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Exploring the connection between geopolitical risks and energy markets

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ABSTRACT

This study delves into the complexities of energy commodity futures and clean energy indexes, analyzing their responses to geopolitical risk. The detrended fluctuation analysis was applied, and the efficiency index was estimated to assess energy market behavior better. This approach allows the evaluation of long-range dependence and market efficiency. The findings show evolving patterns influenced by significant geopolitical events such as the COVID-19 pandemic and geopolitical conflicts. Transfer entropy analysis also uncovers directional dependence between energy markets and geopolitical risk, highlighting energy commodities' influential (or anticipated) role on geopolitical indexes. The dynamic analysis emphasizes time-varying relationships, with fluctuations notably impacted by global events like the European sovereign debt crisis and escalating geopolitical tensions. Additionally, clean energy indexes exhibit sensitivity to geopolitical risk, offering valuable insights into market behavior and informing risk management strategies. The study highlights the complex and dynamic relationships between energy markets and geopolitical factors and provides useful information for investors and policymakers on energy markets.

1. Introduction

Over the past decades, energy markets have experienced challenging transformations, motivated market deregulation, technological advances, and even renewable energy deployment. These transformations, combined with extreme events (such as occasional shocks and crises with financial or non-financial origin), can not only impact and influence market behavior and investors' sentiment but also disrupt the dynamics of spillovers in the energy markets and make it more complex. This situation will have important implications for price discovery, asset allocation, and risk management, highlighting the need for a deeper understanding of these interconnections.

A critical focus in financial markets is determining whether prices follow a random walk, as Fama's (1970) Efficient Market Hypothesis (EMH) suggests. According to this theory, all the information available is reflected in the asset prices, so it is impossible to consistently predict when prices will go up or down, i.e., consistently obtaining abnormal returns. In finance, several models attempt to price assets efficiently [e.g., the Capital Asset Pricing Model (CAPM) of Sharpe (1964) or the Fama and French (1993)]. However, extensive empirical evidence has questioned this hypothesis, demonstrating inefficiencies in several markets. Consequently, evaluating market efficiency, particularly during periods of uncertainty, remains an essential area of research.

In parallel, understanding the relationships between different markets and assets has gained renewed importance, especially with the increasing integration of financial markets due to globalization and deregulation. For energy markets, the stakes are particularly high, given their pivotal role in economic stability and their sensitivity to external shocks. Historical examples, such as the 1973 OPEC oil embargo, caused oil prices to skyrocket, leading to a global recession and job losses (Mitchell, 2010). Moreover, the 2008 oil price surge and the 2022 Russia–European Union (EU) gas prices dispute have demonstrated the profound impact geopolitical events can have on energy prices and their ripple effects on the global economy.

While traditional approaches to analyzing relationships in financial markets often rely on linear and static methods, these are insufficient to capture the bidirectional and dynamic linkages between markets during crises. This study addresses this limitation by employing advanced

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techniques, including detrended fluctuation analysis (DFA) and transfer entropy (TE), which can capture non-linear dynamics, directional dependencies, and time-varying relationships.

Energy commodities such as oil and natural gas remain cornerstones of the global economy, characterized by their high liquidity and crucial role in trade, portfolio diversification, and economic growth. Spot and future contracts are usually used to trade several energy commodities. As long as commodity contracts become more acceptable as a viable asset class, due to their increasing access and liquidity, they have attracted more investors' attention and increased commodity futures trading (Tang and Xiong, 2012) on what is called financialization (Duc Huynh et al., 2020). For several reasons (e.g., lower costs, high leverage effect of futures, less liquidity risk, the dominance of futures to the contribution to price discovery in commodities), investors prefer future contracts over the spot market (Ameur et al., 2022). Thus, commodities futures markets were selected.

At the same time, the growing focus on sustainability and environmental concerns has led to increased interest in clean energy investments. Climate change and shifting energy policies have elevated the importance of renewable energy, making the study of clean energy indexes particularly timely and relevant (Chang et al., 2020). Comparing the performance of clean energy indexes with those of energy commodities is also important, as it provides new insights into the effectiveness of conventional versus clean energy investment strategies and the response of financial markets to changes in environmental policies and energy.

The energy market is one of the world's largest, most liquid, and most important, which motivates this study. Understanding the efficiency of energy indexes can help investors and portfolio managers make informed decisions about resource allocation and diversification. Crises or extreme events often have a significant impact on financial markets, and geopolitical risk has gained increasing relevance (Engle and Campos-Martins, 2023). Therefore, including a geopolitical risk index can help quantify and evaluate this impact, allowing investors and analysts to adjust their investment strategies according to risk conditions. Furthermore, a geopolitical risk index can help anticipate potential crises, allowing more effective decision-making regarding adverse events, whether regarding asset allocations, hedging positions, or even adopting defensive strategies to protect investments. Although much of the literature focuses on traditional energy commodities, there is limited critical analysis of how clean energy assets respond to geopolitical risks compared to conventional counterparts. This gap is significant because clean energy investments are often considered key to the global energy transition, yet their market dynamics and sensitivity to external shocks remain underexplored. Therefore, the present study evaluates the efficiency and spillover dynamics of six energy commodity futures and two clean energy indexes across a broad timeframe encompassing major crises such as the COVID-19 pandemic and the Russia-Ukraine conflict.

This study has two major goals: (i) to assess whether the energy commodities and indexes are (in)efficient (considering the weak form of informational efficiency); (ii) to identify whether specific global risk factors could act as net transmitters of spillovers for the energy markets. Considering both main goals, we apply the DFA and estimate the efficiency index (EI) to analyze the fluctuations of six energy commodities' futures prices and two indexes for renewable energy. As we aim to explore their dynamics over time, we applied sliding windows in both analyses. The EI, calculated using the estimated values of the dynamic DFA as a reference, allows us to evaluate the efficiency level of the analyzed time series. To assess and quantify the dynamics of the information flow and simultaneously identify the direction of the information flow between energy commodities and energy indexes and the geopolitical risk, we also estimate the TE. The geopolitical risk was measured by the geopolitical risk index (GPR) and by its two sub-indexes, namely the geopolitical threats (GPRT) and the geopolitical acts (GPRA). This analysis will allow us to identify whether specific global risk factors could act as transmitting channels for spillovers in energy markets and offer new insights into how energy markets respond to crises and external shocks.

These two main goals are interconnected and complementary. Assessing the informational efficiency of energy commodities and indexes provides insights into the predictability and behavior of these markets, particularly during periods of external shocks. Informational efficiency is crucial to understanding how quickly and accurately markets absorb new information, such as changes in geopolitical risks. An inefficient market may exhibit delayed or disproportionate responses to new information, influencing the dynamics of spillovers within the system (Kristoufek and Vosvrda, 2013). Simultaneously, identifying whether global risk factors act as net transmitters or receivers of spillovers complements this assessment by shedding light on the external drivers that may affect market efficiency. For instance, geopolitical risks can amplify inefficiencies by introducing uncertainty and changing the flow of information between markets (Gabriel et al., 2024). Understanding these dynamics helps to clarify how exogenous shocks propagate through energy markets and how such shocks influence market stability and interconnections. The complementary nature of these goals lies in their focus on endogenous market characteristics (efficiency) and exogenous influences (spillover transmission).

