Oil Price and Geopolitics Risk: New Causality Insights in Frequency-Domain[1]

*Mihai MUTASCU**

Abstract

The paper explores the causality between oil price and geopolitical risk at global level by using the short- and long-run test of causality in the frequency-domain, over the period May, 1987 – April, 2020. For robustness checks, alternative tools in time-domain and additional variables are also considered. The key result claims that the oil price is a crucial signal for geopolitical risk on short- (i.e. up to 3 months) and long-run (i.e. more than 9 months) through its threats component. Interesting, no evidence shows that the oil price can explain the geopolitical acts per se. The results remain robust under the influence of global real economic activity in industrial commodity market. Surprisingly, no causality running from geopolitical risk to oil price is found.

Keywords: *oil price, geopolitical risk, global economic activity, causality in frequency*

JEL Classificatioon: Q41, F50, C32

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Introduction

Over the last decades the investigation of oil price arose a special interest as its exhibited sinuous evolution, the periods of growth and fall being accompanied by accentuated peaks and troughs. In this context, many researches tried to explain

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those episodes by identifying different determinants, the most important being the economic activity and financial market conditions (Abdel-Latif and El-Gamal, 2020). In a simple way, a global economic expansion is expected to drive-up the oil price and vice-versa. Such process adjusts further the speculative behaviour of investors additionally modelling oil price shocks.

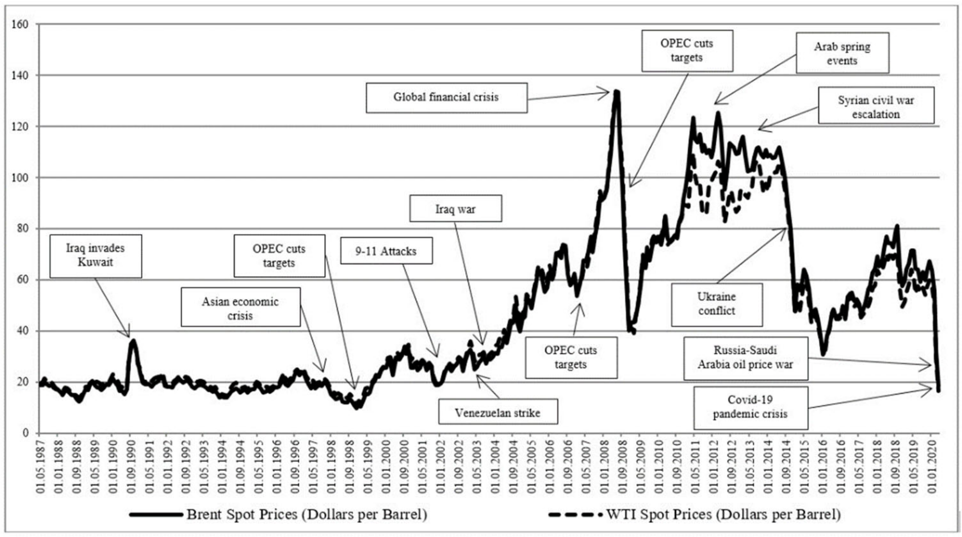
As the movement of oil price has also deep economic implications, an inverse link of study was considered running from oil price to whole economy (Kilian, 2009; Jo, 2014). Subsequently, the exploration was extended over the effect of oil price shocks on aggregate economic activity, also including the generated impulse through busts or booms of financial market.

During the time, the analyses became more sophisticated allowing the inclusion of geopolitical context as additional driver of both economic and social processes. Therefore, this new determinant also gained a special attention in oil price area through its risk components, from political conflicts and civil wars to international wars and terrorist attacks (Blattman and Edward, 2010).

The Figure 1 illustrates the stylized facts regarding the evolution of both Brent and West Texas Intermediate (WTI) oil spot prices and the main geopolitical events occurred over the period May, 1987 – April, 2020.

F i g u r e 1

Brent and WTI Spot Oil Prices and Major Geopolitical Events during the Period May, 1987 – April, 2020



Source: Performed based on Brent and WTI spot prices offered by Energy Information Administration of United States online database (2020) by extending the Figure 1 of Chen et al.'s (2016, p. 43).

The figure shows that the increasing and decreasing trends of oil price as well as their related peaks and troughs are generally linked to the major geopolitical events. For example, episodes such as the Organization of the Petroleum Exporting Countries (OPEC) cuts targets, 9 – 11 attacks, Venezuelan strike, Ukraine conflict, Russia-Saudi Arabia oil price war or Covid-19 pandemic crisis negatively impacted the oil price. Unlike those ones, the Iraq-Kuwait war, global financial crisis from 2007 – 2008, Arab spring events or Syrian war escalation have a positive effect on oil price.

Although it is expected that the geopolitical events to have relevant oil price implications, the sign and direction of causality remain rather questionable. To support this, Caldara and Iacoviello (2019) propose a broad treatment of geopolitical events by discriminating between threats and acts. The threats represent the signals about future geopolitical developments, while the acts are the geopolitical developments *per se*. Therefore, there is a unique one-way causality driving from geopolitical threats to geopolitical acts.

Within this framework, the paper investigates the worldwide causality between geopolitical risk and oil price. The theoretical ground of study is given by two transmission channels: one going from oil price to geopolitical risk, and another one running from geopolitical risk to oil price.

The 'oil price – geopolitical risk' resort supports the idea that the oil price induces a given level of accessibility. Therefore, not only the scarcity or lack of access (Leder and Shapiro, 2008; Toft et al., 2010), but also the abundance (Cotet and Tsui, 2013) can trigger potential conflicts basically having as target the oil control.

The 'geopolitical risk – oil price' resort claims that the geopolitical context can influence the level of oil price because of anticipations or market disruptions as result of conflicts. As Ciner et al. (2013) note, the wars, terrorist attacks, social protests or any other geopolitical threats and acts affect the anticipations and decisions of both investors and risk managers influencing the oil price.

The analysis covers the period May, 1987 – April, 2020 by using the short- and long-run test of causality in the frequency-domain proposed by Bretitung and Candelon (2006). Additionally, the tool is doubled in time-domain by classical Granger causality (Granger, 1969) and Toda-Yamamoto non-causality tests (Toda and Yamamoto, 1995).

The findings show that the oil price fully explains the geopolitical risk on short- and long-run through its threats component. Additionally, the oil price is distinguished as a good predictor on short- and long-run not only for geopolitical risk but also for global economic activity in industrial commodity market. Surprisingly, no causality running from geopolitical risk to oil price is found.

The contribution of paper is twofold. First, unlike the majority of works which quasi ignores the causality being especially devoted to the correlation between oil price and geopolitical risk, the paper complexly focuses on this issue with a battery of mixed time-frequency methods. Second, the study offers deep worldwide insights regarding the short- and long-run 'oil price – geopolitical risk' causality for a whole period of time. Comparing to our approach, the studies using the wavelet (e.g. Dong et al., 2019; Li et al., 2020) investigate the interaction between oil price and geopolitical risk but in terms of co-movement (i.e. lead-lag status) and not as causality approach.

The remainder of the paper is organized as follows: Section 1 reviews the literature, Section 2 describes the data and methodology, Section 3 checks for robustness, while Section 4 presents the results. Finally, the last section concludes.

