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Application of Multifractal Analysis in Estimating the Reaction of Energy Markets to Geopolitical Acts and Threats

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Abstract: Since the industrial revolution, the geopolitics of energy has been a driver of global prosperity and security, and determines the survival of life on our planet. This study examines the nonlinear structure and multifractal behavior of the cross-correlation between geopolitical risk and energy markets (West Texas Intermediate (WTI), Brent, natural gas and heating oil), using the multifractal detrended cross-correlation analysis. Furthermore, an in-depth analysis reveals different associations of the indices of overall geopolitical risk, geopolitical acts, and geopolitical threats against the four energy products. Based on daily data ranging from 1 January 1985 to 30 August 2021, the findings confirm the presence of nonlinear dependencies, suggesting that geopolitical risk and energy markets are interlinked. Furthermore, significant multifractal characteristics are found and the degree of multifractality is stronger between the overall geopolitical risk and WTI while the lowest degree of multifractality is with Brent. Overall, for the WTI and heating-oil markets, the influence of geopolitical threats is more pronounced rather than their fulfilment. Contrarily, the Brent and natural gas are more correlated to geopolitical acts. Energy products exhibit heterogeneous persistence levels of cross-correlation with all the indicators of geopolitical risk, being more persistent in the case of small fluctuations compared to large fluctuations.

Keywords: geopolitical risk; acts and threats; energy markets; crude oil; natural gas; heating oil; multifractal detrended cross-correlation analysis

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1. Introduction

Geopolitical risk (GPR), according to Caldara and Iacoviello [1], is defined as the risk associated with terror threats, war threats, nuclear threats and military build-ups between states or countries that disrupt the usual, peaceful conduct of international affairs. For instance, Russia's recent invasion of Ukraine on 24 February 2022 has rattled human capital, physical infrastructure, financial markets, international peace and the security system [2]. It is producing a major humanitarian crisis and running amok on an already frail global economy, which was recently hit by the COVID-19 pandemic [3]. GPR has been on the rise in recent decades, with extreme events such as the US bombing of Libya (April 1986), invasion of Kuwait (August 1990), Iraq airstrikes (January 1993), Bosnian war (February 1994), 9/11 attacks (September 2001), Iraq war (March 2003), London bombing (July 2005), the global financial crisis (GFC 2007–2008), Paris attacks (November 2015), US–North Korea (2017–2018), US–Iran tensions (2020), and the current COVID-19 pandemic (2019) [1]. GPR is now ranked even higher than economic uncertainty [4] and is emphasized as a key driver of the state of the economy [5]. Carney [6] includes GPR with economic and policy uncertainty as the "uncertainty trinity" with major financial and economic impacts. "Uncertainty" and "risk" are different, as "uncertainty" cannot be quantified while "risk" is measurable using probabilities, either subjective or physical. Since 1921, economists have debated and modeled this issue. However, the macroeconomics literature muddles this distinction, and explicitly measures "uncertainty" by developing indices described in the text, which most likely also capture some parts of "risk" [7].

Asset prices reflect investors' hopes and fears for the future and generate a tidal wave of activity. In an uncertain and risky environment, investors search for other safe heavens and withdraw their investments, thereby adversely affecting markets. GPR immediately affects the financial and commodity markets by increasing the risk aversion of investors, consumers and firms, which leads to lower consumption and investments, triggering economic slowdown and spilling over to other alternative markets. Furthermore, due to psychological fear, ambiguity, and the desire to avoid future loss, individual investors become reluctant to trade, which negatively affects financial markets [7]. Despite this, there is a lack of literature on the impact of GPR on financial markets because of the difficulty in measuring GPR. Some studies examined the impact of GPR on stock markets [8–10], cryptocurrencies [11,12], metals [13,14], energies [15,16], and oil markets [4,17–19].

Despite the development of electric cars, renewable-energy production, and ambitious climate goals, the oil market is still regarded as the lifeblood of the world's economic engine [20], meeting around two-thirds of the global energy demand [21]. For this reason, a large body of literature has investigated oil markets from various perspectives, such as the pricing formation [22–24], the relationship with the macroeconomy [25–27], interlinkages with stock markets [28,29], financialization [30,31], forecasting [32,33] or multifractal characteristics [34,35], among others. The crude-oil market is extraordinarily large and complicated. According to the Crude Oil Global Market Report 2020 (https://www.thebusinessresearchcompany.com/report/crude-oil-global-market-report#:~:text=Crude%20Oil%20Market%20Size,1.2%25%20during%20the%20forecast%20period (accessed on 19 April 2022)) and Natural Gas Global Market Report 2020 (https://www.thebusinessresearchcompany.com/report/natural-gas-global-market-report#:~:text=Natural%20Gas%20Market%20Size,7.7%25%20during%20the%20forecast%20period (accessed on 19 April 2022)), the crude-oil and natural-gas markets are expected to reach market values of about \$1407.65 billion and \$1031.55 billion by 2022, respectively. It is the geopolitical aspect which distinguishes crude-oil markets from other energies, commodities, and financial assets. Heating oil, on the other hand, commonly known as No. 2 fuel oil, accounts for around 25% of a barrel's yield and had a market value of \$163.3 billion in 2019 (https://www.verifiedmarketresearch.com/product/fuel-oil-market/ (accessed on 19 April 2022)).

The consumption of oil, natural gas and coal increases carbon emissions, which represents a barrier to sustainable economic development and contributes to the creation of new geopolitical conditions. For example, GPR can reduce carbon emissions by limiting economic growth and energy consumption. On other hand, it may deter innovation and clean energy and result in increased carbon emissions [36]. Therefore, oil-related issues should be widely investigated from a geopolitical perspective, as governments frequently regard crude oil as a political weapon [37]. Even though oil prices have recovered from historic lows in 2014 and 2015, recent volatility fueled by the Russians, Iran sanctions, United States (US) and China conflicts, and the recent shale revolution has left many concerned, and it shows no signs of easing. This means that GPR has an impact on economic aspects including oil price, production, resource mobility, demand and supply, extraction costs, exchange rates and other alternative investments. A large imbalance could occur if supply channels are blocked or demand collapses due to economic shutdowns triggered by unrest, as happened during the recent COVID-19 pandemic.

Other major energy markets such as natural gas are also prone to geopolitical risk. Russia is one of the world's main producers of primary energy resources, with a particularly strong position in global gas markets [38]. It has the world's largest gas reserves and is the world's second-largest gas producer, trailing only the US, which recently overtook Russia due to the shale revolution [39]. Most Russian gas exports go to European and Commonwealth of Independent States (CIS) countries, while Asian exports are likely to grow significantly in the future (https://scholarship.rice.edu/bitstream/handle/1911/91291/CES-pub-GeoGasRussiax-022114.pdf?sequence=1 (accessed on 19 April 2022)). As a result, Russia wields huge influence over prices and geopolitical leverage as well as on the "rules of the game". Along with oil, natural gas is also being used as a key geopolitical weapon. Therefore, the importance of the natural-gas industry for the current and future political and economic situation should not be overlooked. However, the relationship between geopolitical-risk indicators and natural gas has been largely ignored in previous studies. Natural gas is not only the energy sector's backbone, but also one of the most important national and foreign policy tools, being greatly influenced by domestic economic and political events.

GPR's connection with other commodity markets has been studied via numerous analytical methods. These include the fixed-effect regression model [40], random-effect regression model [41], quantile regression [42,43], linear and non-linear probabilistic models and feasible generalized least-square estimator [44,45], time–frequency-based wavelet analysis [46], decomposition and the STVAR model [47] or Bayesian graphical structural VAR [48], among others. However, multifractal aspects of GPR with energies as well as other financial markets have been largely ignored in these studies.

Since their popularization by the Polish-born mathematician Mandelbrot [49], the idea of fractals has roused curiosity and has now been applied in various fields to examine the self-similarity and Hausdorff dimension of an object [50]. Mandelbrot [51] used fractals to study the behavior of cotton prices and discovered that commodity prices follow self-similar complicated patterns rather than being random. Primarily, there are two types of fractal-based methodologies, i.e., mono-fractal and multifractality. The anti-persistent or persistent behavior, also known as long-memory features, were mainly studied by mono-fractals. However, scholars later found that financial markets have complex multi-scale properties, which present a challenge for mono-fractality. Multifractality, according to Mandelbrot [52], may quantify the complexity of financial time series better than mono-fractality and it has a wider use in empirical studies such as physics [53,54], chemistry [55,56] (10–11), biology [57,58], hydrology [59], environment [60], linguistics [61], physiology [62], psychology [63,64], behavioral sciences [65] economics [66] and even in music [67].

At the same time, several researchers recognize multifractality in energy markets as a stylized fact [68]. Multifractal dynamics, for example, give us a new model with appealing stochastic qualities that can reproduce some stylized facts including volatility clustering, fat tails, multi-scaling, and long-term dependence [69]. However, the combinatorial character of older versions of multifractal models, as well as their non-stationarity due to the constraint to a finite interval, limit their practical application. The pioneer methodologies involved rescaled range analysis (R/S) [70] and detrended fluctuation analysis (DFA) [71] for mono-fractality. However, R/S is prone to causing the bias error because of its vulnerability to short-range dependence (Lo, [72]). Hence, DFA compared to R/S and other above-mentioned methodologies has the benefit of long-range correlation detection in non-stationary time series. Furthermore, it eliminates the spurious analysis of long-range correlations, which is a non-stationary artifact [73].