This dual perspective allows for a more comprehensive understanding of energy market behavior. For instance, findings from efficiency analysis can inform the evaluation of spillover dynamics by identifying periods of heightened inefficiency that may be more susceptible to external shocks. Conversely, understanding spillover effects can help contextualize inefficiency patterns by linking them to specific global risk events, as supported by recent literature (Hoque et al., 2023). These goals are particularly relevant given the interconnected nature of energy markets and their sensitivity to global risks. By addressing them jointly, this study provides a comprehensive framework to analyze energy market dynamics, offering valuable insights for investors, policymakers, and academics seeking to understand and mitigate risks in these complex systems.

This study contributes to the literature in three key ways. First, it provides an in-depth evaluation of energy market efficiency, offering evidence of persistent and evolving inefficiencies in conventional and clean energy markets. Second, it analyzes the directional interconnections between energy markets and geopolitical risks, identifying how information is transferred within these systems. Third, it highlights the time-varying nature of these relationships, particularly during heightened geopolitical tensions, providing practical implications for investors, policymakers, and risk managers. Moreover, we cover a broad period where extreme events (geopolitical and others) occurred, which allows a deeper assessment of the impact of these events on the energy sector. By doing so, we aimed to shed light on how these critical occurrences can influence the energy sector dynamics, including in different regions. Thus, our work is valuable for understanding the intricate web of relationships within energy commodities markets and how significant events and global risks can profoundly influence them. By understanding these dynamics comprehensively, we can confidently make informed decisions.

After this introduction, Section 2 presents a literature review. Section 3 describes the data used and the methods applied. Section 4 discusses the empirical results. Finally, Section 5 presents the main conclusions, implications, and future lines of research.

2. Literature review

Since 2002, the commodity market has undergone several fundamental changes that financialization may explain. This trend has increased the flow of investments into commodity markets, attracting specialized investors and creating new financial instruments and derivatives (Domanski and Heath, 2007). While these developments have enhanced market liquidity and accessibility, they have also introduced periods of instability, heightened volatility, and pronounced seasonal patterns. These stylized facts revive the issue of price discovery and market efficiency.

In the energy sector, there exists a broader set of energy commodities, and they do not necessarily exhibit homogenous relationships between them but rather heterogeneous ones that can be shaped by crisis periods [see, for example, Lin and Su, 2021 or Umar et al., 2021]. Furthermore, the market participants consider several energy commodities as alternative investment options (Lin and Bai, 2021), accentuating one energy commodity's difficulty in resisting the shock spillovers faced by another. Thus, the study of energy price linkages is of extreme importance not only for market participants but also for academics [see, for example, Bravo Caro et al., 2020] due to the important role played by energy commodities for international trade, economic activities, accumulation of wealth, and portfolio diversification. One area of academic debate concerns the relationship between fossil fuel-based energy and clean energy investments. Reboredo (2015) argues that these markets exhibit a competitive substitution relationship, where higher fossil energy prices make clean energy investments more attractive. In contrast, Ahmad (2017) and Ferrer et al. (2018) argue that crude oil and clean energy assets operate in distinct markets with limited substitutability. However, these studies provide little evidence of the key influencers in the energy markets and lack comprehensive insights into the dynamic interconnections between traditional and clean energy markets, particularly under extreme events. Given the extreme events, crisis periods, and potential asymmetry and nonlinearity features, this situation is extremely important.

Energy markets and geopolitics have always been closely intertwined (Liu et al., 2021), but our understanding of how energy commodities react to geopolitical risk remains limited. Some studies show that, especially in the post-financialization era, macroeconomic and political uncertainty significantly impacts the commodity markets (Bakas and Triantafyllou, 2018; Joëts et al., 2017; Kelly et al., 2016; Wei et al., 2017; among others). However, most studies focus narrowly on equity markets[see, for example, Shahzad et al., 2023 for an extensive literature review], on oil-specific analyses (e.g., Antonakakis et al., 2017; Bouoiyour et al., 2019; Liu et al., 2020, 2021; Mei et al., 2020; Noguera-Santaella, 2016; Omar et al., 2017; Ramiah et al., 2019), and on natural resources, agricultural and metal commodities (e.g., Zheng et al., 2023), often neglecting other energy commodities and clean energy indexes.

Recent research has begun to explore the impact of geopolitical risks on energy markets using advanced methods. For instance, Alqahtani and Taillard (2020) analyzed the impact of GPR on oil price returns and found that oil prices do not respond to shocks in GPR, and the GPR does not cause oil returns. Liu et al. (2021) show that geopolitical uncertainty increases the volatility of crude oil and natural gas. Meanwhile, Zheng et al. (2023) highlighted that short-term geopolitical risk shocks induce substantial and prolonged volatility changes in commodity futures prices. Hoque et al. (2023) analyzed returns and volatility connectedness and spillover among carbon, climate, and energy futures. The authors found that geopolitical risk, equity market volatility, financial stress, and clean energy innovations drive market connectedness.

Despite these advances, several limitations persist in the literature. Many studies are restricted to specific crises, such as the COVID-19 pandemic or the Russia–Ukraine war (Chatziantoniou et al., 2022; Armeanu et al., 2023), and predominantly analyze oil and gas commodities (Gong et al., 2021). Few studies adopt a comprehensive approach that spans multiple crises and integrates clean energy markets with traditional energy commodities (Ferreira et al., 2022). Additionally, conventional methods often rely on static or linear frameworks, which fail to capture the non-linear and time-varying nature of spillovers and information flow in energy markets.

Despite these advances and although some recent studies evaluate the return relationship between energy commodities or between energy commodities and clean energy indexes (Ahmad, 2017; Asl et al., 2021; Batten et al., 2017; Bondia et al., 2016; Dawar et al., 2021; Ferreira et al., 2022; Geng et al., 2017; Saeed et al., 2020; Saeed et al., 2021), several limitations persist in the literature. Many studies are restricted to specific crises, such as the COVID-19 pandemic or the Russia–Ukraine conflict [e.g., Armeanu et al., 2023, Chatziantoniou et al., 2022 or Roy et al., 2023 for an extensive literature review in this regard] and consider mostly oil and gas commodities (Gong et al., 2021; Mensi et al., 2021). Few studies adopt a comprehensive approach that covers multiple crises, integrates clean energy markets with traditional energy commodities, consider the geopolitical risk and its sub-indexes in their evaluation (except Alqahtani and Taillard, 2020; Hoque et al., 2023; Liu et al., 2021; Zheng et al., 2023) and apply methods that simultaneously can capture the non-linear dependence, identify the direction of the influence between commodities (allowing a refined analysis of the cause-effect relationship), and be robust against noise (which is particularly useful in markets with high levels of volatility, as in this case) or can be applied in situations of non-stationarity and asymmetries. Additionally, traditional methods often rely on static or linear frameworks, which fail to capture the non-linear and time-varying nature of spillovers and information flow in energy markets. This study adopts a dynamic and non-linear approach to address these gaps, using DFA and TE to evaluate market efficiency and directional spillovers. By incorporating six energy commodities and two clean energy indexes over a broad period, this research extends existing studies by focusing on the role of geopolitical risks as net transmitters/receivers of spillovers. We used the Geopolitical Risk Index (GPR) created by Caldara and Iacoviello (2018) and its sub-indexes, Geopolitical Threats (GPRT) and Geopolitical Acts (GPRA), to measure risk transmission dynamics. This index has been used in several recent studies [see, for example, Gabriel et al., 2024 for an extensive list of studies where it has been applied]. Indeed, this comprehensive approach provides a deeper understanding of how energy markets respond to geopolitical risks and extreme events, offering new insights for investors and policymakers.