1. Literature Review

The link between oil price and geopolitical risk has been intensively explored in the literature, both theoretical and empirical analyses being performed. Although many papers consider both directions of interaction by generally targeting the correlation in terms of sign and intensity, curiously just few of them seriously paid attention to causality issue. In other words, despite a large number of papers treating the correlation between oil price and geopolitical risk, often the causality test is ignored, those works not proving if one variable can explain the other and vice-versa. This aspect is very important because the causality is a crucial condition in the analysis of the economic, social and political processes or phenomena, having deep policy implications.

There is a prolific literature in the field, offering many theoretical approaches, different methodologies and datasets, various targets and, as consequence, heterogeneous results.

Four strands of literature are identified. First strand covers the investigation of oil price implications on geopolitical risk. Second strand is devoted to the exploration of geopolitical risk impact on oil price. Third strand targets the bidirectional 'oil price - geopolitical risk' interaction, while the last one claims no link between them.

The first strand of literature shows that there is one-way connection running from *oil price to geopolitical risk*, the correlation with different signs often being the base of approach. Ross (2006) offers a seminal work by focusing on the fuel rents. His Logit estimations over the period 1960 – 1999 prove that higher fuel rents are linked to the risk of conflict if those rents support the augmentation of GDP. Moreover, the negative price shocks are rather connected with separatist conflict, while the positive one with governmental conflicts. Unlike him, Le Billon and Cervantes (2009) documents the causality between high prices and war threats by finding that a low oil price can trigger wars. Further, Dube and Vargas (2013) target the case of Columbia. They find that the oil price augmentation generates more municipal revenues but also triggers local violence. Additionally, the authors stress that the effect has different directions depending on the type of the commodity. Bazzi and Blattman (2014) include the oil price in an extended sample of 65 global traded commodities, for all developing economies, covering the period 1957 – 2007. Their Linear Probability Models (LPM) show that the oil price shocks do not attract new wars but can be rather responsible of shorter and less deadly conflicts. Differently, Abdel-Latif and El-Gamal (2018) select the Discrete Wavelet Transform (DWT) as core methodology to investigate the oil production in several countries, such as Venezuela, Iraq, Iran and United Kingdom (UK). Based on this approach, the authors state that the increase of oil prices from 2011 – 2014 determined military instability of the oil producers in the Middle East, further escalating conflicts once oil prices fall during 2014 – 2016. Finally, considering oil as mineral in a panel with 14 sorts, Berman et al. (2017) combine different geo-referenced data between 1997 – 2010 by focusing on Africa. The main conclusion reveals that the general augmentation of mineral prices "might explain up to one-fourth of the average level of violence across African countries over the period" (Berman et al., 2017, p. 1564).

The second strand of literature is more generous, claiming that there is one-way link going from *geopolitical risk to oil price.*

One of the first papers in this topic belong to Alhajji and Huettner (2000), exploring the OPEC area. The theoretical base is given by Cournot Model doubled by Two-Stage Least Squares (TSLS) estimations, for the period 1973 – 1994. They find that the political risk has strong influence on oil prices. More nuanced, Hamilton (2009) sustains that the oil price shocks between 2007 – 2008 are conducted by geopolitical turbulences, which induced oil production halts. In the same year, Blomberg et al. (2009) use Instrumental Variable (IV) models, with motherly dataset, covering the period 1968 – 2005. The authors explore the impact of terrorism on oil prices. The main findings show that the terrorist attacks and conflicts affect the investor's perception of the market, put pressure on oil rising its price. No reverse direction of influence is registered. Unlike aforementioned partisans of linear models, Kollias et al. (2013) propose a non-linear BEKK-GARCH approach, with daily data, over 1990 – 2008. They reveal that the war and terrorism induce significant movements in the level of oil price, affecting also both CAC40 and DAX stock market indexes. Similar outputs register Wu and Zhang (2014) analyzing the case of China. In a recent paper, Li et al. (2020) globally document the 'geopolitical risk-oil price' nexus over period of 1985 – 2016 by performing wavelet estimations. Their time-frequency approach shows that the geopolitical risk positively contributes to oil price for both WTI and Brent indices.

Contrary, based on structural VAR estimations, Caldara and Iacoviello (2019) claim a negative impact of geopolitical risks on oil price in both developed and emerging countries. An identical negative effect obtain Antonakakis et al. (2017) with their VAR(p)-BEKK-GARCH(1,1) model over a century of data. In the same note, Cunado et al. (2019) invoke similar results by using time-varying parameter structural vector autoregressive (TVP-SVAR) model.

The third strand of literature is quite scarce, claiming that there is *bidirectional interaction between oil price and geopolitical risk.* More precisely, the oil price runs the geopolitical risk and vice-versa. For example, preferring linear estimators, Noguera-Santaella (2016) uses data since 1859 and classical time-series analysis, with 32 different geopolitical events related to oil prices. He invokes a positive impact of geopolitical events on oil price before the year 2000 and a weak one afterwards. Global Vector Autoregression (GVA) estimations with quarterly data over 1979 – 2017 and 70 countries propose Abdel-Latif and El-Gamal (2019). The authors interact the oil prices, financial liquidity and geopolitical risk demonstrating that the increase of geopolitical risk is driven by lower oil prices. Further, such higher geopolitical risk results in significantly higher oil prices. Those findings are reinforced few years ago by Abdel-Latif and El-Gamal (2020), demonstrating that the cycle of low oil prices from the late 1980s leads geopolitical strife (i.e. first Iraq War), which further falls in higher oil prices.

Finally, the fourth strand of literature declares *no relationship between oil price and geopolitical risk.* Only two papers seems to be advocate of this research direction. In this light, Monge et al. (2016) propose a battery of tools by mixing the unit root and fractional integration techniques. No significant differences in oil price before and after the geopolitical conflicts are proved.

Dong et al. (2019) prefer the more complex wavelet methodology. They stress that there is no impact of geopolitical risk on positively correlated global economic activity and oil price.

Nuanced results obtain Bouoiyour et al. (2018) by following a flexible Markov-switching dynamic (autoregressive) copula approach. Considering both threat and act components of geopolitical risk, they interestingly find that the acts manifest a strong positive impact on oil price, while the threats have moderate or rather no effect. The combined effects have a positive influence on the oil price.

Overall, two main literature gaps can be identified. First, there is no paper seriously investigating the causality between geopolitical risk and oil price, many contributions being devoted to correlation details. Second, although the 'wavelet' papers cover the direction of co-movement between the geopolitical risk and oil price, they fall to offer a compact conclusion for extended horizons of time. Therefore, the present paper fully addresses to both aforementioned gaps.

2. Data and Methodology

2.1. Data

The empirical analysis is based on a dataset including four main variables. The first variable represents the oil price, while the last three denote the geopolitical risk and its two components, geopolitical threats and geopolitical acts, respectively. The sample has motherly frequency, covering the period May, 1987 – April, 2020.

The oil price is monthly measured by Europe Brent *(Brent)* spot oil price expressed in United Stated (US) Dollars per Barrel. It is related to the traded oil market based around North Sea of Northwest Europe. The source of data is the Energy Information Administration (AIS) US online database (2020).