Later, an extension of the DFA, i.e., multifractal detrended fluctuation analysis (MFDFA) by Kantelhardt, et al. [74] was derived, and this has been employed to examine the multifractality of various financial time series such as crude oil [75], stock markets [76–78], cryptocurrencies [79], and even sin markets [80]. Meanwhile, based on the concept of the DFA, Podobnik, et al. [81] developed the detrended cross-correlation analysis (DCCA) to examine the long-range cross-correlations between two non-stationary time series, which has been applied to various analyses [82,83]. However, it is easy to obtain λ as a scaling exponent in the case of the DCCA, but it lacks complete interpretation and severely distorts or even spuriously amplifies multifractal cross-correlation measures. To overcome this issue, Zhou [84] proposed the multifractal detrended cross-correlation analysis (MF-DCCA) by combining the DCCA and MFDFA, which has lately become popular [85–87]. The MF-DCCA approach can detect and quantify subtle features of multifractal cross-correlations between two financial time series. Furthermore, the multifractal spectrum analysis in the MF-DCCA quantifies the multifractal intensity of cross-correlations and explains the time series' internal complexity and local properties.

Understanding the relationship and the role of geopolitical risk in asset prices is important for investors, companies, and government policymakers, in order to incorporate the magnitude of geopolitical risk into the valuation of asset prices and risk insurance, as well as to support markets in effectively absorbing the impacts of such risks. Our purpose is thus to use the robust econophysics-based MF-DCCA to investigate the multifractal aspects of the cross-correlation between geopolitical-risk indicators and four major energy markets, i.e., West Texas Intermediate (WTI), Brent, natural gas and heating oil, from 1 January 1985 to 30 August 2021. Our study is different from others in three major aspects. Firstly, to the best of our knowledge, this paper is the first to investigate multifractal features in terms of cross-correlations. Only Bouoiyour, Selmi, Hammoudeh and Wohar [5] examined the effect of geopolitical risk on the informational efficiency of the oil market by employing MFDFA. Secondly, the interactions among oil prices and geopolitical risk and uncertainties have been a focal point of research in academia and policy circles [88], and have largely ignored the other major energy markets such as natural gas and heating oil. This study includes natural-gas and heating-oil markets as the major variables. Thirdly, we use the large daily data sets of about 36 years to reach conclusive results for market participants and government policy makers.

This study is crucial since it contributes to the literature in several ways. Firstly, we use Caldara and Iacoviello [1]'s recently constructed daily GPR indices (overall, acts and threats), instead of monthly GPR which has been used in most previous studies [5,17,89]. Daily GPR indices are noisier than monthly GPR indices, but they capture better the multifractal characteristics. Hence, they provide a detailed view of a bigger range of incidents that the monthly counterpart may appear to overlook. For example, the ethnic violence in former Yugoslavia and attempted overthrow in the Soviet Union in August 1991 and The North Atlantic Treaty Organization (NATO) air strikes in Kosovo in March 1999 have little bearing on monthly GPR indices [1]. Secondly, to capture the inner dynamics of energy markets better, the impact of geopolitical threats is distinguished from geopolitical acts. This is because threats of future attacks may increase as a result of terrorist attacks or war. This underlines the need to identify risk-inducing shocks by searching for actual events rather than threats. Furthermore, distinguishing between acts and threats could be an effective learning mechanism for risk managers and investors. Thirdly, we employ MF-DCCA, which is flexible enough to capture the complexity and multifractality in the cross-correlations of energies and geopolitical risk. We believe that the strengths of multifractality between GPRs and energy markets varies, which can be used as a measure of how closely the two are linked.

Our study is laid out as follows. We provide a brief assessment of the literature in the Section 2, concerning the relationship of GPR with energy markets. The data and methodology are described in Section 3. The empirical results are provided in Section 4, while Section 5 deals with the discussion and presents some conclusions and policy implications.

2. Literature Review

The pioneering literature on GPR was based on individual geopolitical events [90–92]. However, after the recent development of the novel GPR index, a new stream of literature has investigated its impact on stock markets, exchange rates, renewable energy markets and energy markets. For instance, Yang and Yang [9] employed the monthly GPR index for stock markets and found that GPR is significant enough to capture the long and medium-term trends of stock markets. Similarly, Yang, et al. [93] employed the GARCH-MIDAS and found that global and regional monthly GPR indices have a significant impact on Chinese stock markets. The monthly GPR index is also found to be the best predictor of Kuwaiti and Omani stock markets [45]. However, Das, et al. [94] and Kannadhasan and Das [95] found that GPR has a less negative impact than Economic Policy Uncertainty (EPU) on the stock markets of emerging countries. Likewise, GPR is a major long run driver for the exchange rate of ASEAN countries [96] as well as the exchange rates of the UK, Republic of Korea, Japan, China and Canada [97]. Yang, Wei, Li and He [15] employed delta conditional Value-at-Risk techniques and found that the geopolitical-risk spillover to renewable energy markets is much smaller than that from equity and oil markets. The major shortcoming in previous literature is that most of it focused either on individual geopolitical events or the monthly frequency of the GPR indices, where major geopolitical events could be missed [1]. Hence, this study fills this gap and employs the daily frequency of the GPR index to provide the multifractal dynamics for energy markets in a more robust way.

The literature on GPR in energy markets deals mostly with the crude-oil market rather than other energy markets. For instance, Antonakakis, et al. [98] employ the VAR-BEKK-GARCH model and find that GPR has a severe impact on the mean return and variability of oil markets compared to stock markets. Similarly, using nonlinear Granger causality tests and a DCC-MVGARCH model, Huang, et al. [99] find that the impact of GPR on the volatility of oil through the jump component is higher than its returns. While the correlation between volatility jumps and GPR seems to be positive, Mei, Ma, Liao and Wang [89] report that GPR is positively linked with the realized volatility of oil and can be used to predict the short-term volatility of oil futures. Liu, Ma, Tang and Zhang [17] proposed a new model, GARCH-MIDAS-GPR, which uses GPR and serious GPR to forecast the volatility of oil futures in order to gain higher economic gains. Despite a great number of empirical studies on the relationship between GPR and energy markets, the multifractal dimension of GPR with energies is mostly overlooked. Therefore, this study employs MF-DCCA to uncover the inner dynamics of multifractality for GPR and major energy markets.

In addition, for better policy making, it is important for policy makers, and market participants to have extensive knowledge about the different impact of geopolitical acts and threats on financial markets. However, only a few studies have examined this. For instance, Bouoiyour, Selmi, Hammoudeh and Wohar [5] separate the shocks and find that the impact of geopolitical threats on oil price dynamics is moderate or non-significant while the impact of geopolitical acts is stronger and positive. Geopolitical acts, as opposed to threats, help to forecast the long-term volatility of oil markets [89]. Likewise, Salisu, Pierdzioch and Gupta [4] report that geopolitical acts decrease tail risk at longer forecasting horizons in oil markets, while threats increase tail risk. Hence, geopolitical threats are the major predictors of oil markets' tail risk.

Society's survival and advancement depends on energy, which can be seen as a key driver of global economic expansion [100,101]. Energy plays an important role in any country's development [102]. There has been a rise in the amount of energy consumed as a percentage of world consumption. Energy price stability has become a major concern for many countries because of the importance of energy for economic growth. However, because of its scarcity, vital strategy, the geographical dispersion of supply and demand, and low price elasticity of demand, the price of energy is particularly susceptible to geopolitical risk [18]. Consequently, it is important to study the impact of geopolitical risk on the energy market.

The current literature has focused primarily on the relationship between GPR and oil markets and ignored other energy markets such as natural gas and heating oil. We could only find the study by Qin, et al. [103], who examined the relationship between GPR indices and energy markets of crude oil as well as natural gas and heating oil by using the quantile regression approach. These authors found no significant impact of GPR on natural gas, while the impact of GPR on heating oil and crude oil seems to be negatively significant. Geopolitical threats, compared to acts, have a statistically negative impact on the volatility of heating oil and natural gas in various quantiles. In a recent study, Aloui and Hamida [104] demonstrate the relevance of geopolitical risk in the oil-stock nexus in a time-frequency domain. The authors applied the wavelet coherence method to show that geopolitical risk weakens oil-stock connectedness in the short term and lowers the oil-stock magnitude and volatility correlation. Similarly, Bouri, et al. [105] used logistic regressions to conclude that Bitcoin jumps are dependent on jumps in the geopolitical-risk index.

Other studies on the relationship of GPR focus on precious metals [13,14], gold [106], corporate cash holdings [107], corporate investments [108], financial constraints [109], insurance [110], merger and acquisition [111], natural resource rents [112], tourism [113] and others.

