geopolitical risk and the Baltic Dry Index and West Texas Intermediate (WTI) crude oil prices, showing evidence of varying dependence between the time series across different frequencies and over time.

Also, this methodology allows us to know when a structural change occurs in the behavior of the Baltic Dry Index and crude oil prices with respect to geopolitical risks.

Fig. 3 represents two different estimations. The left panel (a) has the wavelet coherency that represents the interrelations between BDI and WTI with respect to GPR, when they are stronger or not and at which frequencies these points occur. Frequencies are shown on the vertical axis, from scale 1 (a single day) up to scale 130 (approximately 10 years), whereas time is shown in the horizontal axis, from the beginning to the end of the sample period. The statistical significance of local correlations in the time-frequency domain was evaluated using Monte Carlo simulations.

Torrence and Compo [82], show how the statistical significance of wavelet power can be assessed against the null hypothesis that the data generating process is given by an AR(0) or AR(1) stationary process with a certain background power spectrum (P_k). For a more general process one has to rely on Monte-Carlo simulations. However in our case we asses the statistical significance of the wavelet power against the null hypotheses that each variable follows an $ARMA$ (p, q) process, with no pre-conditions on p and q. The simulations are done using the amplitude adjusted Fourier-transformed surrogates proposed by Schreiber and Schmitz [83].

The regions surrounded by the black contour are the high frequency and the high coherence regions with significance values at 5%, that are the outcome obtained. The right panel has the phase differences: on the top (b) is the phase difference in the 1–12 frequency band for monthly data; at the bottom (c) is the phase difference in the 12.5–130 frequency band for monthly data. The frequency bands help us to understand the movement of both time series, one in relation to the other.

In addition, the structural breaks found in geopolitical risk time series (1991:01; 2001:09; 2007:05 and 2014:03), using Bai and Perron [23] and Gil-Alana [24] are used to analyze the relationship between BDI and WTI and GPR using wavelet analysis.

Analyzing the wavelet coherency between the GPR and the BDI, as well as GPR and WTI it is noticed that the time series are weakly related at the short-time (higher frequencies) and this weakness persist throughout the sample period. This behavior is consistent with the results of Li et al. [42]. Focusing on the wavelet coherence results of GPR and the BDI it is observed that geopolitical risks have a persistent impact