The geopolitical risk is captured via the monthly Geopolitical Risk Index *(GPR)* proposed by Caldara and Iacoviello (2019). As a composite index, it is constructed by counting the words expressing the geopolitical tensions in 11 leading international newspapers (i.e. The Boston Globe, Chicago Tribune, The Daily Telegraph, Financial Times, The Globe and Mail, The Guardian, Los Angeles Times, The New York Times, The Times, The Wall Street Journal, and The Washington Post). The words are classified in six groups reflecting: military tensions, nuclear tensions, war and terrorism threats, and war and terrorism acts, respectively. The first four groups are converged in the Geopolitical Threats *(GPT)* index, while the last two in the Geopolitical Acts *(GPA)* index. Both of them give the content of more general *GPR*. According to authors, the geopolitical threats predict geopolitical acts, the GPT suggesting signals about future geopolitical developments. Herein, the *GPA* does not Granger cause the *GPT*. Those indexes have been initially normalized to 100 over the period 2000 – 2009, 0 being the lowest risk intensity. Dataset comes from Caldara and Iacoviello (2019).

For robustness checks, three additional variables are also considered: West Texas Intermediate spot price, global economic activity, and an interacted determinant.

The West Texas Intermediate spot price *(WTI)* is expressed in United Stated (US) Dollars per Barrel being an alternative variable to *Brent*. As in the case of *Brent*, the variable is taken from the Energy Information Administration (AIS) US online database (2020).

The global economic activity controls for global real economic magnitude being captured through the Kilian Index *(Kilian)* proposed by Kilian (2019). Kilian (2009) documents that there is a strong relationship between the oil price volatility and economic outcomes. The index measures the global real economic activity in industrial commodity markets going from negative values (low magnitude of economic activity) to positive ones (high magnitude of economic activity). In order to allow the logarithm calculus, the raw index is rescaled to strict positive values by adding '160', without affecting its time-series distribution.

The interacted determinant *(GPR x Kilian)* controls for both geopolitical and economic shocks being calculated as product between *GPR* and *Kilian* indexes. According to the literature, the main assumption is that the geopolitical risk models the oil price but being strongly impregnated by global economic context (Kilian, 2009).

All variables are treated as natural logarithms being finally used in their first difference. The descriptive statistics of variables is presented in the Tables A1 (Appendix), while their unit root status is showed in the Table A2 (Appendix). For all notations, the variables denote their natural logarithm first difference, with exception of those from Tables A1 – strict raw values, and Table A2 – natural logarithm forms. A battery of three unit root tests is employed, with intercept and intercept & trend, as follows: ADF (Dickey and Fuller, 1979), PP (Phillips and Perron, 1988) and KPSS (Kwiatkowski et al., 1992).

2.2. Methodology

The causality between oil price and geopolitical risk is tested by using short- and long-run test of causality in the frequency-domain developed by Bretitung and Candelon (2006). This tool has a major advantage compared to the classical Granger's (1969) causality test because takes into account the variability of causality across different bands of frequency. More precisely, if Granger (1969) considers very important the time, Bretitung and Candelon (2006) exclusively focus on the frequency by using signals.

In time-domain, the core idea of Granger (1969) is that a variable *X* causes another one *Y* based on how much of the current values of *Y* can be explained by the past values of *X*. More precisely, the test claims that *X* Granger causes *Y* when the variable *X* can be used to predict a variable *Y* or the related coefficients of lagged *X* are significant. Herein, it is also important to fix the optimal added lags of *X* generating more accuracy in prediction.

Unfortunately, that causality can vary across different bands of frequency, as Granger and Lin (1995) note. In this light, Lemmens et al. (2008) remark that the stationary series register uncorrelated components with a single frequency ordinate. Therefore, they can be easily decomposed by frequency.

As the classical test of Granger (1969) does not offer such facility, Breitung and Candelon (2006) fix aforementioned issue by considering the causality in frequency only. In fact, the authors covert the Granger's (1969) test in a spectral causality as interdependence between two decomposed series representing a sum of 'instantaneous', 'feed-forward' and 'feedback' causality terms.

Their stating point is a Vector Autoregressive (VAR) by order p and time t ($t = 1, \dots T$) between two stationary variables X_t and Y_t, as follows:

$$\begin{bmatrix} \theta_{11}(L) & \theta_{12}(L) \\ \theta_{21}(L) & \theta_{22}(L) \end{bmatrix} \begin{bmatrix} X_t \\ Y_t \end{bmatrix} = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \tag{1}$$

where $\theta(L)$ denotes the lag polynomial, with the noise error vector $\varepsilon_t \left[\varepsilon_{1t}, \varepsilon_{2t}\right]'$, $E(\varepsilon_t) = 0$ and positive variance-covariance matrix $\Sigma = E\left(\varepsilon_t \varepsilon_t'\right)$. The optimal lag p is chosen based on the Akaike information criterion (AIC) and VAR(p) constructed model.

A lower triangular matrix of the Cholesky decomposition $\Sigma^{-1} = G'G$ is introduced as G, with $E\left(\eta_t \eta_t'\right) = I$ and $\eta_t = G\varepsilon_t$. Therefore, as a stationary system, (1) becomes:

$$\begin{bmatrix} X_t \\ Y_t \end{bmatrix} = \Phi(L)\varepsilon_t = \begin{bmatrix} \Phi_{11}(L) & \Phi_{12}(L) \\ \Phi_{21}(L) & \Phi_{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} = \Psi(L)\eta_t = \begin{bmatrix} \Psi_{11}(L) & \Psi_{12}(L) \\ \Psi_{21}(L) & \Psi_{22}(L) \end{bmatrix} \begin{bmatrix} \eta_{1t} \\ \eta_{2t} \end{bmatrix} \tag{2}$$

with $\Phi(L) = \theta(L)^{-1}$ and $\Psi(L) = \Phi(L)G^{-1}$. Further, the spectral density of X_t based on Fourier transforms is:

$$f_x(\omega) = \frac{1}{2\pi}\left\{\left|\Psi_{11}\left(e^{-i\omega}\right)\right|^2 + \left|\Psi_{21}\left(e^{-i\omega}\right)\right|^2\right\} \tag{3}$$

By following Geweke (1982) and Hosoya (1991), the measure of causality M running from Y to X with frequency ω is:

$$M_{Y \to X}(\omega) = \log\left[\frac{2\pi f_x(\omega)}{\left|\Psi_{11}\left(e^{-i\omega}\right)\right|^2}\right] = \log\left[1 + \frac{\left|\Psi_{12}\left(e^{-i\omega}\right)\right|^2}{\left|\Psi_{11}\left(e^{-i\omega}\right)\right|^2}\right] \tag{4}$$

Herein, Y does not cause X at frequency ω under $\left|\Psi_{12}\left(e^{-i\omega}\right)\right| = 0$ condition or

$$H_0 : M_{Y \to X}(\omega) = 0 \tag{5}$$

Breitung and Candelon (2006) revised (5) by considering $\Psi(L)=\theta(L)^{-1}G^{-1}$, as follows:

$$\Psi_{11}(L)=-\frac{g^{22}\theta_{12}(L)}{\left|\theta(L)\right|} \tag{6}$$

with lower diagonal element g^{22} attributed to G^{-1} and $\left|\theta(L)\right|$ as determinant of $\theta(L)$. Based on above $\left|\Psi_{12}\left(e^{-i\omega}\right)\right|=0$ conditions, *Y* does not cause *X* at frequency ω if:

$$\left|\theta_{12}\left(e^{-i\omega}\right)\right|=\left|\sum_{k=1}^{p}\theta_{12,k}\cos(k\omega)-\sum_{k=1}^{p}\theta_{12,k}\sin(k\omega)\,i\right|=0 \tag{7}$$

Hence, $\left|\theta_{12}\left(e^{-i\omega}\right)\right|=0$ only if $\sum_{k=1}^{p}\theta_{12,k}\cos(k\omega)=\sum_{k=1}^{p}\theta_{12,k}\sin(k\omega)=0$, while second condition can be withdrawn as $\sin(k\omega)=0$ for $\omega=0$ and $\pi=\omega$. By noting $\alpha_j=\theta_{11,j}$ and $\beta_j=\theta_{12,j}$, the VAR equation for X_t can be written as:

$$X_t=\alpha_1 X_{t-1}+\ldots+\alpha_p X_{t-p}+\ldots+\beta_1 Y_{t-p}+\ldots+\beta_1 Y_{t-p}+\varepsilon_{1t} \tag{8}$$

where *t* is the time, *p* denotes the optimal lag, while $\alpha_{1,2\ldots p}$ and $\beta_{1,2\ldots p}$ are the coefficients of *x* and *y*, respectively. ε stands for errors.