3. Data and methods

3.1. Data

The data comprises six energy commodity futures, two clean energy indexes, the geopolitical risk index (GPR), and its two subindexes (GPRA and GPRT). All the variables are identified and described in detail in Table A1. The selection of variables for this study reflects their significance in capturing key dynamics within the energy sector and the geopolitical environment. Each variable contributes uniquely to understanding market behaviors, spillovers, and the influence of external risks, as detailed in Table A1 in the Appendix. The combination of these variables ensures a comprehensive analysis of energy market efficiency, spillover dynamics, and the role of geopolitical risks, capturing both traditional and renewable energy markets. Their inclusion provides robust insights into market behaviors under diverse economic and geopolitical conditions, enabling a nuanced understanding of energy sector dynamics.

Considering the referred and the market significance, the sample covers different energy types, allowing a better understanding of the relationships in this sector. Furthermore, these energy commodities are extensively traded in the global energy market, exerting a significant influence on the dynamics of the worldwide energy market and the overall economic situation. Considering geographic dispersion, commodities and indexes from different continents were selected, increasing coverage of the analysis performed.

The data on the commodity futures in the energy sector were obtained from the Thomson Reuters DataStream, and the GPR data and its sub-indexes were retrieved from the Geopolitical Risk website (https://www.matteoiacoviello.com/gpr.htm). The data covers February 13, 2007 (due to data availability) to February 20, 2024. This period includes several extreme events, such as the European Sovereign Debt Crisis (ESDC) of 2011/2012, the Arab Spring of 2011/2012, the Crimea occupation by Russia in March 2014, Brexit in June 2016, the

COVID-19 pandemic, which began at the end of 2019 but intensified in 2020, and the war between Russia and Ukraine, among others. This long period allows a comprehensive view of long-term market trends and structural changes in commodity markets.

Including these crises provides a comprehensive understanding of how cleaner energy markets react to diverse economic, geopolitical, and social disruptions. The ESDC, which destabilized financial systems, tested the resilience of cleaner energy investments under financial stress. Similarly, the Arab Spring highlighted the role of geopolitical instability in driving the need for energy diversification and secure alternatives. The Crimea occupation by Russia in 2014 marked a significant escalation in geopolitical tensions, impacting energy supply chains, particularly in Europe. Brexit in 2016 introduced political and economic uncertainty, influencing European energy policies and investment flows. The COVID-19 pandemic intensified in 2020, disrupting global supply chains and emphasizing the importance of resilient energy systems. Finally, the Russia–Ukraine war, ongoing since 2022, has drastically impacted global energy markets by reshaping energy trade dynamics and pricing mechanisms and the prioritizing cleaner energy alternatives. These crises collectively offer a unique lens to examine the interconnectedness of cleaner energy and traditional energy commodities during systemic shocks, enabling a nuanced analysis of market efficiency and spillover dynamics.

The frequency of data is of utmost importance, both statistically and economically (Narayan and Sharma, 2015). As we aim to assess the informational efficiency of energy commodity markets and continuously evaluate the connectivity between energy commodities' future markets and the GPR index (and its sub-indexes), having as much information as possible is important. Since daily frequency is superior to monthly, quarterly, or weekly data when the objective is to extract maximum information (Bannigidadmath and Narayan, 2016; Umar et al., 2020), our data has a daily frequency.

As already mentioned, the data set comprises six energy commodity futures, two renewable energy indexes, and the GPR index (as its two sub-indexes) GPR, as detailed in Table 1. Before starting to apply the DFA approach with sliding windows, the daily return rates of the different commodities were calculated as the difference of logarithms between consecutive observations, i.e., $r_t = ln(P_t) - ln(P_{t-1})$, where P_t and P_{t-1} represent the daily values of a given series on days t and $t-1$, respectively. On April 20, 2020, crude oil prices briefly dipped into negative territory, with WTI futures contracts for May delivery closing at around -37.63 USD/Bbl. As the return rate is calculated as the difference of logarithms, the price observation of this date was not considered for all commodities.

To evaluate the stationarity, we performed an augmented Dickey–Fuller (ADF) test, being the return series stationary. The Shapiro–Wilk (S–W) test was conducted to determine whether the return series is normally distributed. The null hypothesis was rejected, meaning the returns do not follow a normal distribution, i.e., the return series are fat-tailed. All the energy commodities (except HB_NatGas) show positive mean and high kurtosis values, i.e., leptokurtic distributions (a stylized fact in financial markets). Both renewable energy indexes display high kurtosis values but negative mean (i.e., these indexes decrease their values). Regarding the skewness, only gas commodities reveal positive values, meaning a higher probability of positive returns than negative ones.

4. Methods

The weak form of efficiency is based on the historical independence of returns. Although short-term memory in financial series can incentivize investors to exploit additional returns (Bariviera, 2017), the long-term correlations motivate investors. Thus, it is important to use methods that allow identification of long-term memory rather than solely providing information about its presence when, in fact, what exists is short-term memory.

Peng et al. (1994) created the DFA to analyze DNA behavior. However, considering its main goal is to evaluate temporal autocorrelation at different moments, it was quickly applied to other research areas. It is frequently used to study financial market behavior (Liu et al., 1997; David et al., 2020; Sukpitak & Hengpunya, 2016; Tiwari et al., 2018; among others), even in the case of non-stationarity.

One of the main goals of this study is to study the long-range autocorrelation in the commodity markets, analyze the existence of serial dependence, and evaluate the efficiency of these markets. The DFA could be employed to this end. As we aim to explore its evolution, we performed a dynamic analysis by applying the DFA approach with sliding windows. This approach allows us to analyze the evolution of the DFA exponent over time.

The DFA is then applied to the return rates series, which are time series x_k with $k = 1, \ldots, t$ equidistant observations. Considering Peng et al. (1994) and Peng et al. (1995), the DFA follows the next steps: (i) integration of the return series, as presented in Eq. (1):

$$X_k = \sum_{t=1}^{k} x_i - \langle x \rangle \tag{1}$$

being $\langle x \rangle$ the average of x; (ii) division of the new series X_k into non-overlapping boxes of size n; (iii) calculate, with ordinary least squares (OLS), the local trend $(\widetilde{X}_k)$ of each box. This step is used to detrend the profile X_k and to obtain the fluctuation function given by Eq. (2):

$$F(n) = \sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(X_k - \widetilde{X}_k\right)^2} \tag{2}$$

The DFA procedure aims to estimate the log–log relationship between the fluctuation function $(F(n))$ and the dimension n, with this

Table 1
Description of the data used and descriptive statistics, stationarity (ADF), and normality (S–W) tests.