3. Materials and Methods

3.1. Data Description

In this paper, we use daily data of four major energy markets, i.e., WTI, Brent, natural gas and heating oil, as well as three geopolitical-risk indicators, namely geopolitical-risk index (*GPR*), geopolitical-act index (*GPRAct*) and geopolitical-threat index (*GPRThreat*). The period extends from 1 January 1985 to 30 August 2021 for geopolitical-risk indicators, WTI, and heating oil, while the initial date for Brent and natural gas differs, as shown in Table 1. The data range and number of observations after data cleaning and matching with GPR Pindices for energy commodities are also documented in Table 1. The daily data for energy markets are collected from Datastream while the data for geopolitical-risk indicators are extracted from Caldara and Iacoviello [1]'s website of GPRs (https://www.matteoiacoviello.com/gpr.htm (accessed on 19 April 2022)). For further analysis, the daily changes in the price of each energy j are estimated as:

$$r_{t,j} = \frac{p_{t,j} - p_{t-1,j}}{p_{t-1,j}} \tag{1}$$

Daily changes in the three geopolitical-risk indicators are calculated as follows:

$$r_{GPR} = \frac{GPR_t - GPR_{t-1}}{GPR_{t-1}} \tag{2}$$

$$r_{GPRThreat} = \frac{GPRThreat_t - GPRThreat_{t-1}}{GPRThreat_{t-1}} \tag{3}$$

$$r_{GPRAct} = \frac{GPRAct_t - GPRAct_{t-1}}{GPRAct_{t-1}} \tag{4}$$

Table 1. List of variables and summary statistics of daily changes *.

	GPR	GPRAct	GPRThreat	WTI Crude	Brent Oil	Natural Gas	Heating Oil
Data Range	1 January 1985–30 August 2021	1 January 1985–30 August 2021	1 January 1985–30 August 2021	1 January 1985–30 August 2021	28 June 1988–30 August 2021	5 April 1990–30 August 2021	1 January 1985–30 August 2021
N	13,336	13,336	13,336	9174	8377	7883	9277
Mean	0.1018	0.1888	0.1590	0.0004	0.0005	0.0007	0.0004
Median	−0.0071	−0.0045	−0.0108	0.0009	0.0003	−0.0004	0.0007
Min	−0.9511	−0.9273	−0.9001	−0.3300	−0.3477	−0.3132	−0.3236
Max	15.4331	13.8347	15.0303	0.2510	0.2102	0.3831	0.1502
S.D.	0.5660	0.8719	0.7754	0.0255	0.0230	0.0344	0.0233
Kurtosis	67.1510	37.2597	51.9419	14.5694	16.3020	8.1301	−0.8772
Skewness	4.5892	4.4100	4.8600	−0.1225	−0.6401	0.6870	0.4738

* The MF-DCCA procedure requires time series of the same length. So, the number of observations for GPR indices changes according to the length of energy indices.

Caldara and Iacoviello [1]'s newly developed geopolitical-risk index (GPR) is based on computerized text searches from the archives of ten newspapers (Chicago Tribune, The Daily Telegraph, Financial Times, The Globe and Mail, The Guardian, The Los Angeles Times, The New York Times, USA Today, The Wall Street Journal, and The Washington Post). GPR is based on the number of articles in each newspaper for each month that were linked to adverse geopolitical events. The text searches are structured in eight main categories, i.e., war threats, peace threats, military buildups, nuclear threats, terror threats, beginning of war, escalation of war, and terror acts.

More importantly, Caldara and Iacoviello [1] further divide the GPR index into two indices, i.e., geopolitical acts (*GPRAct*) and geopolitical threats (*GPRThreat*). As seen in the past, geopolitical acts of war have frequently fueled panic and threats about future adverse events. Terrorist attacks, for example, may heighten the possibility of future attacks or a conflict. Hence, *GPRThreat* comprises articles based on threats and military (categories 1–5), while *GPRAct* corresponds to the occurrence or escalation of negative events (categories 6–8).

Figure 1 plots the daily index values as well as the daily returns in GPR, *GPRThreat* and *GPRAct*. Interestingly, even if the spikes of *GPRThreat* and *GPRAct* overlap, there is still independent variation. For example, *GPRThreat* rises in 1990 at the beginning of the Gulf war and in response to the threat from Iraq to the US embassy. *GPRAct* on the other hand, spikes at the Gulf War, 9/11 terrorist attacks in New York and the Iraqi war in 2003. GPRThreat also seems to be high during the recent conflicts between the US and North Korea in 2018 and the US with Iran in 2020.

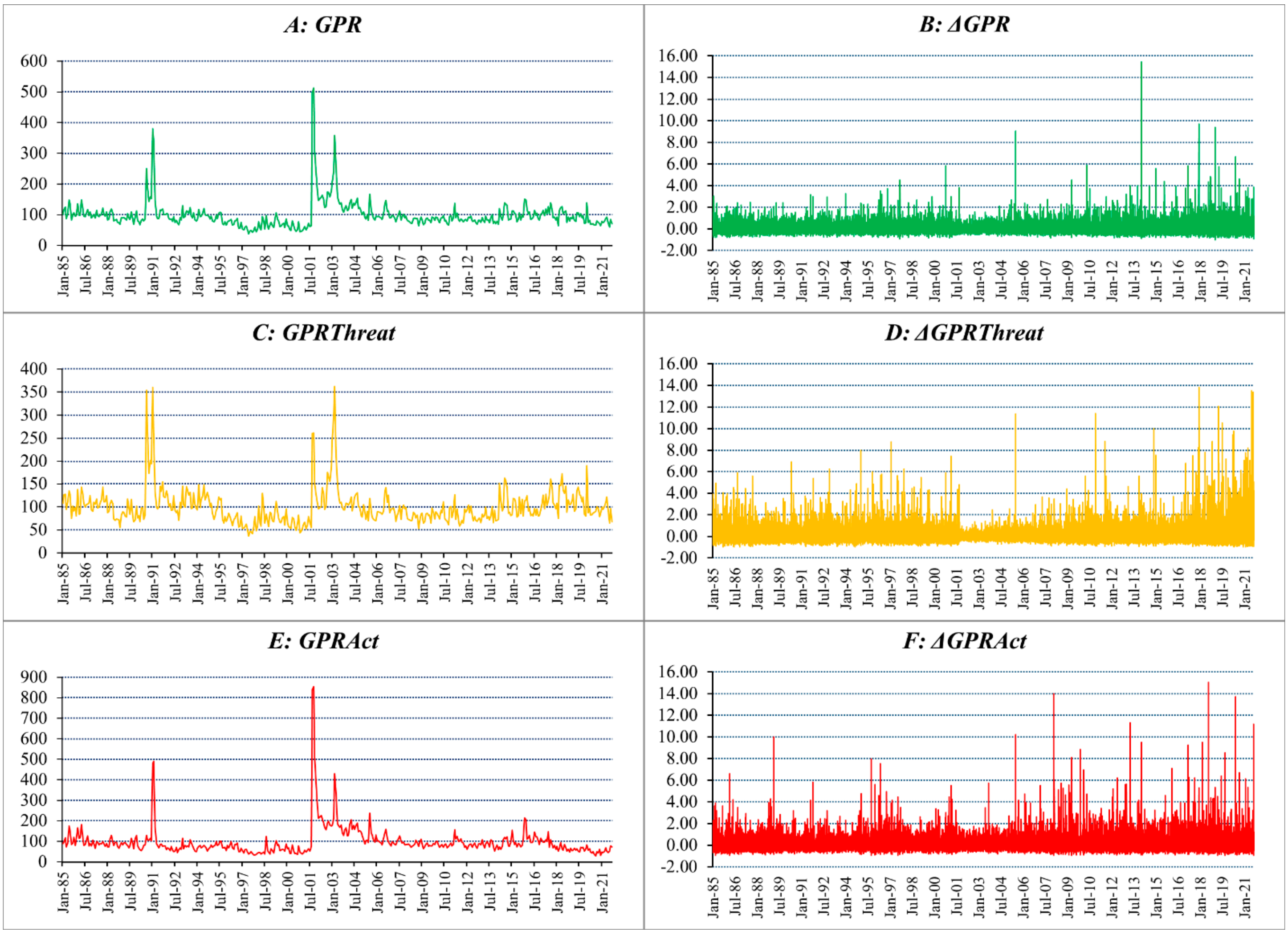

Figure 1. Daily Index Values (**Left**) and daily percentage changes (**Right**) in GPR, GPR Acts and GPR Threats.

Figures 2 and 3 present the evolution of daily prices and returns over time in the energy markets. Interestingly, the graphical evidence suggests that energies appear to be positively correlated with significant geopolitical events. For instance, a significant increase in the prices of crude oil and heating oil during the 1990–1991 Gulf War is observed. This is because Iraqi forces burned down over 700 oil wells and dumped around 400 million gallons of oil in the Persian Gulf [114]. This led to a decrease of 2 million barrels per day in Iraqi crude-oil production [115]. The next rise in oil markets occurred after the September 11 attacks (9/11) and the Afghanistan war in 2001. Moreover, the Iraqi War, US occupation of Iraq, and the following Iraqi resistance to occupation in 2003 appear to have influenced oil markets. Finally, the Great Financial Crisis (GFC) of 2008–2009 and the Arab Spring, which saw the removal of Ben Ali (Tunisia), Muammar Gaddafi (Libya) and Hosni Mubarak (Egypt), also affected oil prices. However, we see a huge drop in oil prices between 2014 and 2016, which corresponds to the great oil-price bust. In addition, all energies have shown a downward tendency during the recent COVID-19 pandemic. WTI on the other hand, crashed and even fell to a negative value by the end of April 2020 (see Figures 2 and 3). This is due to the sharp decline in demand and the price war between Saudi Arabia and Russia in March 2020 (https://www.cnbc.com/2020/06/16/how-negative-oil-prices-revealed-the-dangers-of-futures-trading.html (accessed on 19 April 2022)). On the other hand, natural-gas prices have followed a different path from oil prices, which have been relatively stable from 2009 to 2019. This substantial disconnection from oil prices is due to the increase in shale gas production (https://www.api.org/-/media/Files/Oil-and-Natural-Gas/Natural-Gas-primer/Understanding-Natural-Gas-Markets-Primer-High.pdf (accessed on 19 April 2022)). However, for specific periods (9/11, hurricanes of 2005, GFC, and COVID-19), an increase in the natural-gas price is accompanied by an increase in geopolitical risk.