In this case, $H_0: M_{Y\to X}(\omega)=0$ is equivalent of $H_0: R(\omega)\beta=0$ with $\beta=\left(\beta_1,\ldots\beta_p\right)'$ and

$$R(\omega)=\left[\frac{\cos(\omega)\ \cos(2\omega)\ \ldots\ \cos(p\omega)}{\sin(\omega)\ \sin(2\omega)\ \ldots\ \sin(p\omega)}\right]. \tag{9}$$

According to Breitung and Candelon (2006), the *F-statistic* regarding $H_0: R(\omega)\beta=0$ is approximately distributed as $F(2,T-2p)$, for $\omega\in(0,\pi)$. The frequency ω of a cycle is related to its period *t* measured in number of observations as $t=2\pi/\omega$.

Therefore, the "causality at low frequencies implies that the additional variable is able to forecast the low frequency component of the variable of interest one period ahead." (Breitung and Candelon, 2006, p. 376).

This routine is used to test the short- and long-run causality in frequency between *Brent* and, alternatively *GPR*, *GPT* and *GPA*, respectively.

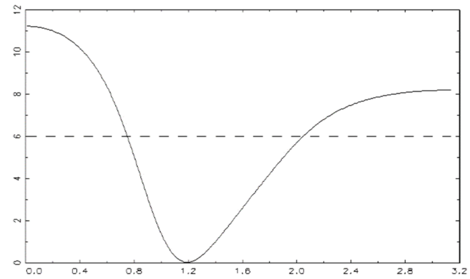
3. Results

The ADF, PP and KPSS unit root tests in the Table A2 (Appendix), with intercept and intercept & trend, clearly show that the *Brent*, *WTI*, *GPR*, *GPT* and *GPA* are I(1), becoming stationary in their first difference. Unlike them, the tests reveal that the *Kilian* and interacted *GPR x Killian* variables are I(0). Therefore, addressing to any biases, all estimations related to the causality in frequency are performed by using the variables in their first difference, as Breitung and Candelon (2006) advice.

The Figures 2 and 3 plot the results of short- and long-run causality in frequency between the *Brent* and *GPR*. For a better understanding, routine steps for testing the short- and long-run causality in frequency between the Brent and GPR are presented at the end of paper (Supplementary material).

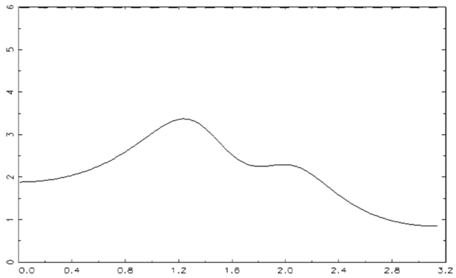
F i g u r e 2
Causality Test in Frequency Running from *Brent* to *GPR* (lag 4)

Frequency (ω)



F i g u r e 3
Causality Test in Frequency Running from *GPR* to *Brent* (lag 4)

Frequency (ω)



Note: The broken lines denote the 5% level of significance, while the frequency *(ω)* = 2π/cycle length *(t)*.
Source: Performed based on author's estimations.

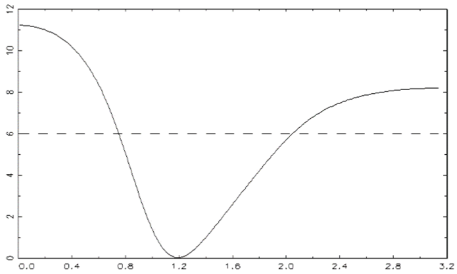
The Figure 2 clearly shows that the *Brent* causes *GPR* at both high (i.e. more than 2.1 range) and low (i.e. up to 0.7 range) frequencies. This coincides to short- (i.e. more than 2.1 range ≈ up to 2.99 ≈ 3 months) and long-run causality (i.e. up to 0.7 range ≈ more than 8.9 ≈ 9 months), respectively. The Figure 3 curiously reveals that the *GPR* does not cause *Brent* at all frequencies. Therefore, there is a one-way short- and long-run causality in frequency driving from oil price to geopolitical risk.

The Figures 4 and 5 present the short- and long-run causality in frequency between the *Brent* and *GPT*. In this case, the findings clearly reveal that the *Brent* also causes *GPT* at both high (i.e. more than 2.1 range) and low (i.e. up to 0.7 range) frequencies, mainly on short- (i.e. up to 2.99 ≈ 3 months) and long-run causality (i.e. more than 8.9 ≈ 9 months), respectively. Otherwise, the *GPT* does not cause *Brent* at all frequencies. Hence, a one-way short- and long-run causality in frequency driving from oil price to geopolitical threats is evidenced.

Finally, Figures 6 and 7 show the results of short- and long-run causality in frequency between the *Brent* and *GPA*.

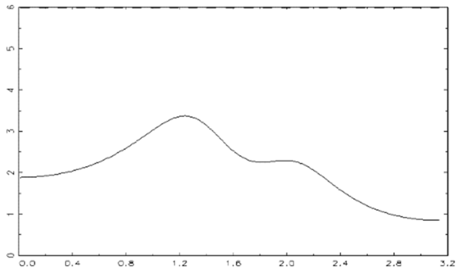
F i g u r e 4
Causality Test in Frequency Running from *Brent* to *GPT* (lag 4)

Frequency (ω)



F i g u r e 5
Causality Test in Frequency Running from *GPT* oo *Brent* (lag 4)

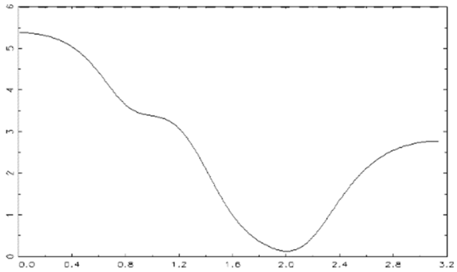
Frequency (ω)



Note: The broken lines denote the 5% level of significance, while the frequency *(ω)* = 2π/cycle length *(t)*.
Source: Performed based on author's estimations.

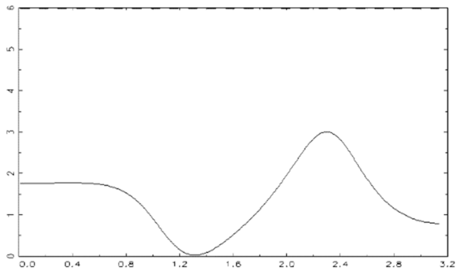
F i g u r e 6
Causality Test in Frequency Running from *Brent* to *GPA* (lag 5)

Frequency (ω)



F i g u r e 7
Causality Test in Frequency Running from *GPA* to *Brent* (lag 5)

Frequency (ω)



Note: The broken lines denote the 5% level of significance, while the frequency *(ω)* = 2π/cycle length *(t)*.
Source: Performed based on author's estimations.