	Mean	Std. Dev.	Kurtosis	Skewness	ADF	S–W	n
WTI	0.00006	0.030	87.680	−2.344	−14.386***	0.777***	
Brent	0.00009	0.024	9.738	−0.398	−14.117***	0.918***	
UK_NatGas	0.00019	0.047	12.293	0.682	−15.976***	0.849***	
HB_NatGas	−0.00037	0.035	7.658	0.306	−15.290***	0.944***	
NY_ULSD	0.00012	0.023	9.665	−0.690	−15.071***	0.920***	
EU_LS	0.00012	0.023	28.775	−1.288	−14.967***	0.888***	4131
RENIXX	−0.00006	0.022	9.160	−0.139	−14.102***	0.913***	
SP_GCE	−0.00017	0.020	10.682	−0.447	−14.497***	0.887***	
GPR	0.00017	0.412	1.529	0.016	−24.426***	0.991***	
GPRA	0.00040	0.010	1.381	0.003	−24.476***	0.033***	
GPRT	0.00002	0.008	1.049	−0.056	−24.341***	0.023***	

Notes: (i) The table presents the six commodity futures, the two renewable energy indexes analyzed, and the geopolitical risk index (as its two sub-indexes) used. It also presents the symbol of each commodity/index used; (ii) n represents the number of observations; (iii) Std. Dev. represents the standard deviation; (ii) ADF corresponds to the Augmented Dickey-Fuller Test; (iv) S–W corresponds to the Shapiro-Wilk normality test; (v) n represents the number of observations; (vi) *** means the values are statistically significant at a 1 % significance level; (vii) the start date is February 13, 2007, and the end date is February 20, 2024.

relationship being a power-law of n, equal to $F(n) = \propto n^{\alpha}$, meaning that $F(n)$ increases with the box size (n). The α exponent corresponds to the slope of the line relating $log(F(n))$ to $log(n)$ quantifies the empirical strength of the long-range power-law auto-correlations of the signal, and it can be used to identify the level of persistence (Zebende et al., 2017). Function $F(n)$ behaves as a power of n, and α can be interpreted as follows: (i) if $\alpha = 0.5$, the series could be described as a random walk, meaning there is no long-range dependence, and the autocorrelation function is zero for any period. This interpretation is consistent with the EMH, and the market could be considered efficient. The series is a white noise; (ii) if $0 < \alpha < 0.5$, there is negative long-range dependence, and the series has an anti-persistent behavior related to the market's inefficiency; (iii) if $0.5 < \alpha < 1$, there is positive long-range dependence, and the series has persistent behavior, which is also related to the market's inefficiency; (iv) If $\alpha > 1$, long-range dependence is not explained by a power-law relation, the series is non-stationary.

The DFA with a sliding windows approach is relatively common in financial literature [Cajueiro and Tabak, 2004a, 2004b]. This approach allows the detection of the evolving nature of non-linear predictability, the changing degree of market efficiency and the analysis of the dynamic behavior of the α_{DFA} exponent. Furthermore, this approach can smooth the trend signal and eliminate the possible discontinuities in the detrended signal (Almeida et al., 2013). In this approach, it is necessary to limit the size of windows, which could be understood as a limitation because it just covers a part of the sample. In financial literature, several window lengths have been used [for example, Vogl (2023) for a detailed overview]. The window length should not be too large or too short to retain sensitivity to changes in the scaling properties occurring over time and provide good statistical significance, respectively (Morales et al., 2012). Thus, our estimations were based on a window of 500 observations (about two years). This situation means that we transform our whole sample into sequential samples of 500 observations, i.e., starting by calculating the DFA for the sample from $t = 1, \ldots, 00$; then for $t = 2, \ldots, 501$; and so on. With this procedure, we have a wide set of exponents, as shown in Figs. 1 to 4. Thus, we will ultimately have a set of DFA exponents instead of a single DFA exponent.

To evaluate each commodity market's degree of efficiency and evolution over time, we adapted the EI introduced by Kristoufek and Vosvrda (2013) and applied a sliding windows approach, too. This index has already been used in several studies that aim to evaluate and conclude about the efficiency of financial markets [e.g., Costa et al., 2019]. This index is given by Eq. (3):

$$EI = \sqrt{\sum_{i=1}^{N} \left(\frac{\widehat{M}_i - M_i^*}{R_i} \right)^2} \quad (3)$$

Where $\widehat{M}_i$ and M_i^* are each of the values for the DFA exponent and the expected value for market efficiency, respectively. The last is equal to 0.5 in the case of the DFA. The R_i is the range of the measure, equal to one in the case of the DFA. The difference between $\widehat{M}_i$ and M_i^* allows us to assess the distance to the random level (0.5).

Specific time-series properties and an asymmetric measure are required to quantify the information flow in a financial context (Dimpfl and Peter, 2014). Based on the Shannon entropy, precisely on mutual information, Schreiber (2000) proposed a measure of the information flow, the TE, as displayed in Eq. (4):