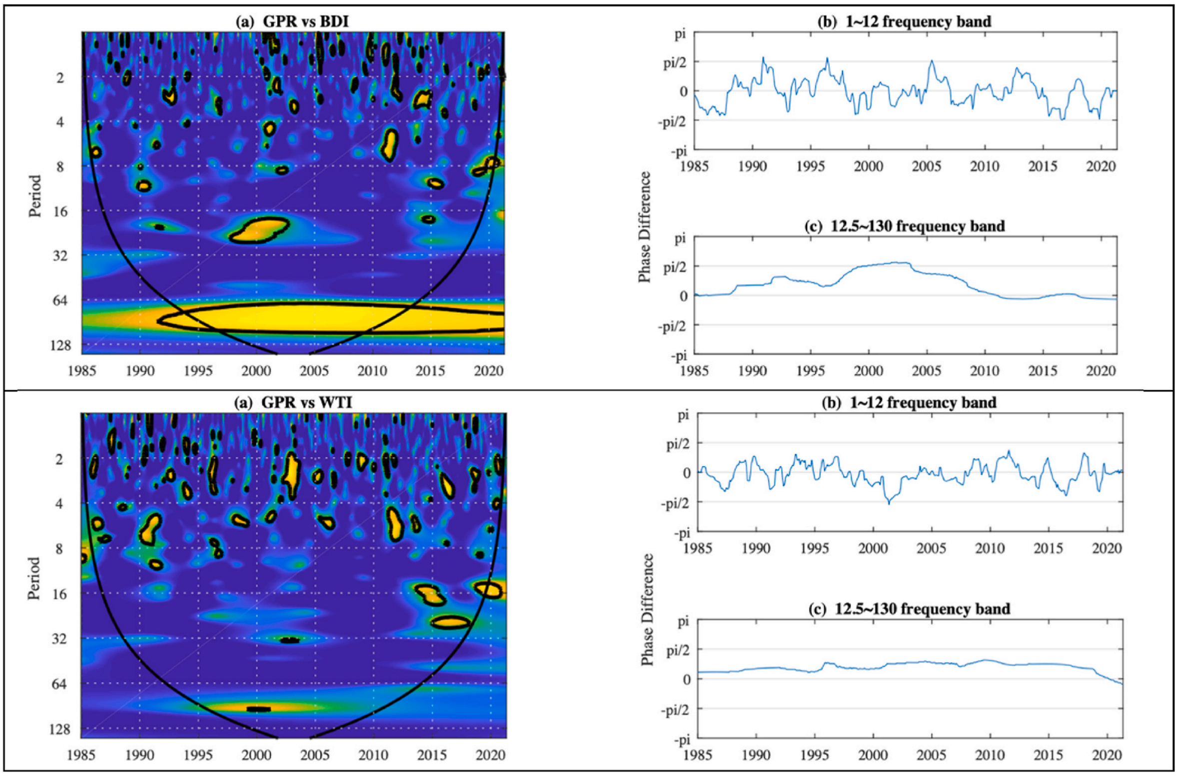

Fig. 3. Wavelet coherency and phase difference results. (a) Wavelet coherency. (b)–(c) Phase difference. The contour designates the 5% significance level. Coherency ranges from blue (low coherency) to yellow (high coherency). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

on the Baltic Dry Index in the long term (between 64 and 100 months) starting mid-2014. Focusing on the wavelet coherence results of GPR and WTI crude oil prices we observe that geopolitical risk has had a very small and short-lived impact on oil prices during the identified structural changes.

Analyzing the phase difference and focusing on the regions mentioned before, it is observed that all these regions stay between 0 and $\pi/2$ which means that geopolitical risks are positively correlated and leading in the behavior of the BDI and WTI crude oil prices.

Once identified the structural changes that have occurred due to the geopolitical risks, and concluding that GPR affected the BDI and WTI on the aforementioned dates, we statistically analyze the behavior of these series after each shock. To do so, ARFIMA models are again applied as in Section 4.2. The results are reported in Table 5.

Table 5 shows that the estimates of d after structural changes in the BDI and WTI crude oil prices are higher than 1 in most of the cases, implying fractional integration in both series. Focusing on the behavior of the BDI time series after the breaks, it is concluded that $d < 1$ in all cases, implying that the shocks were transitory, with the series recovering its original trend in the short term. However, there is a different pattern in the behaviour in the first two breaks compared with the last two. Thus, regarding the behavior of the time series after the first and second breaks, the hypothesis of I(1) cannot be rejected, while this hypothesis is decisively rejected in favor of mean reversion and transitory shocks in the series corresponding to the last two breaks. In conclusion, it seems that there has been a reduction in the degree of persistence of the series as time goes by as a consequence of the last two breaks.

On the other hand and related to the behavior of the WTI crude oil prices after the breaks, it is concluded that the term d is equal or very close to 1 where the hypothesis of I(1) behavior cannot rejected in the four cases, implying a lack of mean reversion and shocks having permanent effects, and causing a change in trend.

Table 5
Results of long memory tests after structural breaks.