Very interesting, the null hypothesis of no causality can be rejected for both directions of test, meaning that the causality in frequency between the *Brent* and *GPA* is not registered. This strongly supports the idea of no causality between oil price and geopolitical acts at all frequencies. Summarizing, the outputs claim that the oil price can predict the geopolitical risk on short- and long-runs. Moreover, seems that the oil price fully explains rather the geopolitical threats than the geopolitical acts, highlighting the crucial role of oil price on geopolitical threats environment.

4. Robustness Checks

The robustness checks are performed by using one alternative variable *(WTI)* to Brent oil price and two control determinants (i.e. *Kilian* and *Kilian x GPR*) as well as two alternative tools in time-domain, mainly the classical Granger causality and Toda-Yamamoto tests.

1. The tests of causality in frequency between the *WTI* and *GPR*, *GPT* and *GPA*, respectively, are illustrated in the Figures A1 – A6 (Appendix). The outputs seem to be quasi-robust under the *WTI*, with the exception of causality driving from the *WTI* to *GPR*. Herein, comparing with the *Brent'*s findings, the Figure A1 shows that the *WTI* causes *GPR* only at low frequency (i.e. up to 0.7 range). This corresponds to the long-run, more precisely to more than 8.9 ≈ 9 months. The difference can be explained through the origins of oil price indexes as the *Brent* is related to Europe, while the *WTI* to the US. Unlike the American's oil price shocks counting only for long-run, the European ones seem to be more complex for geopolitical risk, covering both short- and long-runs.

Additionally, for both *Brent* and *WTI* prices, the routine of Breitung and Candelon (2006) is repeated by alternatively using as determinants the *Kilian* index, and *Kilian x GPR* interacted variable, respectively. The findings are plot in Figures A7 – A14. Both *Brent* and *WTI* show the same results in respect to *Kilian* index. The *Brent/WTI* causes *Kilian* index at both now high (i.e. 0.9 – 1.7 range) and low (i.e. up to 0.7 range) frequencies, meaning short- (i.e. between 3.69 and 6.98 ≈ 4 – 7 months) and long-run causality (i.e. more than 8.9 ≈ 9 months), respectively. No causality running from the *Kilian* index to *Brent/WTI* is found.

Further, by interacting the *GPR* with *Kilian* index, the outcomes in Figures A11 – A14 remain robust as for *GPR* variable. Herein, a strict one-way causality running from the *Brent/WTI* to *Kilian x GPR* interacted variable is evidenced. Like in the case of GPR, the *Brent* causes *Kilian x GPR* in frequency on both short- (i.e. up to 2.99 ≈ 3 months) and long-run (i.e. more than 8.9 ≈ 9 months), respectively, while the *WTI* causes *Kilian x GPR* only on long-run, for more than 8.9 ≈ 9 months.

2. Two alternative methods in time-domain are also used to check for robustness: the classical Granger causality (Table A3, Appendix) and Toda-Yamamoto (Table A4, Appendix) tests. The tools are run by using all variables in the dataset, more precisely by including the alternative *WTI* to *Brent* and controls, respectively.

The Granger causality test belongs to Granger (1969). It simply shows that a variable *x* causes another one *y* then the current values of *y* can be explained by the past values of *x*.

The Toda-Yamamoto non-causality test is proposed by Toda and Yamamoto (1995). The method is superior to the classical Granger's (1969) proposal allowing overcoming the problem of model specification. Moreover, the Toda-Yamamoto test considers variables with different orders of integration, while the co-integration condition or conversion of VAR into VEC (Vector Error Correction) model are not required.

For both tests, the optimal lags are obtained based on AIC. The results of Granger test in Table A3 show that there is one-way causality running from the oil price to geopolitical risk, the main impact being transmitted on geopolitical threats. The outputs remain robust under global economic activity. Those findings are reinforced by Toda-Yamamoto non-causality tests in Table A4.

All in all, corroborating with the results of causality in frequency, it is clear that the oil price fully explains the geopolitical risk, being in accord to Ross (2006), Dube and Vargas (2013), Bazzi and Blattman (2014), Abdel-Latif and El-Gamal (2018), and Berman et al. (2017), respectively. Unfortunately, the geopolitical risk seems falling to predict the oil price. Moreover, oil price is related rather to geopolitical threats than geopolitical acts, validating the results of Le Billon and Cervantes (2009) in term of war threats. The geopolitical acts *per se* are not significant under oil price prediction. Not at least, the results are robust under global economic activity also supporting the Kilian's (2009) findings. More precisely, the oil price can explain the global economic activity but also the geopolitical risk under a given global economic context.

Unlike existing contributions, those new results are explained through their innovative methodological strategy (i.e. mixing time and frequency approaches), extended and updated span with monthly frequency as well as special treatment of variables (i.e. working in both level and first difference).

Conclusion

The study connects the oil price with geopolitical risk by using short- and long-run causality in frequency over the period May, 1987 – April, 2020. Additional tools and control variables are also considered for robustness checks.

The main results claim that the oil price one-way causing the geopolitical risk. The causality's implications are strong in the first 3 months (i.e. short-run), disappears after that to become permanent for more than 9 months (i.e. long-run). Noteworthy is that the oil price can fully predict on short- and long-runs rather the geopolitical threats than the geopolitical acts *per se*. Not at least, the oil price perfectly explains the global economic activity but also the geopolitical risk under its context. No reverse causality is found in any scenarios.

The findings prove the quality of oil price as crucial signal for geopolitical risk, independent of the global real economic activity. Interesting, the signal transmitted by oil price is suddenly converted into geopolitical, nuclear, war or terrorist threats, being very strong in the first 3 months. Further, after a period of 'inoperability' of around 6 months, that signal is converted in permanent threats (i.e. more than 9 months). There is no evidence that the oil price signal directly triggers geopolitical acts, such as wars or terrorist attacks. Those critical developments are the result of geopolitical threats revaluation. In any instance, the geopolitical risk cannot explain the oil price, seeming that other factors are prominent at global level to do that.

Regarding the policy implications, the results are very useful not only for governments but also for the non-governmental organizations, intergovernmental organizations, intergovernmental military alliances, companies, and any other interested actors in the field. In this context, it is required for policymakers in the geopolitical area to continuously follow any particular oil price movement, carefully analysing the global geopolitical threats may occur. Having intensive implications on very short-run, the oil price can be also one of the main pillars for designing the geopolitical strategy on long-run.

As for further developments of research, the parallel using of wavelet, extension of 'oil price – geopolitical risk' determinants, and control for pandemic crisis can be seriously considered.

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Appendix

Table A1

Descriptive Statistics

Variable	*Brent*	*WTI*	*GPR*	*GPT*	*GPA*	*Kilian*	*GPR x Kilian*
Mean	46.48672	45.26394	85.79987	88.41126	72.42043	163.4109	13601.23
Median	31.645	33.31	63.97	65.80855	57.725	154.9042	9732.7
Maximum	132.72	133.88	545.09	602.4485	496.89	350.7287	97549.5
Minimum	9.82	11.35	23.7	20.23246	11.09	0.35585	31.9
Std. Dev.	32.58835	29.06052	65.10381	71.78791	58.96002	59.2341	10898.6
Skewness	0.868392	0.823813	2.959146	2.977497	3.872705	0.819262	2.891355
Kurtosis	2.551223	2.555798	16.01766	16.25558	23.19797	3.999009	17.36241
Jarque-Bera	53.094	48.0478	3374.012	3484.343	7721.162	60.76591	3955.356
Probability	0	0	0	0	0	0	0
Sum	18408.74	17924.52	33976.75	35010.86	28678.49	64710.71	5386086
Sum Sq. Dev.	419490.3	333583.1	1674210	2035634	1373132	1385928	4.69E+10
Observations	396	396	396	396	396	396	396

Source: Performed based on author's estimations.