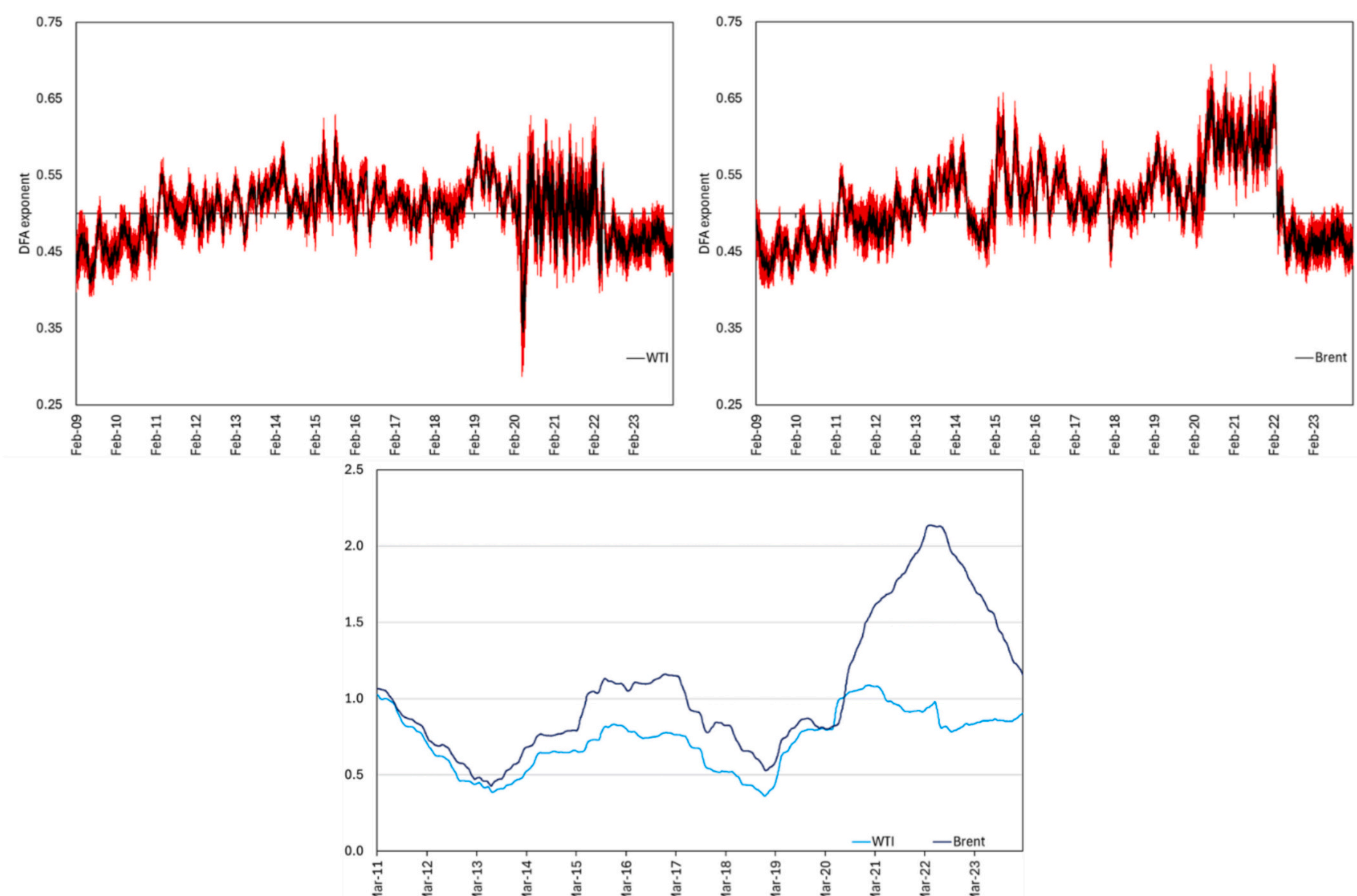

Fig. 1. Evolution of the DFA exponents (on the top) and the EI (on the bottom) for the WTI and Brent commodity futures.
Note: (i) the figure shows the evolution of the DFA exponents for WTI (on the top left) and for Brent (on the top right) commodity futures; (ii) the length of the window is 500 observations.

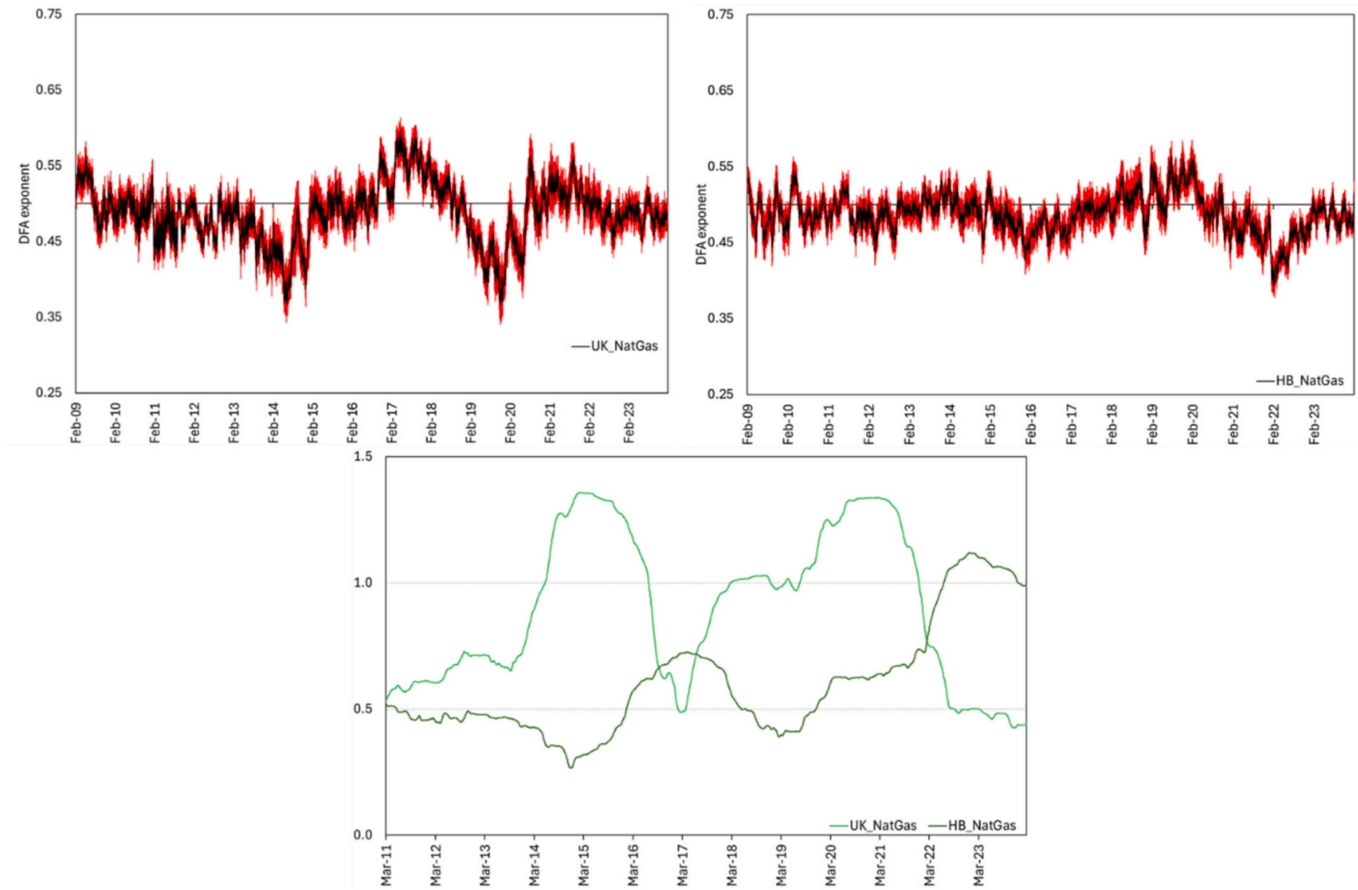

Fig. 2. Evolution of the DFA exponents (on the top) and the EI (on the bottom) for the UK_NatGas and HB_NatGas commodity futures.
Note: (i) the figure shows the evolution of the DFA exponents for UK_NatGas (on the top left) and for HB_NatGas (on the top right) commodity futures; (ii) the length of the window is 500 observations.

$$TE_{YX}(k,l) = \sum\nolimits_{x,y} p\left(y_{t+1}, y_t^{(k)}, x_t^{(l)}\right) log \frac{p\left(y_{t+1}|y_t^{(k)}, x_t^{(l)}\right)}{p\left(y_{t+1}|y_t^{(k)}\right)} \tag{4}$$

The TE is a directional measure of the dependence between two variables [see, for example, Behrendt et al., 2019] and widely used in several research areas, from neuroscience (Haresign et al., 2022), engineering (Naef et al., 2022), physics (Fidani, 2022), economics and finance (Dimpfl and Peter, 2013; Ferreira et al., 2022; Kwon and Yang, 2008; Sensoy et al., 2014), among others. The presence of information flow may be tested using the bootstrap method proposed by Dimpfl and Peter (2013). To identify which of the paired variables influence each other, we used the net TE, which is given by $NET\ TE_{YX} = TE_{YX} - TE_{XY}$. Thus, the dominant direction of the information flow could be, in this case, (i) positive, if $TE_{Y\rightarrow X}(k,l) > TE_{X\rightarrow Y}(k,l)$, meaning the dominant direction flow is from Y to X; (ii) negative, if $TE_{Y\rightarrow X}(k,l) < TE_{X\rightarrow Y}(k,l)$, meaning the dominant direction flow is from X to Y; (iii) equal to zero, if $TE_{Y\rightarrow X}(k,l) = TE_{X\rightarrow Y}(k,l)$, meaning the flow in both directions has the same dominance.

For a time-varying analysis of the behavior between variables and to evaluate the relationship dynamics between them, we apply the sliding windows approach considering consecutive windows of 500 observations, as was done in the dynamic long-range autocorrelation assessment (when the DFA approach was used). For example, this approach facilitates, as in the case of crises or other extraordinary events, the identification of how those events affect the bidirectional relationship between variables. All the estimations of the TE were made using the R package RTransferEntropy.