Table 1 reports the descriptive statistics for the returns of geopolitical-risk indicators and energy markets. The mean values for geopolitical-risk indices are high, with a maximum of 0.19 for acts (*GPRAct*) and a minimum of 0.10 for the overall index (GPR). Similarly, the highest maximum return of 0.38 in a day is observed for natural gas, and the highest loss of 0.35 is observed for Brent. Moreover, geopolitical acts are seen to be more volatile than threats, while natural gas is found to be more volatile among energy markets. The skewness values are positive for all return series, except WTI and Brent crude oil. Likewise, all series except heating oil have kurtosis values above three, meaning that all series are peaked and have fat tails. The presence of fat tails in energies could be related to multifractality, which supports the fractal-market hypothesis [116] in contrast to the efficient-market hypothesis of [117].

Besides the advantage of being used with non-stationary data, multifractal approaches could also be used with stationary data. However, it is desirable that variables do not have structural breaks, due to the possible sensitivity of the results. The use of returns usually solves the possible problems of non-stationarity and structural breaks. Aiming to confirm these results, we used the one-break tests proposed by Perron and Vogelsang [118], which model both additive-outlier (AO) and innovational-outlier (IO) approaches. We use the tests with the possibility of structural breaks since their occurrence could result in misleading results (see, for example, Perron [119]). The results in Table 2 confirm that none of the series suffers from a structural break and that in all cases, the variables are stationary, using both AO and IO approaches.

Table 2. Unit root tests (RU) in the presence of structural breaks for the variables under analysis.

Asset	IO Test		AO Test	
	SB Test	**UR *t*-Test**	**SB Test**	**UR *t*-Test**
WTI	−0.149	−33.697 **	−0.123	−37.319 **
Brent	−1.267	−38.988 **	−1.035	−28.526 **
Natural gas	−1.03	−34.781 **	−0.785	−24.152 **
Heating oil	−0.173	−36.464 **	−0.214	−27.508 **

The first column of each test (IO and AO) shows the result of the existence of a structural break in the series under analysis. The second column presents the Perron and Vogelsang [118] unit root test. ** denotes significance at the 1% level.

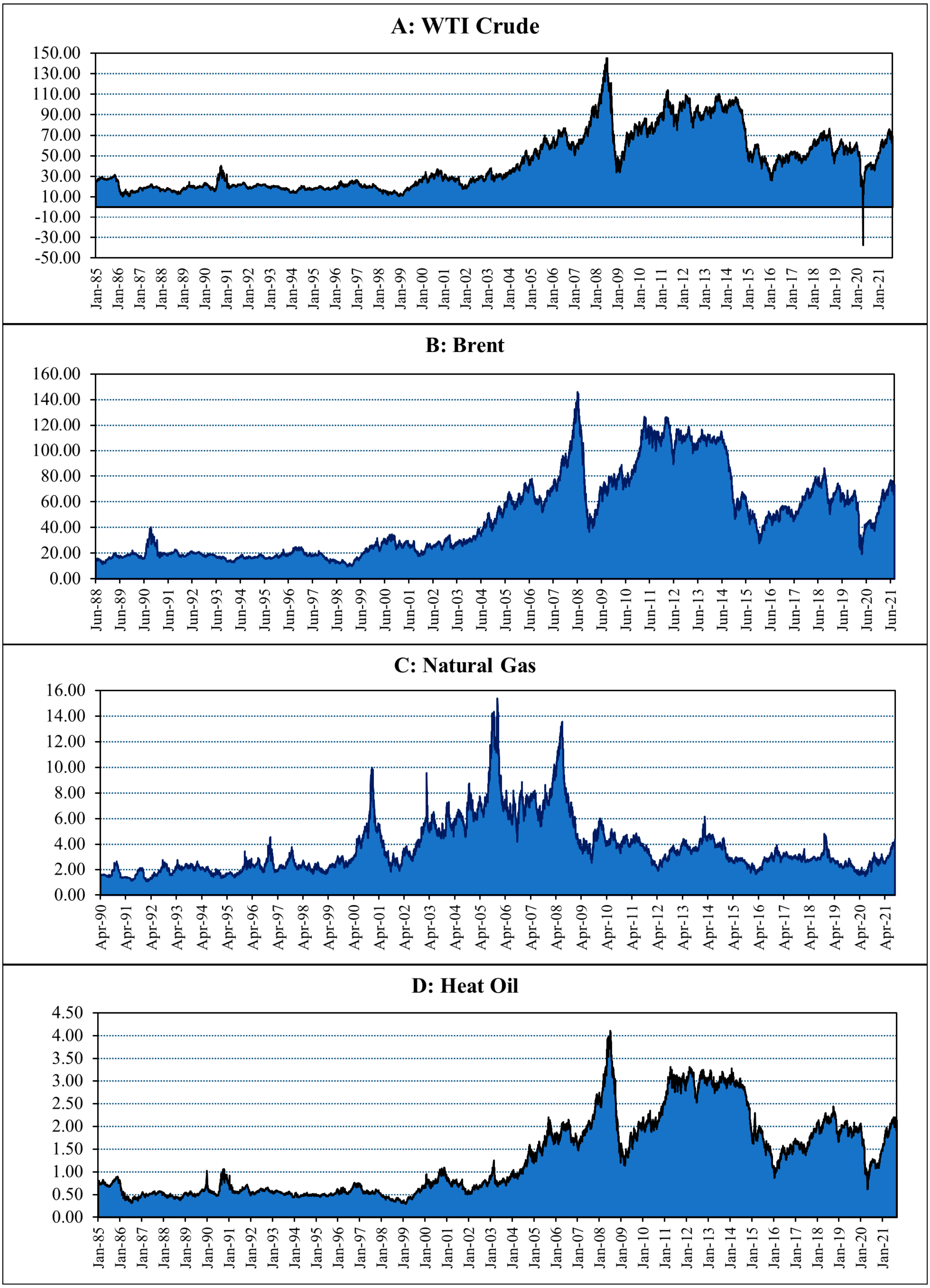

Figure 2. Evolution of daily prices over time, where the price unit of WTI and Brent is USD per Barrel, the natural-gas price unit is USD per MMBtu while heating oil is expressed in USD per gallon.