Table A2

Unit Root Tests

Test/ Variable	ADF		PP		KPSS	
	Intercept	*Intercept + trend*	*Intercept*	*Intercept + trend*	*Intercept*	*Intercept + trend*
Brent	–1.837***	–1.768***	–1.634***	–1.399***	1.907	0.254
WTI	–1.878***	–1.687***	–1.671***	–1.296***	1.868	0.269
GPR	–4.083***	–4.876***	–6.056***	–7.474***	0.997	0.121
GPT	–3.864***	–4.737***	–6.007***	–7.609***	1.057	0.133*
GPA	–9.835***	–9.895***	–10.06***	–10.12***	0.312	0.196*
Kilian	–7.116	–7.322	–6.809	–7.089	0.418**	0.263
GPR x Kilian	–4.859	–5.062	–7.149	–7.525	0.495*	0.151*
d(Brent)	–13.09	–13.12	–12.39	–12.41	0.181***	0.109***
d(WTI)	–12.36	–12.40	–11.61	–11.64	0.195***	0.103***
d(GPR)	–20.66	–20.63	–41.37	–41.36	0.083***	0.084***
d(GPT)	–21.24	–21.21	–41.02	–41.09	0.082***	0.081***
d(GPA)	–14.41	–14.39	–73.62	–77.53	0.166***	0.108***
d(Kilian)	–18.84	–18.82	–44.37	–44.61	0.109***	0.064***
d(GPR x Kilian)	–15.83	–15.81	–41.51	–41.52	0.089***	0.077***

Note: d(...) represents the first difference of variable, while ***, ** and * denote 1%, 5% and 10% level of significance, respectively.

Source: Performed based on author's estimations.

T a b l e A3

Granger Causality Test (first difference)

Null hypothesis	F-Statistic	Conclusion	Null hypothesis	F-Statistic	Conclusion	Lag
Brent Granger causes *GPR*	3.451***	Reject	*GPR* Granger causes *Brent*	1.281	Fail to reject	4
Brent Granger causes *GPT*	4.005***	Reject	*GPT* Granger causes *Brent*	1.349	Fail to reject	4
Brent Granger causes *GPA*	0.569	Fail to reject	*GPA* Granger causes *Brent*	0.817	Fail to reject	5
Brent Granger causes *Kilian*	4.442***	Reject	*Kilian* Granger causes *Brent*	0.535	Fail to reject	7
Brent Granger causes *Kilian x GPR*	8.241***	Reject	*Kilian x GPR* Granger causes *Brent*	0.286	Fail to reject	4
WTI Granger causes *GPR*	2.965**	Reject	*GPR* Granger causes *WTI*	0.949	Fail to reject	4
WTI Granger causes *GPT*	3.405***	Reject	*GPT* Granger causes *WTI*	1.119	Fail to reject	4
WTI Granger causes *GPA*	0.684	Fail to reject	*GPA* Granger causes *WTI*	0.839	Fail to reject	5
WTI Granger causes *Kilian*	3.772***	Reject	*Kilian* Granger causes *WTI*	0.625	Fail to reject	7
WTI Granger causes *Kilian x GPR*	6.671***	Reject	*Kilian x GPR* Granger causes *WTI*	0.125	Fail to reject	4

Note: ***, ** and * show 1%, 5% and 10% level of significance, respectively.

Source: Performed based on author's estimations.

T a b l e A4

Toda-Yamamoto Causality Test (all variables in level)

Null hypothesis	Chi-sq.	Conclusion	Null hypothesis	Chi-sq.	Conclusion	Lag
Brent Granger causes *GPR*	11.87***	Reject	*GPR* Granger causes *Brent*	5.118	Fail to reject	3
Brent Granger causes *GPT*	14.02***	Reject	*GPT* Granger causes *Brent*	5.387	Fail to reject	3
Brent Granger causes *GPA*	6.866	Fail to reject	*GPA* Granger causes *Brent*	4.487	Fail to reject	6
Brent Granger causes *Kilian*	22.45***	Reject	*Kilian* Granger causes *Brent*	1.262	Fail to reject	3
Brent Granger causes *Kilian x GPR*	32.45***	Reject	*Kilian x GPR* Granger causes *Brent*	1.108	Fail to reject	3
WTI Granger causes *GPR*	10.25**	Reject	*GPR* Granger causes *WTI*	3.794	Fail to reject	3
WTI Granger causes *GPT*	12.01***	Reject	*GPT* Granger causes *WTI*	4.477	Fail to reject	3
WTI Granger causes *GPA*	0.414	Fail to reject	*GPA* Granger causes *WTI*	0.554	Fail to reject	2
WTI Granger causes *Kilian*	16.01***	Reject	*Kilian* Granger causes *WTI*	2.422	Fail to reject	3
WTI Granger causes *Kilian x GPR*	27.52***	Reject	*Kilian x GPR* Granger causes *WTI*	0.396	Fail to reject	4

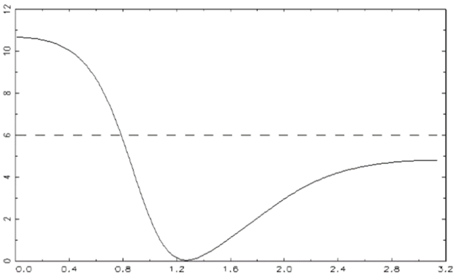
Note: ***, ** and * show 1%, 5% and 10% level of significance, respectively.

Source: Performed based on author's estimations.

F i g u r e A1

Causality Test in Frequency Running from *WTI* to *GPR* (lag 4)

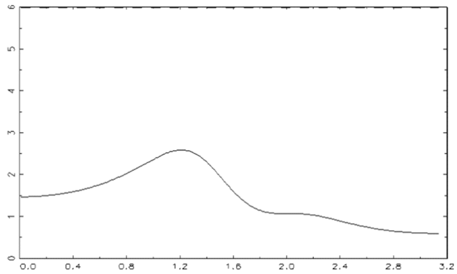
Frequency (ω)



F i g u r e A2

Causality Test in Frequency Running from *GPR* to *WTI* (lag 4)

Frequency (ω)

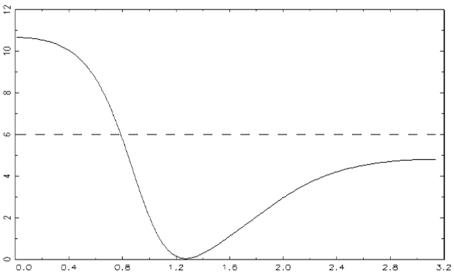


Note: The broken lines denote the 5% level of significance, while the frequency *(ω)* = 2π/cycle length *(t)*.
Source: Performed based on author's estimations.