The combination of DFA and TE provides a robust framework for analyzing long-range dependence, market efficiency, and information flow dynamics in energy markets. DFA helps identify persistence in time-series data, while TE quantifies bidirectional information flow between variables. EI captures deviation from randomness in market evolution. Integrating these methods allows for a comprehensive understanding of market behavior, particularly in the context of energy markets and geopolitical risks. TE's directional analysis reveals how global risk factors impact the energy sector, enriching assessments of market interconnectivity. The sliding windows approach in TE analysis helps identify temporal changes in bidirectional relationships during crises. This multidimensional perspective enhances understanding of energy market efficiency and interdependence.

5. Empirical results and discussion

5.1. Long-range dependence and market efficiency

Aiming to analyze the dependence dynamically, we performed a sliding windows DFA based on windows of 500 observations. These windows were considered to allow the analysis of these markets' behavior under several extreme events, including the ESDC. With this analysis, we can understand the evolution of those exponents over time, obtaining information about the evolution of long-range autocorrelation. The results are presented in Figs. 1–4, where the black lines represent the evolution of the α_{DFA} exponents over time and the red bars are the standard deviations of the DFA estimations.

We calculated the EI using the estimated values of the dynamic DFA as a reference and applied a sliding windows approach to evaluate the efficiency level of the commodity futures series. In this case, an $EI = 0$

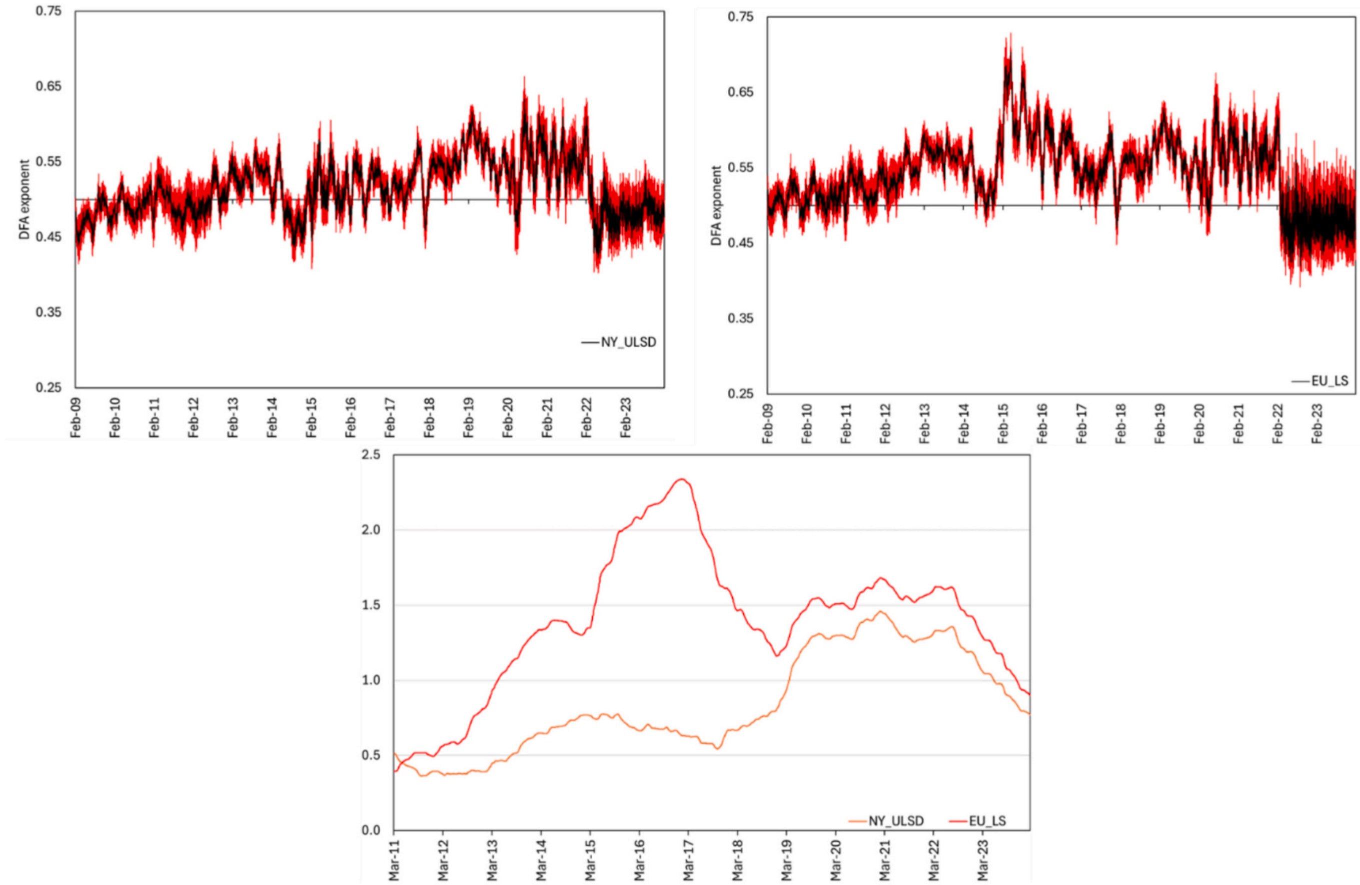

Fig. 3. Evolution of the DFA exponents (on the top) and the EI (on the bottom) for the NY_ULSD and EU_LS commodity futures.
Note: (i) the figure shows the evolution of the DFA exponents for NY_ULSD (on the top left) and for EU_LS (on the top right) commodity futures; (ii) the length of the window is 500 observations.

means the market is considered efficient, while on the opposite side, the higher the value of the EI, the further away from the efficiency of the market. The evolution of EI is displayed in Fig. 1 to Fig. 4.

5.1.1. *Crude oil*

Brent and WTI display a similar pattern except from 2020 to 2022, where Brent clearly shows persistent behavior, while WTI displays α_{DFA} exponents near 0.5, a result that aligns with Cheong (2009). In the period near the ESDC and the Arab Spring, both changed their behavior from anti-persistent to persistent. The beginning of this period, in which Brent and WTI display different behavior, coincides with the spread of COVID-19, and the WTI reversed its anti-persistent trend, approaching what is considered an efficiency level. At the same time, Brent accentuated its persistent trend, moving away from the considered efficiency level. Thus, this crisis seems to have affected the efficiency of these commodities, corroborating Agyei et al. (2023) and Shehzad et al. (2021). In the period near the beginning of the war between Russia and Ukraine, both commodities changed their pattern, with Brent changing from a persistent to anti-persistent behavior and WTI changing from a pattern near the efficiency level to an anti-persistent behavior.

The EI for both WTI and Brent commodity futures display similar patterns almost all the time, with Brent displaying a higher level of inefficiency. After the first quarter of 2020, Brent and WTI increased the level of EI, meaning they became more inefficient. Near March 2021, WTI reversed this pattern, reducing its level of EI, while Brent only reversed this pattern by the end of the first quarter of 2022. Although Brent displays a higher level of inefficiency, their values converge to a similar level by the end of the sample.

Our findings align with those of Tiwari et al. (2019), who found that Brent oil futures are less efficient compared to WTI oil futures but contradict those of Mensi et al. (2014), whose results show that the European Brent index is less inefficient than the WTI index. This evidence highlights the need for continuous assessment of market efficiency.