Long memory test						
Data analyzed	Sample size	Model Selected	d	Std. Error	Interval	I (d)
BDI						
After break 1991:03	126	ARFIMA (0, d, 0)	0.96	0.2544209	[0.54, 1.38]	I (1)
After break 2001:08	67	ARFIMA (0, d, 1)	0.81	0.139964	[0.58, 1.04]	I (1)
After break 2007:02	85	ARFIMA (1, d, 2)	0.13	0.3730952	[-0.48, 0.74]	I (0)
After break 2014:02	88	ARFIMA (2, d, 1)	0.18	0.298865	[-0.31, 0.67]	I (0)
WTI crude oil prices						
After break 1991:03	126	ARFIMA (1, d, 2)	1.05	0.1616787	[0.78, 1.32]	I (1)
After break 2001:08	67	ARFIMA (0, d, 0)	0.90	0.0960109	[0.74, 1.06]	I (I)
After break 2007:02	85	ARFIMA (0, d, 0)	1.49	0.008322646	[1.48, 1.50]	I (1)
After break 2014:02	88	ARFIMA (2, d, 2)	0.96	0.3086908	[0.45, 1.47]	I (1)

5. Concluding comments

Oil is the main energy source for the transport of commodities by sea all over the world, and shipping markets play a role in the final prices of energy, agricultural goods and metals [3]. Ruan et al. state that the cost to transport raw materials and oil prices are linked [4]. Monge et al. argue that crude oil price behavior depends on any event that has the potential to disrupt the flow of oil [17]. So, the purpose of this research paper is to analyze how the impact of geopolitical risk affects the behavior of oil prices and consequently the freight rates from January 1985 until May 2021.

To carry out this research, some unit root methods (ADF, PP and KPSS) are first performed. From the results obtained, it can be concluded that the shipping and trade index created by the London-based Baltic Exchange and geopolitical risk index have a stationary behavior I(0). On the other hand, oil prices have a different statistical behavior following these non-stationary I(1) processes.

Fractional integration techniques are also used in this study to measure the degree of persistence. The results show that GPR and the BDI series are both mean reverting, showing that in the event of an exogenous shock, the series will return to their original trend. However, in the case of WTI crude oil prices the values of d are close to 1 and the unit root null hypothesis cannot be rejected implying permanency of shocks and requiring strong measures if we want the series to return back to their long term projections. These results are in good agreement to those from the FCVAR model, which is used to contrast the possible existence of persistence in the long-run co-movements of the series.

In addition, various approaches such as those of Bai and Perron [23], Gil-Alana [24] as well as a wavelet transform approach (see Aguiar-Conraria and Soares [84]) for detecting breaks in the data are employed in the paper. These methodologies were used to see when a structural change occurred in the behavior of the BDI and WTI crude oil prices with respect to GPR. Analyzing the wavelet coherency between GPR and the BDI and GPR and WTI it is observed on the one hand, that the time series are weakly related in the short-time (higher frequencies) and this weakness persists throughout the sample period. On the other hand, it was observed that geopolitical risks have a persistent impact on the Baltic Dry Index in the long term, however, the geopolitical risk has had a very small and short-lived impact on oil prices during the identified structural changes. Allowing for structural breaks, four breaks are detected and the behavior of BDI seems to change to lower orders of persistence with the last two breaks in 2007 and 2014. Lastly, the findings are of great interest to analyze what the effects of geopolitical risks may be for oil prices and for the prices paid for the maritime transport of raw materials. This is important because plays a role in final prices of energy, agricultural goods and metals. With this research paper we try to help market participants to understand better what the impact of geopolitical risks on the prices paid for the maritime transport of raw materials and crude oil prices movements may be and its subsequent potential effects on hedging strategies.

From a methodological viewpoint, noting that fractional integration is very much related to the presence of non-linearities, this opens another avenue for future work, using, for example, the approach developed in Cuestas and Gil-Alana [85] that allows for Chebyshev's polynomials in time in the context of I(d) models. In addition, there are other additional forms of incorporating non-linear deterministic structures still in the context of fractional integration such as Fourier functions in time [86] and neural networks [87]. This line of research will be pursued in a future paper.

Credit author statement

Manuel Monge: Conceptualization, Methodology, Software, Formal analysis, Writing – Original Draft, Writing-Review Draft. **María Fátima Romero Rojo**: Conceptualization, Data Curation, Writing – Original Draft. **Luis A. Gil-Alana**: Writing-Review Draft, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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