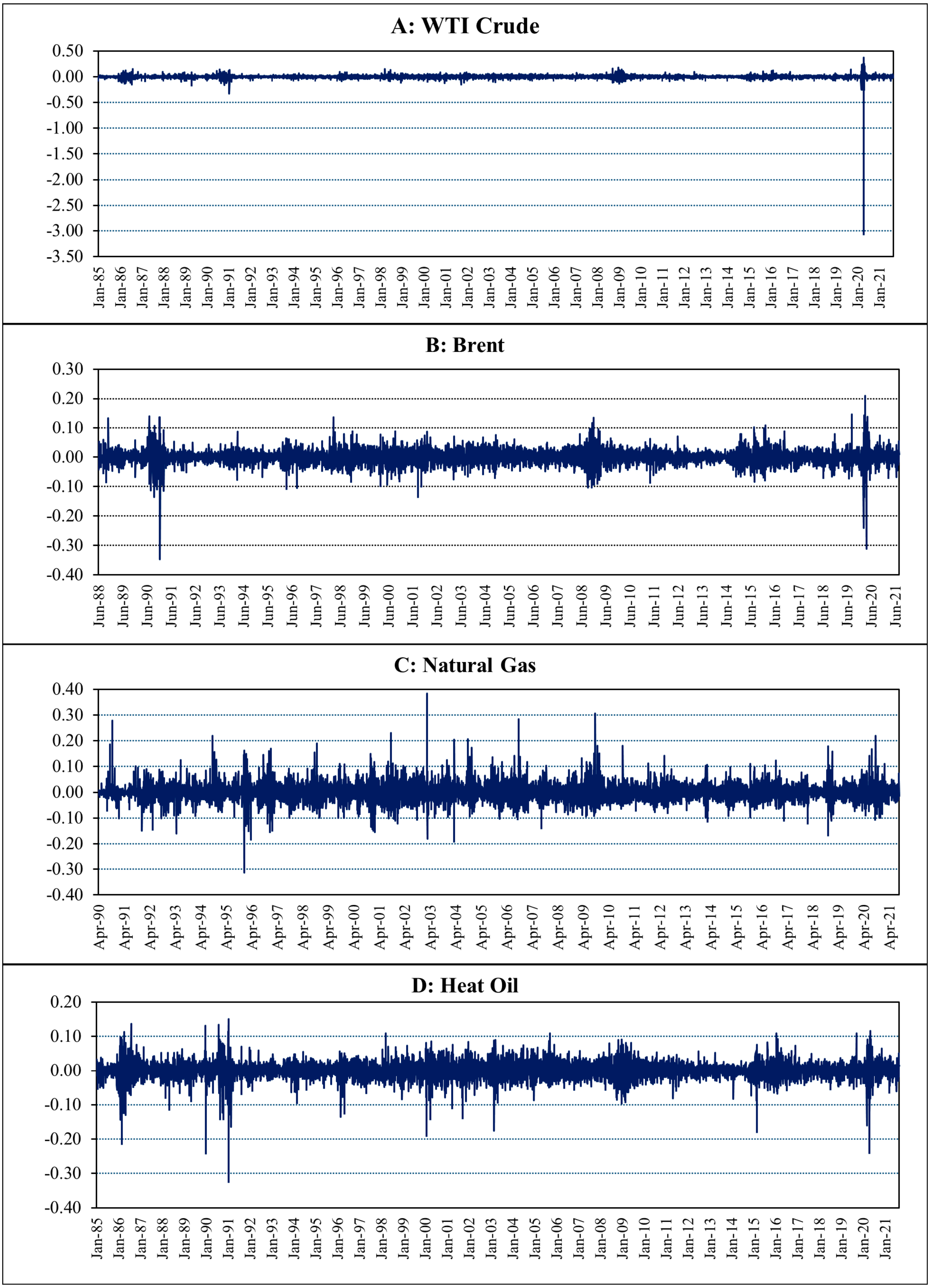

Figure 3. Movement of Daily returns in energy markets.

3.2. Multifractal Detrended Cross-Correlation Analysis (MF-DCCA)

Combining both MF-DFA and DCCA, Zhou [84] developed the multifractal detrended cross-correlation (MF-DCCA/MF-DXA) to deal with multifractal aspects of two cross-correlated, possibly non-stationary signals. Calculating the cross-correlation of the daily data of three geopolitical-risk indices (*GPR*, *GPRAct*, *GPRThreat*) with four major energy markets (WTI, Brent, natural gas, heating oil), applying the MF-DCCA technique, makes this study more detailed, robust, and more in-depth.

The five steps of the MF-DCCA method are represented as follows.

Let $\{(X_i)\}$ and $\{(Y_i)\}$ be two possible equal-length time series, in our case the energy-market returns and daily changes in three geopolitical-risk indices, with N indicating the length of the series. In the first step, the new corresponding time-series profile is constructed as follows:

$$X_{(j)} = \sum_{t=1}^{j}(x_t - \overline{x}),\ Y_{(j)} = \sum_{t=1}^{j}(y_t - \overline{y}),\ t = 1,2,3\ldots\ldots,\ N \tag{5}$$

Being,

$$\overline{x} = \frac{1}{N}\sum_{t=1}^{N} x(t) \text{ and } \overline{y} = \frac{1}{N}\sum_{t=1}^{N} y(t)$$

The second step consists of dividing the profile $\{(X_i)\}$ and $\{(Y_i)\}$ into $M_s = [N/s]$ non-overlapping boxes of length s. For each box ν, the assumed trend is estimated by fitting a polynomial of order m ($P_{X,v}^{(m)}$ for X and $P_{Y,v}^{(m)}$ for Y). Considering the possibility of N being a non-multiple of s, with the objective of considering all existing information, the same procedure is repeated starting from the reverse end of each series, as proposed by [120], resulting in $2N_s$ segments.

The third step consists of estimating the local trend $X^v(i)$ and $Y^v(i)$ of each segment, through ordinary least squares, for each $v = 1,\ 2,\ \ldots,\ 2N_s$, from which the variance is determined, given by

$$F^2(s,v) = \frac{1}{s}\sum_{i=1}^{s}|X[(v-1)s+i] - X^v(i)| \cdot |Y[(v-1)s+i] - Y^v(i)| \tag{6}$$

or each segment $v = 1, 2, \ldots, N_s$, and

$$F^2(s,v) = \frac{1}{s}\sum_{j=1}^{s}|X[N-(v-N_s)s+i] - X^v(i)| \cdot |Y[N-(v-N_s)s+i] - Y^v(i)| \tag{7}$$

for $v = N_{s+1}, \ldots, 2N_s$.

In the fourth step, the qth-order fluctuation function is obtained as follows

$$F_{q(s)} = \left\{\frac{1}{2N_s}\sum_{v=1}^{2N_s}\left[F^2(s,v)\right]^{q/2}\right\}^{1/q} \tag{8}$$

for any $q \neq 0$, while for $q = 0$ it is given by

$$F_{0(s)} = exp\left\{\frac{1}{4N_s}\sum_{v=1}^{2N_s} ln\left[F^2(s,v)\right]\right\} \tag{9}$$

The q parameter is used to distinguish between small and large fluctuations, with $q < 0$ representing small and $q > 0$ large fluctuations. The standard DCCA procedure is retrieved at $q = 2$ and with $F_{q(s)}$ being an increasing function of s.

Finally, in step 5, the scaling behavior of the fluctuations is obtained from the log–log regression between $F_q(s)$ and s, for the different values of q, which could be defined as a power law given by

$$F_q(s) \sim s^{H_{xy}(q)} \tag{10}$$

The scaling exponent $H_{xy}(q)$ describes the power-law relationship between two different time series, showing how fast $F_q(s)$ of local fluctuations grows with an increase in the s scale. When two time series y_1 and y_2 are identical, MF-DCCA is a special case of MFDFA.

Just like the univariate Hurst exponent, the bivariate Hurst exponent $H_{xy}(2)$ exhibits similar properties [121]. The scaling component $H_{xy}(q)$ ranges from 0 to 1, and remains constant for different values of q, in the case of mono-fractal cross-correlation. If the scaling exponent $H_{xy}(q)$ is dependent on q, then the cross-correlations between two time series are multifractal. Furthermore, for $q > 0$ and $q < 0$, $H_{xy}(q)$ describes the scaling behavior of the segments with large and small fluctuations. The range of the Hurst exponent $0.5 < H_{xy}(q) < 1$ indicates the presence of long-term memory, and the series display persistent (positive) cross-correlation. On the contrary, the range $0 < H_{xy}(q) < 0.\ 5$ indicates an anti-persistent (negative) cross-correlation, and an increase (decrease) in a time series is most probably followed by another decrease (increase). Finally, in the case of $H_{xy}(q) = 0.5$, the two series are not cross-correlated.

The strength of the multifractality can be estimated with the ΔH proposed by [122] and given by

$$\Delta H = H_{max}(q) - H_{min}(q) \tag{11}$$

Using the respective values of $H_{xy}(q)$, we can identify the degree of multifractality of the respective cross-correlations.

From the Legendre transform, we obtain the following:

$$\alpha_{xy} = H_{xy}(q) + q \cdot H'_{xy}(q) \tag{12}$$

Hence, the spectrum of singularity $f(\alpha)$ can be identified as:

$$f(\alpha) = q(\alpha - H_{xy}(q)) + 1 \tag{13}$$

Whereas the multifractal spectrum width is estimated to examine the multifractality level and can be shown as:

$$\Delta\alpha_{xy} = \max\alpha_{xy} - \min\alpha_{xy} \tag{14}$$

Therefore, higher levels of multifractality are related to the higher variability of $h(q)$, the usual generalized Hurst exponent, being possible to compute it as $\Delta h = h_{(qmin)} - h_{(qmax)}$, with a decreasing relationship between $H_{xy}(q)$ and q [123].

For the MF-DCCA analysis, the R package "MFDFA" developed by [124,125] was used. (The detailed documentation is available at https://www.rdocumentation.org/packages/MFDFA/versions/1.1/topics/MFDFA. (accessed on 19 April 2022)).

4. Empirical Results

To reveal multifractal behavior and to measure the degree of cross-correlation, we adopted the MF-DCCA method to further analyze the role of three geopolitical-risk indicators, i.e., overall (*GPR*), acts (*GPRAct*) and threats (*GPRThreat*), in the cross-correlation with energy markets of WTI, Brent, natural gas and heating oil. Figures 4–6 graphically represent the multifractal detrended cross-correlation analysis in the four energy markets with the three geopolitical-risk indices. As suggested by [126], we calculated the fluctuation function $F_{xyq}(S)$ from -10 to $+10$ scaling order and the scales are selected according to the series length N while the maximum scale is taken as $S_{max} < N/5$. Figure 4 shows the relationship between log(s) and log($F_{xyq}(S)$) for $q = -10$ (*blue*), $q = 0$ (*red*) and $q = 10$ (*black*), changing with time length s for all the pairs of geopolitical risks (*GPR*, *GPRThreat*, *GPRAct*) with energy markets (WTI, Brent, natural gas, heating oil). The log–log plots are well shaped and grow linearly with the scale s, which indicates that the power-law behavior and long-range cross-correlations exist between all pairs of geopolitical risks and energy markets. The power-law cross-correlation behavior reveals that large fluctuations in the prices of energy markets tend to be accompanied by considerable fluctuations in geopolitical risk, and vice versa.