5.1.2. *Natural gas*

Concerning both natural gas commodity futures, they display patterns that change from persistence to anti-persistence, with HB_NatGas closer to the level of 0.5 from the middle of 2013 until the middle of 2014, when it also displays lower EI values. On the other hand, the UK_NatGas is closer to the level of 0.5 near the period of the Brexit referendum, which could mean that the British government could have implemented more transparent policies and regulations related to the energy sector during the Brexit process, including the adequate disclosure of relevant information about energy policies, infrastructure projects and regulatory changes, allowing market participants to make informed decisions.

At the beginning of the COVID-19 pandemic, the UK_NatGas became less anti-persistent, while the HB_NatGas did not significantly change its behavior. On the other hand, near the period of the invasion of Ukraine by Russia, the HB_Natgas became less anti-persistent, while the UK_NatGas did not significantly change its behavior. This result could indicate that these two energy commodities do not react similarly under the same events. The UK_NatGas seems less sensible to geopolitical events, while the HB_NatGas seems less sensible to pandemic events. It is curious to observe that a geopolitical event in Europe appears to exert a higher effect on the US natural gas market than the UK's.

Our results are consistent with those of Anderson and James (2021)

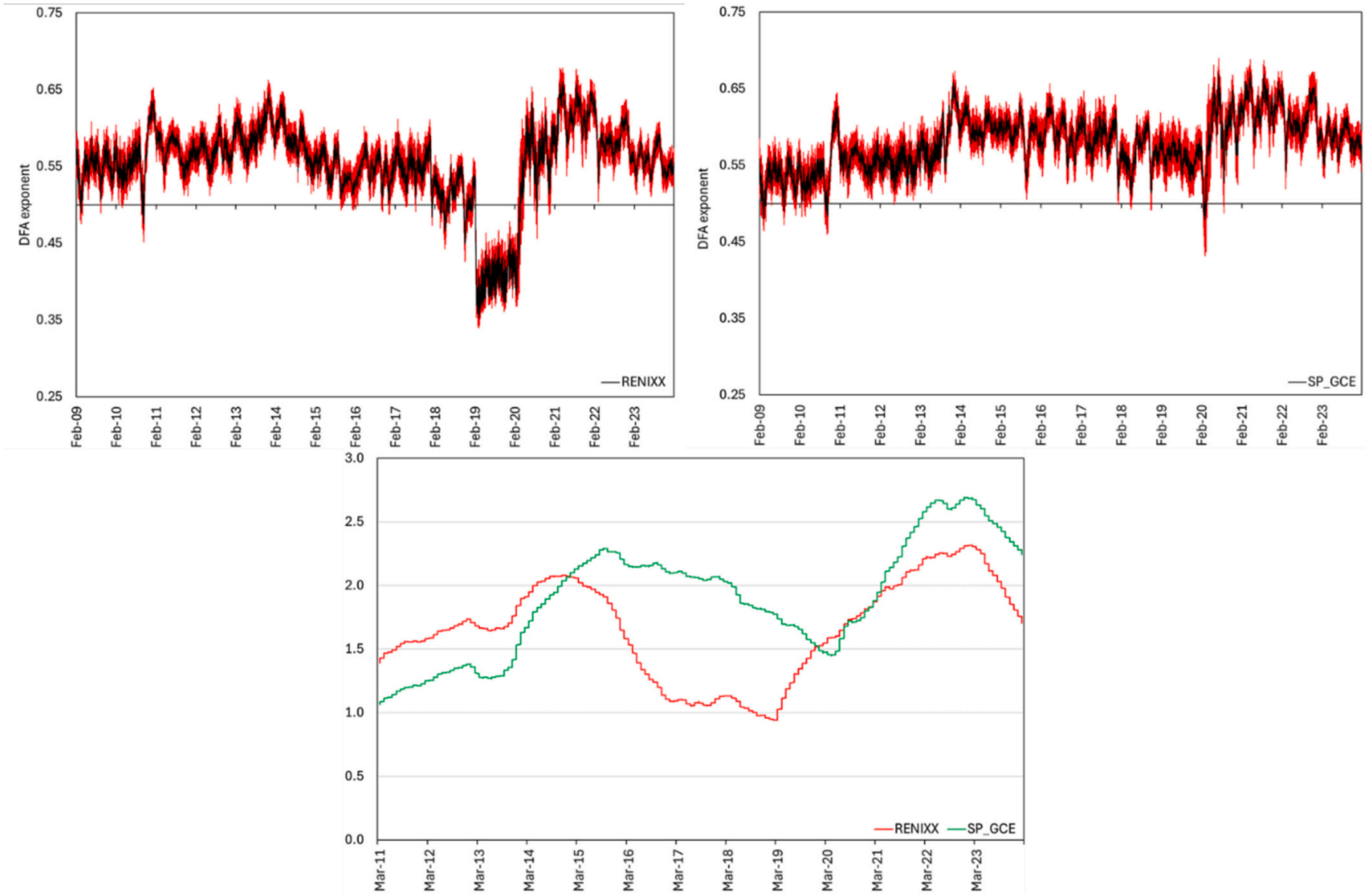

Fig. 4. Evolution of the DFA exponents (on the top) and the EI (on the bottom) for the RENIXX and SP_GCE commodity futures.
Note: (i) the figure shows the evolution of the DFA exponents for RENIXX (on the top left) and for SP_GCE (on the top right) commodity futures; (ii) the length of the window is 500 observations.

and Biresselioglu et al. (2023), who observed significant changes in energy demand and emissions during the COVID-19 pandemic. For instance, the UK experienced a notable reduction in energy demand and shifts in the energy mix, with a decrease in fossil fuel usage and an increase in renewable energy sources. These changes could correlate with the observed less anti-persistent behavior of UK_NatGas. Regarding the Russia–Ukraine invasion, this event caused significant disruptions in the European energy market, particularly affecting natural gas supplies. This observation aligns with the findings of Aliu et al. (2023), Astrov et al. (2022), Moskalenko et al. (2024), Nikas et al. (2024) and Zhou et al. (2023), and with our observed changes in the anti-persistence behavior of HB_NatGas.

The UK_NatGas reveals a higher EI than HB_NatGas during almost all the periods; the exceptions are between September 2016 and June 2017 and after February 14, 2022. The HB_NatGas significantly increased its inefficiency level near the beginning of Russia's invasion of Ukraine. The HB_NatGas efficiency seems to be more affected by geopolitical events occurring in Europe or the Middle East, which could mean that US natural gas production appears to be more affected by these kinds of events than European natural gas production. This evidence may also reveal that demand and supply dynamics for each natural gas commodity can vary significantly. While sudden changes in demand or supply may have impacted the HB_NatGas due to this crisis, the natural UK_NatGas market may have been less affected. Factors like seasonality in demand (e.g., winter heating demand in the US) and the availability of domestic production can explain this different pattern between the EI of UK_NatGas and HB_NatGas.

The natural gas market is more geographically diverse than other commodities, which can help mitigate the impact of specific events in a region. As natural gas can be produced in various parts of the world and transported through pipelines and LNG (liquefied natural gas) terminals, shocks in a specific region can offset supply from other regions. These facts may explain the lower EI of the natural gas commodity futures than the remaining ones.