F i g u r e A3

Causality Test in Frequency Running from *WTI* to *GPT* (lag 4)

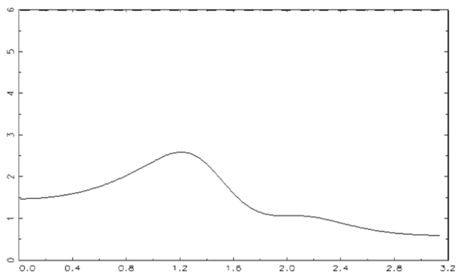
Frequency (ω)



F i g u r e A4

Causality Test in Frequency Running from *GPT* to *WTI* (lag 4)

Frequency (ω)

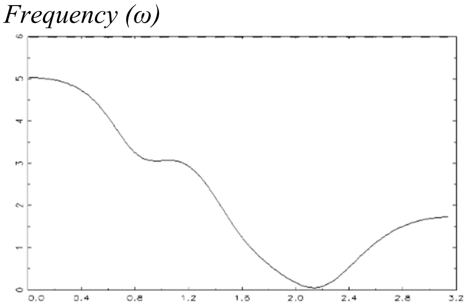


Note: The broken lines denote the 5% level of significance, while the frequency *(ω)* = 2π/cycle length *(t)*.
Source: Performed based on author's estimations.

F i g u r e A5

Causality Test in Frequency Running from *WTI* to *GPA* (lag 5)

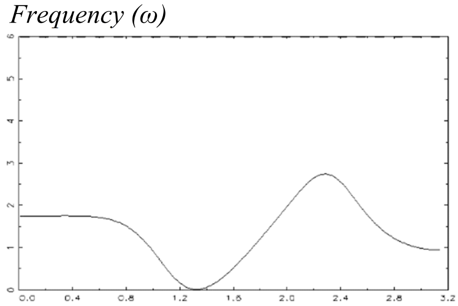
Frequency (ω)



F i g u r e A6

Causality Test in Frequency Running from *GPA* to *WTI* (lag 5)

Frequency (ω)

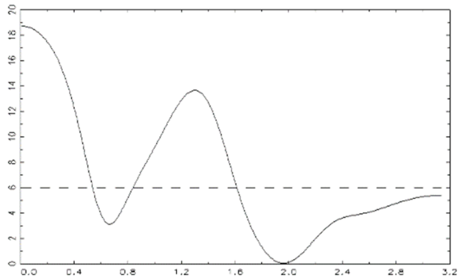


Note: The broken lines denote the 5% level of significance, while the frequency *(ω)* = 2π/cycle length *(t)*.
Source: Performed based on author's estimations.

F i g u r e A7

Causality Test in Frequency Running from *Brent to Kilian* (lag 7)

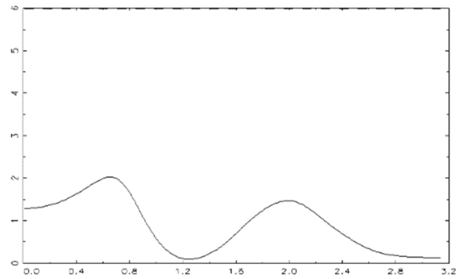
Frequency (ω)



F i g u r e A8

Causality Test in Frequency Running from *Kilian to Brent* (lag 7)

Frequency (ω)

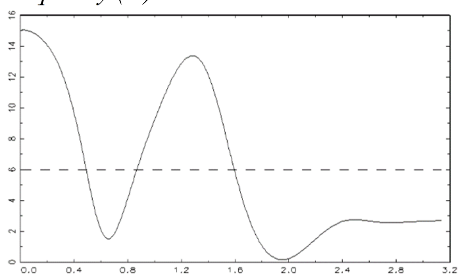


Note: The broken lines denote the 5% level of significance, while the frequency *(ω)* = 2π/cycle length *(t)*.
Source: Performed based on author's estimations.

F i g u r e A9

Causality Test in Frequency Running from *WTI to Kilian* (lag 7)

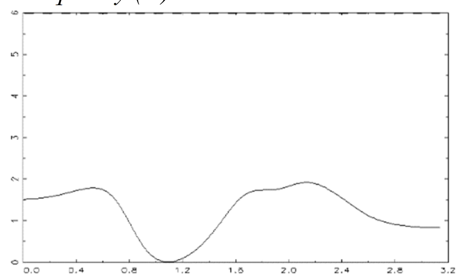
Frequency (ω)



F i g u r e A10

Causality Test in Frequency Running from *Kilian to WTI* (lag 7)

Frequency (ω)

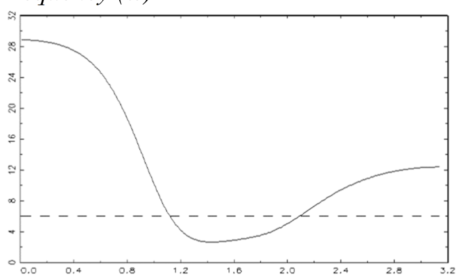


Note: The broken lines denote the 5% level of significance, while the frequency *(ω)* = 2π/cycle length *(t)*.
Source: Performed based on author's estimations.

F i g u r e A11

Causality Test in Frequency Running from *Brent to GPR x Kilian* (lag 4)

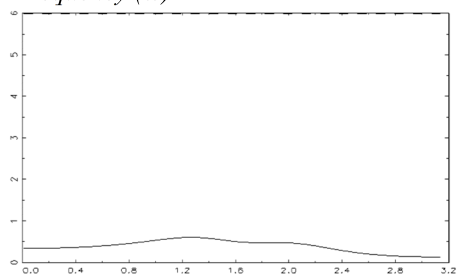
Frequency (ω)



F i g u r e A12

Causality Test in Frequency Running from *GPR x Kilian to Brent* (lag 4)

Frequency (ω)

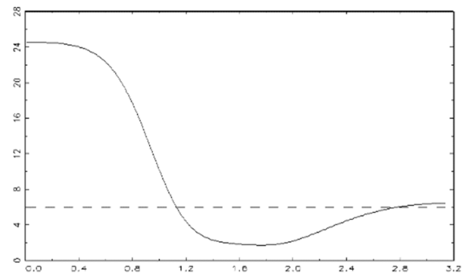


Note: The broken lines denote the 5% level of significance, while the frequency *(ω)* = 2π/cycle length *(t)*.
Source: Performed based on author's estimations.

F i g u r e A13

Causality Test in Frequency Running from *WTI to GPR x Kilian* (lag 4)

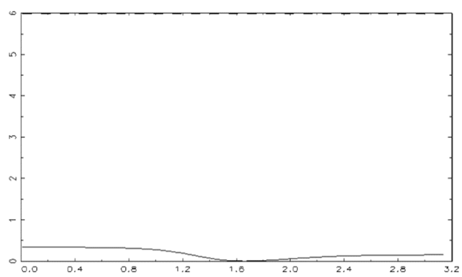
Frequency (ω)



F i g u r e A14

Causality Test in Frequency Running from *GPR x Kilian to WTI* (lag 4)

Frequency (ω)



Note: The broken lines denote the 5% level of significance, while the frequency *(ω)* = 2π/cycle length *(t)*.
Source: Performed based on author's estimations.

Supplementary Material

Routine steps for testing the short- and long-run causality in frequency between the *Brent* and *GPR.*

1. ***Treatment of variables*****:** all considered variables have been rescaled by using their natural logarithm form for comparability reasons.

2. ***Unit root test*****:** variables are tested for unit root in their natural logarithm forms in order to identify how they are I(0) or I(1) processes (Table A2).

3. ***Stationarity adjustments*****:** all variables are converted in their first-difference to obtain stationary processes (Table A2).