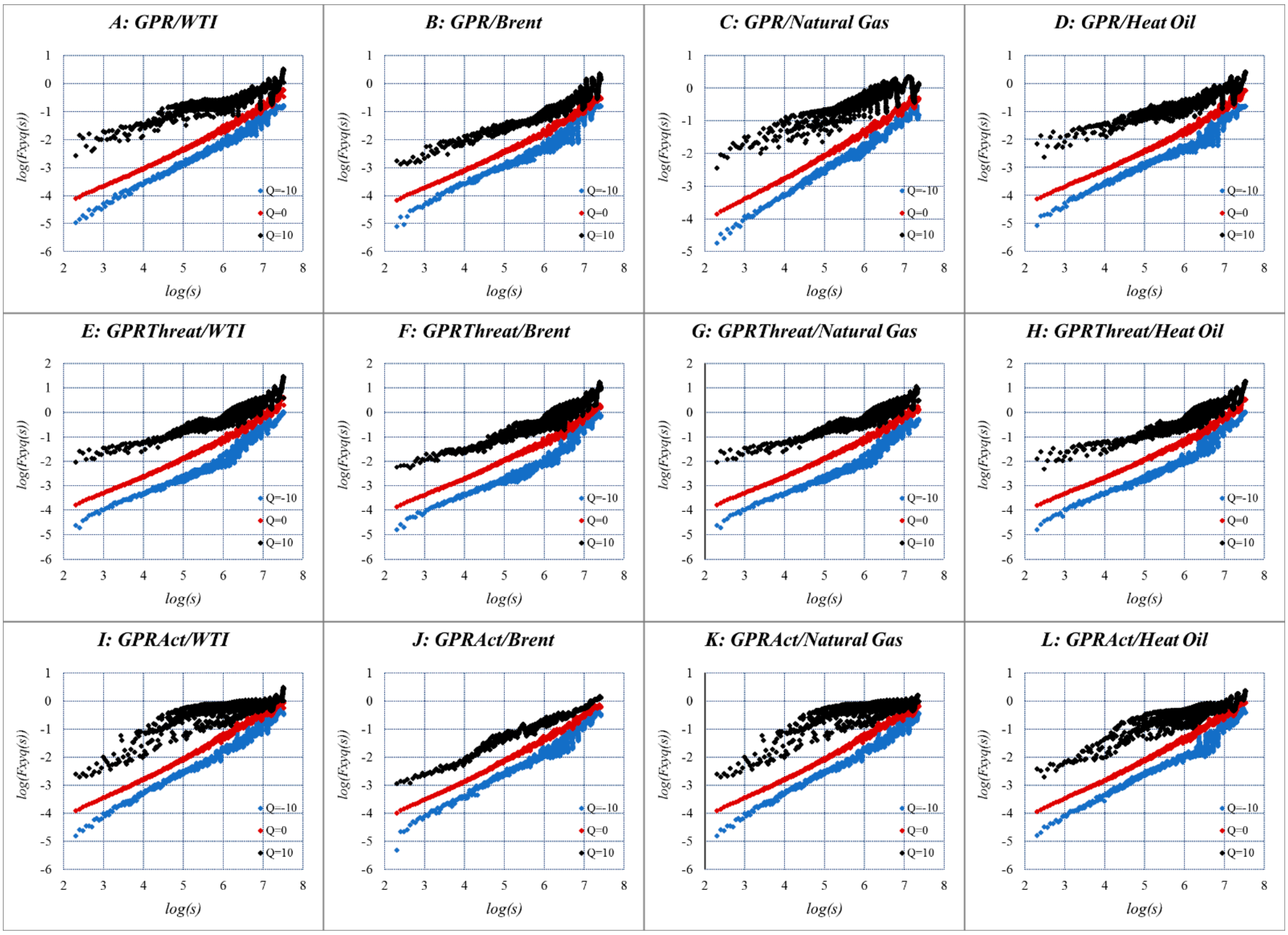

Figure 4. Log–Log plot of Fluctuation functions Fxyq (S) versus s for q = [−10, 0, +10].

Figure 5 shows the generalized Hurst exponent $H_{xy}(q)$ for all the pairs, which are not constant and show a declining trend with q ranging from −10 to 10. The dependence of the generalized Hurst exponent $H_{xy}(q)$ on the increasing value of q shows that the cross-correlations between different geopolitical-risk indices and energy markets have multifractal properties. For example, in Table 3, the highest value of $H_{xy}(q)$ for the pair WTI/GPR (overall geopolitical risk) for $q = -10$ is 0.57, dropping to 0.54 at $q = 0$ and with the lowest value of 0.29 for $q = 10$. Similarly, the $H_{xy}(q)$ for the pairs WTI/GPRAct (geopolitical acts), and WTI/GPRThreat (geopolitical threats) achieves a maximum of 0.68 and 0.61 when $q = -10$, declining to 0.61 and 0.54 at $q = 0$ and dropping to its lowest values of, respectively, 0.42 and 0.24 at $q = 10$. The declining trend of $H_{xy}(q)$ verifies its dependency on q, suggesting that all the pairs of geopolitical risks and energy markets have multifractal properties.

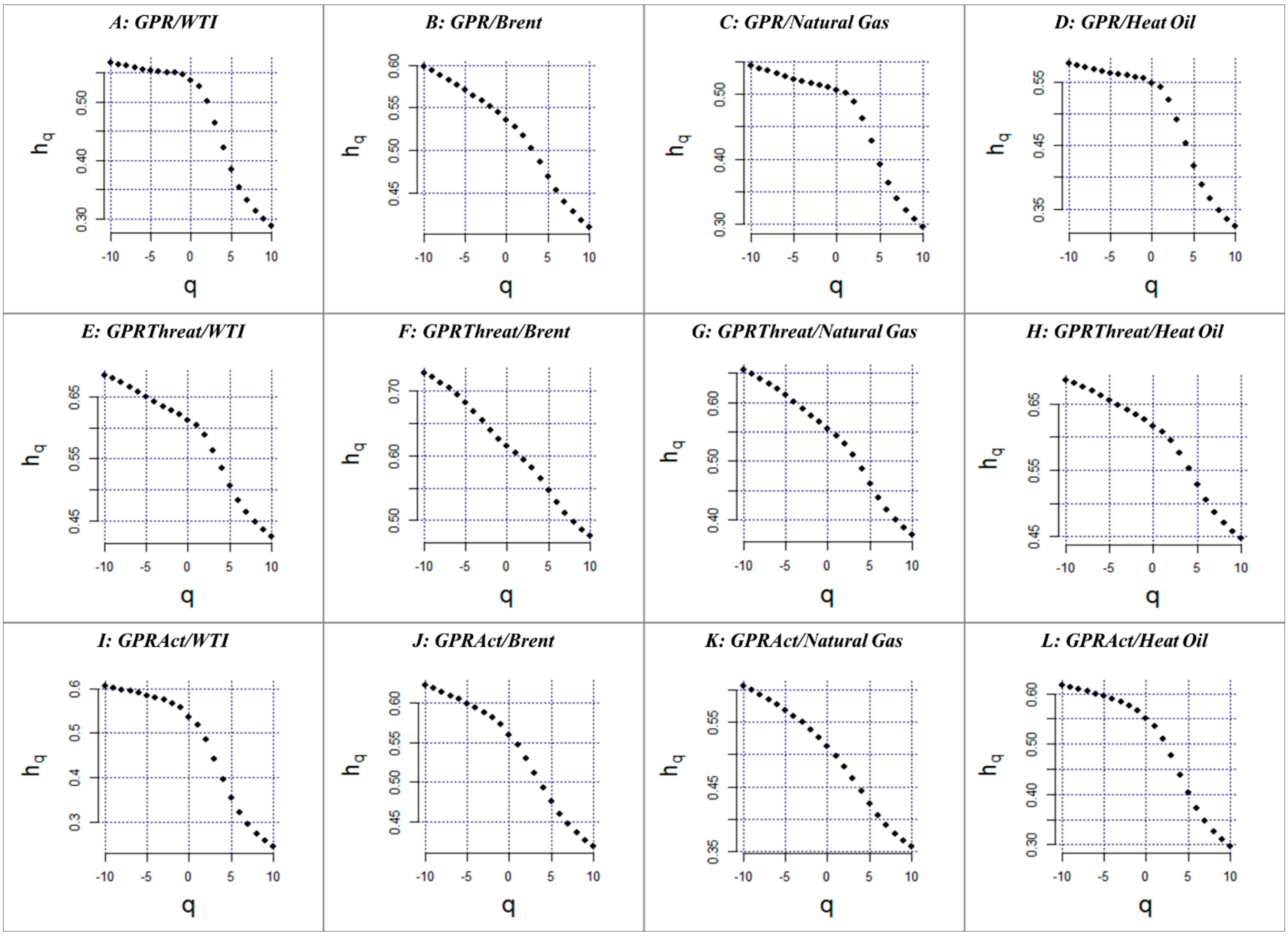

Figure 5. Generalized Hurst exponent Hxy dependence on q for $q = -10$, $q = 0$, $q = 10$.

The strength of the multifractal behavior differs among the different pairs under study, and this can be measured through the width/range of the generalized Hurst exponent (ΔH), as expressed in Table 3. The strength of multifractality between these pairs can be analyzed in several ways. For instance, the overall geopolitical risk (GPR) has the highest multifractal pattern with WTI ($\Delta H = 0.28$) followed by heating oil ($\Delta H = 0.26$) and natural gas ($\Delta H = 0.25$). Brent, on other hand, has the lowest level of multifractality ($\Delta H = 0.19$) with GPR. Similar findings are observed for multifractality in the cross-correlations of geopolitical threats *(GPRThreat)* with energy markets. The highest multifractality is found in WTI ($\Delta H = 0.36$), while heating oil ($\Delta H = 0.32$) is the second highest. On other hand, Brent ($\Delta H = 0.20$) and natural gas ($\Delta H = 0.25$) reveal the lowest level of multifractality with *GPRThreat*. However, we find different results in terms of the relationship with geopolitical acts (*GPRAct*), where natural gas and WTI show the highest ΔH of 0.28 and 0.26, respectively. Heating oil ($\Delta H = 0.24$) and Brent ($\Delta H = 0.25$) exhibit the lowest multifractality in the cross-correlations with *GPRAct*. Furthermore, for the markets of WTI and heating oil, the influence of geopolitical threats is more pronounced than their occurrence. Contrarily, Brent and natural gas are more correlated with geopolitical acts. The width of multiple spectra shown in Figure 6 further confirms these findings.

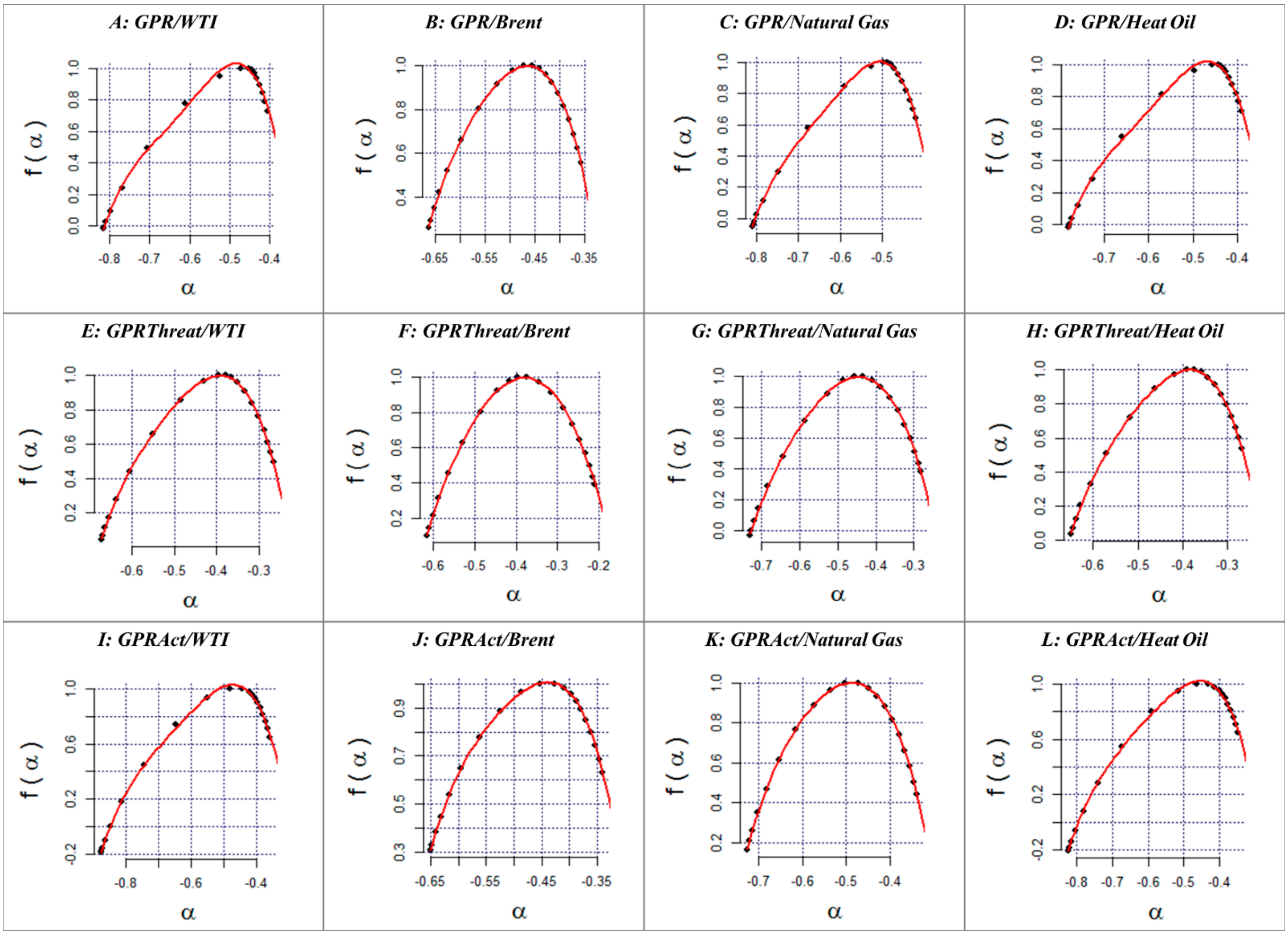

Figure 6. Multifractal spectrum.

Table 3. Generalized Hurst exponents for the energy markets ranging from $q = -10$ to $q = 10$.

Q	GPR/ WTI	GPRAct/ WTI	GPRThreat/ WTI	GPR/ Brent	GPRAct/ Brent	GPRThreat / Brent	GPR/ Natural Gas	GPRAct/ Natural Gas	GPRThreat/ Natural Gas	GPR/ Heating Oil	GPRAct/ Heating Oil	GPRThreat/ Heating Oil
−10	0.5671	0.6849	0.6062	0.5984	0.7284	0.6226	0.5441	0.6559	0.6056	0.5801	0.6858	0.6167
−9	0.5641	0.6793	0.6023	0.5935	0.7216	0.6185	0.5401	0.649	0.5994	0.5769	0.6807	0.6128
−8	0.5612	0.6731	0.5983	0.5883	0.7137	0.6141	0.5359	0.6412	0.5925	0.5737	0.6752	0.6087
−7	0.5584	0.6662	0.5941	0.5827	0.7047	0.6095	0.5316	0.6325	0.5851	0.5705	0.6692	0.6044
−6	0.5559	0.6586	0.5897	0.5768	0.6944	0.6047	0.5274	0.6229	0.577	0.5675	0.6627	0.5998
−5	0.5538	0.6506	0.5851	0.5707	0.6825	0.5996	0.5233	0.6125	0.5683	0.5648	0.6558	0.595
−4	0.5521	0.6424	0.5802	0.5645	0.6692	0.5943	0.5195	0.6014	0.5591	0.5625	0.6486	0.5898
−3	0.5508	0.6346	0.5744	0.5581	0.6548	0.5883	0.5163	0.5898	0.5492	0.5606	0.6412	0.5839
−2	0.5495	0.6276	0.5671	0.5515	0.6401	0.5813	0.5136	0.578	0.5384	0.5589	0.6337	0.5766
−1	0.5469	0.6213	0.5568	0.5445	0.6262	0.5726	0.5113	0.5664	0.5265	0.5566	0.6262	0.5671
0	0.5364	0.6122	0.5369	0.5359	0.6146	0.5594	0.5066	0.5544	0.5118	0.5489	0.6166	0.5505
1	0.527	0.6042	0.5188	0.5281	0.6044	0.5473	0.5022	0.5437	0.4981	0.542	0.6083	0.5354
2	0.5015	0.5876	0.4853	0.517	0.5943	0.5305	0.4883	0.5297	0.4813	0.5225	0.5947	0.5097
3	0.464	0.5635	0.4417	0.5028	0.5814	0.5119	0.4624	0.5108	0.4628	0.4916	0.5757	0.4763
4	0.4218	0.5349	0.3954	0.4863	0.5648	0.4932	0.4275	0.4866	0.4434	0.4539	0.5522	0.4388
5	0.384	0.5069	0.3542	0.4692	0.5462	0.4756	0.3925	0.4606	0.4242	0.4181	0.5278	0.4029
6	0.3538	0.4829	0.3209	0.4533	0.528	0.4602	0.363	0.4367	0.4065	0.3888	0.5055	0.3721
7	0.3306	0.4632	0.2947	0.4396	0.5117	0.447	0.3397	0.4162	0.3911	0.3659	0.4866	0.3468
8	0.3126	0.4474	0.274	0.428	0.4977	0.436	0.3215	0.3994	0.3779	0.3481	0.471	0.3264
9	0.2985	0.4345	0.2576	0.4182	0.4858	0.4267	0.3071	0.3855	0.3669	0.334	0.4581	0.31
10	0.2872	0.4239	0.2444	0.41	0.4758	0.419	0.2954	0.374	0.3576	0.3227	0.4474	0.2966
ΔH	0.2799	0.261	0.3618	0.1884	0.2526	0.2036	0.2487	0.2819	0.248	0.2574	0.2384	0.3201

The multiple spectra with greater widths exhibit higher variations in the form of various types of fluctuation distributions. These asymmetrical and varying shapes are to be expected because of the fluctuating nature of energy prices. All the pairs have significant non-zero widths, which indicates a deviation from the random walk process. The presence of multifractality in the cross-correlations indicates that the variables under study behave according to the adaptive-market hypothesis (AMH) of Lo [127], which is supported by others [128–130]. According to the efficient-market hypothesis (EMH) of Fama [117], market prices randomly fluctuate and there are no long-memory properties. Hence, investors are unable to beat the efficient market (no multifractal markets). However, in the real world, as confirmed by our results, these efficient markets are not observed and there are multifractal patterns. Therefore, Lo [126] called this phenomenon the AMH, where achieving perfect market efficiency is not possible.