4. ***VAR construction and optimal lag*****:** a bivariate VAR is constructed based on *Brent* and *GPR* variables (Table S1) in order to identify their optimal based on AIC criterion, doubled by an extended set of alternative criteria (Table S2).

Out of six criteria, four indicate an optimal lag of 4 including AIC, while two suggest an optimal lag of 2. Therefore, the final optimal lag sets in further calculus is 4.

VAR's quality is demonstrated by Roots of Characteristic Polynomial test (Table S3), and VAR Residual Portmanteau Tests for Autocorrelations (Table S4). Table S3 shows that VAR satisfies the stability condition as modulus values are less than 1, while no residual auto-correlations are observed at optimal lag 4, the null of no residual auto-correlations not being rejected for all level of significances –1, 5 and 10% (Table S4).

T a b l e S1

VAR '*Brent – GPR*'

Variable	*Brent*	*GPR*
Brent (–1)	0.354080 (0.05218) [6.78537]	0.547094 (0.18913) [2.89264]
Brent (–2)	–0.038026 (0.05678) [–0.66968]	–0.079838 (0.20581) [–0.38793]
Brent (–3)	0.036714 (0.05651) [0.64972]	0.291275 (0.20481) [1.42219]
Brent (–4)	–0.128003 (0.05481) [–2.33523]	0.293905 (0.19867) [1.47937]
GPR(–1)	–0.005283 (0.01396) [–0.37835]	–0.322293 (0.05061) [–6.36803]
GPR(–2)	–0.031873 (0.01455) [–2.19097]	–0.375164 (0.05273) [–7.11528]
GPR(–3)	–0.008670 (0.01490) [–0.58167]	–0.138555 (0.05402) [–2.56484]
GPR(–4)	–0.005121 (0.01425) [–0.35932]	–0.144262 (0.05165) [–2.79307]
Constant	2.79E-05 (0.00462) [0.00604]	–0.002104 (0.01675) [–0.12564]
R-squared	0.137453	0.178237
Adj. R-squared	0.119389	0.161027
Sum sq. resids	3.180853	41.78513
S.E. equation	0.091252	0.330734
F-statistic	7.609318	10.35677
Log likelihood	385.8546	–117.6343
Akaike AIC	–1.927645	0.647746
Schwarz SC	–1.836294	0.739097
Mean dependent	9.76E-06	–0.000824
S.D. dependent	0.097241	0.361082
Akaike information criterion	–1.280773	
Schwarz criterion	–1.098070	

Note: Standard errors in (…), while t-statistics in […].

Source: Performed based on author's estimations.

Table S2

VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	197.6982	n.a.	0.001247	–1.011360	–0.990903	–1.003248
1	232.1290	68.32789	0.001065	–1.168625	–1.107254	–1.144290
2	252.1709	39.56597	0.000981	–1.251529	**–1.149245***	**–1.210971***
3	255.0633	5.680115	0.000986	–1.245805	–1.102606	–1.189023
4	262.8326	**15.17723***	**0.000967***	**–1.265285***	–1.081172	–1.192280
5	264.1776	2.613616	0.000981	–1.251564	–1.026537	–1.162335
6	265.6074	2.763378	0.000994	–1.238281	–0.972340	–1.132829
7	266.9473	2.576041	0.001008	–1.224534	–0.917679	–1.102859
8	267.2080	0.498400	0.001027	–1.205209	–0.857441	–1.067310

Note: (1) * indicates lag order selected by the criterion; (2) LR: sequential modified LR test statistic (each test at 5% level); (3) FPE: Final prediction error; (4) AIC: Akaike information criterion; (5) SC: Schwarz information criterion; (6) HQ: Hannan-Quinn information criterion.

Source: Performed based on author's estimations.

Table S3

Roots of Characteristic Polynomial Test

Root	Modulus
0.529389 – 0.415171i	0.672770
0.529389 + 0.415171i	0.672770
0.222594 – 0.580968i	0.622151
0.222594 + 0.580968i	0.622151
–0.428496 – 0.429791i	0.606901
–0.428496 + 0.429791i	0.606901
–0.307593 – 0.463540i	0.556312
–0.307593 + 0.463540i	0.556312

Source: Performed based on author's estimations.

Table S4

VAR Residual Portmanteau Tests for Autocorrelations

Lags	Q-Stat	Prob.*	Adj Q-Stat	Prob.*	df
1	0.055177	---	0.055319	---	---
2	0.115387	---	0.115838	---	---
3	0.381619	---	0.384128	---	---
4	0.530473	---	0.534521	---	---
5	2.400690	0.6625	2.428964	0.6574	4

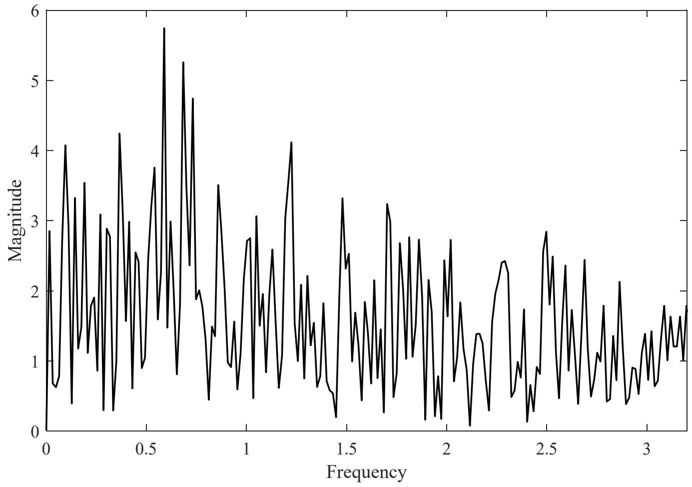
Source: Performed based on author's estimations.

5. *Fourier transformation*: variables are transformed in frequency by considering the Fourier transformation according to (3). Their new transformed forms as spectral density are plot in Figures S1 and S2.

6. *Causality test in frequency Brent – GPR (lag 4)*: based on Fourier transformed series, the causality test in frequency is performed à Breitung and Candelon (2006), with optimal lag 4, as Figures 2 and 3 show.

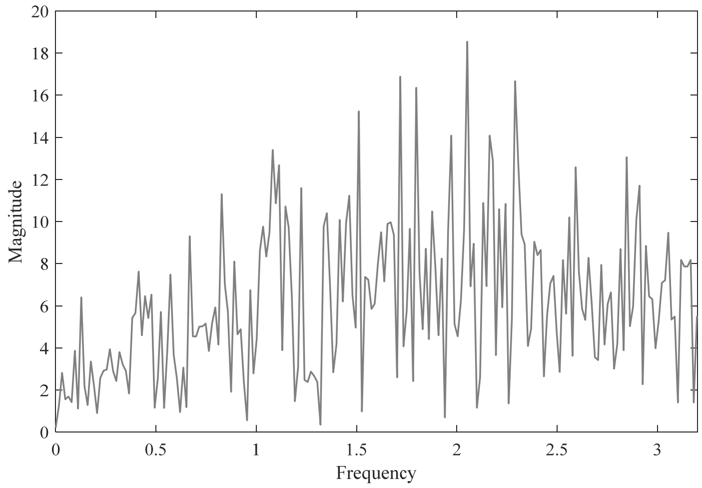
Further, the full routine is sequentially replicated for all considered variables pair.

F i g u r e S1
Spectral Density of *Brent*



Source: Performed based on author's estimations.

F i g u r e S2
Spectral Density of *GPR*



Source: Performed based on author's estimations.