The scaling cross-correlation exponents $H_{xy}(q = 2)$ are reported in Table 3 and show the persistent behavior of the cross-correlation between geopolitical-risk indicators and energy markets. The findings show that the value of $H_{xy}(q = 2)$ for the pairs of overall geopolitical risk (*GPR*) with energy markets is greater than 0.5 except for natural gas. This indicates that WTI, Brent, and heating oil have a persistent cross-correlation with *GPR* while natural gas has an anti-persistent cross-correlation. On the other hand, all the pairs of geopolitical acts (*GPRAct*) show persistent cross-correlation behavior with energy markets. Regarding the connection with geopolitical threats (*GPRThreat*), WTI and natural gas show anti-persistence while Brent and heating oil show persistent cross-correlation behavior.

Kristoufek [121] specifies that a cross-persistent series has an $H_{xy}(q = 2)$ greater than 0.5, which indicates that a positive or negative value of a relationship between two variables has a higher probability of another positive or negative value of that relationship at the following moment [131]. A long-range cross-correlation indicates that both time series have long-memory properties in their own lags [132,133]. The presence of cross-correlations, according to Podobnik and Stanley [132], further suggests that an increase or decrease in one variable is more likely to be followed by an increase or decrease in another variable.

Accordingly, all pairs except for GPRThreat/WTI, GPR/natural gas and GPRThreat/natural gas are found to be cross-persistent. For these exceptions, this implies that an increase (decrease) in GPR and GPRThreat is more likely to be accompanied by a decrease (increase) in the returns of those energies, while for the other pairs, an increase (decrease) in geopolitical-risk indicators is likely to be accompanied by an increase (decrease) in the returns of energy markets.

5. Conclusions and Discussion

Geopolitical risk is regarded as one of the critical factors in determining the prices of energy markets, especially crude oil. Over the past decades, many political events have occurred, often changing price dynamics and causing large fluctuations in oil markets. Hence, it is critical to determine whether energies can be a useful insurance option for investors seeking protection during times of escalating global tension. Similarly, whether the impact of increasing GPR on energy-price dynamics is more sensitive to threats or their occurrence (i.e., geopolitical acts) is an interesting subject. In this context, we examine the multifractal characteristics of the cross-correlation between major energy markets, i.e., WTI, Brent, natural gas and heating oil, and three geopolitical-risk indices (overall, threats and acts). In order to understand these connections, we applied MF-DCCA to daily data covering the period from 1 January 1985 to 30 August 2021. However, the initial dates vary for Brent and natural gas. The data span around 35 years, which is long enough to contain key historical geopolitical events and evaluate multifractality.

The findings of this study suggest that all the pairs of geopolitical risks with energy markets have long-range correlations, indicating the presence of multifractality. However, the strength of multifractality in the cross-correlation varies across all pairs. The pairs of WTI with *GPR* and *GPRThreat* have the highest multifractal behavior, whereas natural gas has the highest multifractal patterns with *GPRAct*. Contrarily, we found the lowest multifractal levels for the pairs of Brent with *GPR* and *GPRThreat*, while heating oil shows the lowest multifractality with *GPRAct*. Furthermore, WTI and heating oil are more influenced by *GPRThreat* than *GPRAct*, while the impact of *GPRAct* is higher in Brent and natural gas. Only Brent and heating oil showed persistent cross-correlation behavior for all geopolitical-risk indices, while *GPRThreat* has anti-persistent cross-correlation with WTI and natural gas.

An interesting finding is that the impact of geopolitical threat is more related with WTI and heating oil, while the impact of acts is more connected with Brent oil and natural gas, which is not an unsurprising result, being consistent with previous studies [5,98,115]. Compared to geopolitical threats, Noguera-Santaella [115] finds a positive and stronger correlation of geopolitical acts with Brent. Furthermore, the association between Brent and geopolitical acts is highly persistent when compared to the association with geopolitical threats. Nonetheless, the finding that geopolitical threats have a less significant impact on Brent defies common intuition and expectations. This could be justified by the underlying complexity and multifractality in Brent prices. As Brent is used to price around 65% of the world's crude-oil market, it is more globally representative than WTI [134,135]. WTI, on other hand, is a higher-quality crude oil than Brent and hence has historically benefitted from a higher price (being traded at a premium over Brent) [136]. However, this is not always the case. Because of the asymmetry of demand and supply at Cushing, the price of WTI has been much lower than Brent since 2011, due to the sudden surge in production in the US. Other considerations include the Libyan war's rapid disruption of oil exports and the market forecasts of optimistic Brent prices being pushed higher due to escalation of the conflict in Syria and the Egyptian revolution of 2011. Hence, Brent prices have risen as a result of these more frequent geopolitical threats in North African and Middle Eastern regions [136]. Furthermore, the degree of global crude-oil-market integration appears to have changed. Even though Brent and WTI are widely regarded as global crude-oil-price benchmarks, they still react differently to external shocks and changing local market conditions. Hence, the impact of threats and acts should not be generalized to other major crude oils such as Dubai and Tapis [137]. Many countries have learned from previous acts or disasters and have implemented proper policies, which may explain their ability to absorb the negative effects of threats on crude-oil prices.

The reason for heating oil having similar behavior to WTI (higher impact of threats than acts) could be that WTI generally acts as a net transmitter and the highest transmissions are towards heating oil [138,139]. On other hand, the natural-gas market is riskier and more complex than the crude-oil market, since its degree of multifractality is more important in the post-crisis period [140]. This complexity in the gas market might be explained by its specificities (transport costs, storage costs, seasonal consumption effect, etc.). Hence, geopolitical threats tend to have a smaller impact on natural-gas prices. Even if financial markets handle geopolitical acts effectively and efficiently, managing geopolitical threats remains difficult, especially with the emergence of populist problems. The development of populism around the world (especially in the US and Europe) is one of the most significant concerns confronting the energy and other financial markets today [5].

The findings of this study have important modeling and policy implications for academics, managers, investors, and policy makers. Firstly, through this multifractal analysis, we find a new perspective to describe and understand the long-range cross-correlation between geopolitical-risk indicators and major energy markets. Financial models including long-range cross-correlations can better reflect the interconnections across financial markets [141]. Secondly, the findings confirm that changes in energy prices are multifractal and interact in a nonlinear way. So, the common linear models such as OLS, correlation and vector-regression techniques are not suitable to model the dynamics of the cross-correlations between geopolitical-risk indicators and major energy markets [99]. This nonlinear dependency in the cross-correlations means that geopolitical risk and energy prices mutually interact, which might assist investors in maximizing the portability of technical trading strategies involving geopolitical acts and threats. Thirdly, from a risk management point of view, it is important to consider the variations in multifractality strength among different pairs of energy markets and geopolitical-risk indices. For instance, geopolitical threats have a greater influence on WTI prices, while natural-gas prices are more vulnerable to geopolitical acts. Most of the energy markets exhibit cross-persistency, which indicates that a positive or negative value of the cross-correlation at a given moment has a higher probability of being followed by another positive or negative value at the next moment. The cross-correlated behavior of a large fluctuation $(q > 0)$ is higher than that of a small fluctuation $(for\ q < 0)$. Therefore, policy makers and market participants should be wary of the impact of geopolitical threats as well as acts on energy-market-price fluctuations. Given that WTI and heating-oil prices are connected to geopolitical threats, policy makers should try to ensure stability during geopolitical threats. For Brent and natural gas, policies should be devised for the occurrence of geopolitical acts. Thirdly, energy investors should be aware that energy prices are not only sensitive to geopolitical and financial crises but also to the law of demand and supply shocks. Specifically, WTI prices crashed into the negative during COVID-19, falling from \$18 to −\$38 per barrel in April 2020. This is due to a drop in demand and the price war between the oil giants of Russia and Saudi Arabia in early March 2020. However, the recent Russian invasion of Ukraine has pushed oil over the \$130 per barrel mark for the first time since 2008 and gas prices have also spiked to all-time highs. (https://www.jpmorgan.com/insights/research/russia-ukraine-crisis-market-impact (accessed on 19 April 2022)) Hence, energy investors can use these findings to make the best investment decisions possible.

This research has some limitations that can provide inspiration for further research. For instance, the impact of geopolitical threats and acts is not uniform and cannot be generalized across all energy markets. Therefore, future research should include more energy markets to find out if the impact of geopolitical-risk indicators varies. Furthermore, this study does not incorporate the asymmetric multiple-scaling behavior of the indices used. Future studies could examine the correlation of asymmetry since the occurrence of major geopolitical events could increase the asymmetry in the cross-correlation. It would also be valuable to use the non-linear Granger Causality test to examine the causal non-linear relationship between GPR indices and energy markets

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