5.1.3. *Refined oil product futures*

Regarding the low sulfur diesel and gasoil, both commodities' futures display similar patterns oscillating between persistence and anti-persistence. In contrast, the low sulfur gasoil has persistent behavior during a higher period. At the beginning of 2011, NY_ULSD and EU_LS changed their behavior from anti-persistent to persistent (a similar pattern to Brent and WTI). EU_LS maintained this behavior until the middle of 2014, while NY_ULSD changed to an anti-persistent behavior in the middle of 2011. Between 2014 and 2015, the NY_ULSD changed from persistent behavior to anti-persistent, while the EU_LS reduced its persistence level (becoming closer than 0.5 level). These changes in the behavior of both commodity futures may be a response to the annexation of Crimea by Russia in 2014, where the US and the EU imposed economic sanctions against Russia (Klomp, 2020), which may have affected energy trade and may have influenced the prices of diesel and low sulfur diesel since Russia is a major producer and exporter of oil and oil products. Since the beginning of 2022 (with the worsening tension between Russia and Ukraine), both commodity futures changed their pattern, displaying anti-persistent behavior. Both commodity futures seem highly sensitive to this kind of regional geopolitical events.

By November 2016, the Organization of the Petroleum Exporting Countries (OPEC) agreed to reduce oil production by about 1.2 million barrels per day, starting in January 2017. This decision was made to stabilize oil prices, which were historically low due to global oversupply. The announcement of the OPEC production cut had an immediate impact on oil prices, which may be a possible explanation for the reduction of the level of inefficiency, which is more pronounced for EU_LS and Brent. On the other hand, natural gas commodities have increased their level of inefficiency.

5.1.4. Clean energy indexes

The behavior of the renewable energy indexes is quite different from that of the energy commodities, with both energy indexes displaying a persistent behavior almost always. Only RENIXX displayed anti-persistent behavior uninterruptedly from February 2019 to February 2020. At the beginning of 2011, during the intensification of the ESDC and Arab Spring, both clean energy indexes intensified their persistent behavior. Both clean energy indexes display similar patterns regarding the EI, with SP_GCE being more inefficient than RENIXX almost all the time. The exceptions occurred from the beginning of the analyzed period until the beginning of 2015 and during 2020 (from January 2020 until the middle of January 2021). During the spread of the COVID-19 pandemic, both renewable energy indexes became more inefficient, but the increase in the EI was higher for the SP_GCE than for RENIXX.

The clean energy indexes display the higher levels of EI of all the samples, and for almost all the periods analyzed, aligned with the findings of Ren et al. (2024) but contradicted those of Choi et al. (2023), who found that clean energy stocks are reaching parity in terms of price fairness and information discovery, suggesting that they may not be as informationally inefficient as implied. Factors such as liquidity, trading volume, experience and knowledge of investors, regulation, or even the profitability-risk binomial can explain this behavior. Energy sector commodities generally have a much higher trading volume and greater market liquidity than clean energy indexes, making it easier and cheaper for investors to buy and sell contracts for these commodities, thereby reducing transaction costs and improving market efficiency. Likewise, investors and traders in traditional energy commodity markets generally have more experience and knowledge about these markets, which can lead to better resource allocation and more accurate price assessment. On the other hand, clean energy markets may be relatively new and less familiar to many investors, resulting in greater volatility and less efficiency due to a lack of experience and understanding of the market. Additionally, clean energy markets may be more susceptible to government regulation and incentive policy changes, which can introduce price uncertainty and volatility. For example, changes to solar or wind energy tax incentive policies could significantly impact investment returns in these areas, making markets less efficient. Due to regulatory uncertainty, dependence on emerging technologies, and commodity price volatility, investors may perceive clean energy investments as riskier than traditional energy commodities. This scenario can result in a lower efficient capital allocation for clean energy projects and lower investor interest, which could affect market efficiency.

5.2. Directional dependence

As previously explained, we applied the TE in two ways. We began with a static analysis and then performed a dynamic analysis (considering sliding windows) for a time-varying assessment.

5.2.1. Static analysis

Our main goals are to evaluate the non-linear and directional dependence between energy commodity futures and clean energy indexes and the geopolitical risk. To perform this analysis, we applied the TE. The results of the TE for the whole sample are presented in the heatmap in Fig. 5. The heatmaps should be read as the variables on the row transmitting information (influencing) to the variable on the column. The lighter shaded pixels are associated with lower TE values and the darker ones with higher TE values. The evidence of the existence of these relationships highlights the non-linear complexity of energy

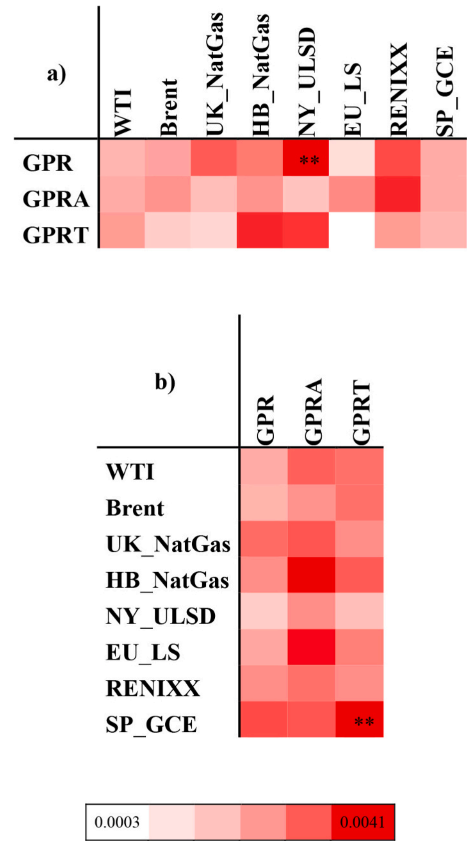

Fig. 5. Heatmaps for the transfer entropy (TE).

markets and asymmetric relationships between energy and geopolitical risk. These results show that the prices of energy commodities and geopolitical risk are inextricably linked, which is consistent with the findings of Foglia et al. (2023), who also found an inextricable linkage between geopolitical risk and commodity prices, with no persistent exogenous shocks (they are quickly absorbed).

All the energy commodity futures and indexes are strong sources of information share (influencers) to the GPR index and its sub-indexes (as evidenced by darker cells). The results could be a sign that oil prices do not respond to shocks in GPR and are aligned with Alqahtani and Taillard (2020) and Liu et al. (2021). However, these findings contradict those of Yang et al. (2024), who found that GPR significantly affects fossil energy prices. Armed conflicts, political tensions, and adverse events in major producers (such as the Middle East and Russia) can lead to interruptions in production, affecting prices and increasing the perception of geopolitical risk. Volatility in energy commodity prices often reflects geopolitical uncertainties, such as territorial disputes, economic sanctions, or changes in government policies. These uncertainties are reflected in media coverage of adverse geopolitical events, which influence the GPR index. Events such as interruptions in oil supplies due to natural disasters, terrorist attacks on energy infrastructure, or environmental issues related to oil and gas exploration can be interpreted as indicators of geopolitical instability, influencing investors' risk perception and, therefore, the index GPR. Commodity prices also reflect future expectations. If investors anticipate more geopolitical tensions, they may adjust their positions. Thus, these expectations influence prices in the present, even before specific events occur, and are covered by the media. Certain energy commodities, such as WTI, Brent, HB_NatGas, UK_NatGas, EU_LS, and the clean energy index RENIXX, appear to exert a greater influence on the GPRA and GPRT sub-indexes than on the GPR index. The GPRA and GPRT are more related to the initiation and escalation of war events, terrorist acts and threats to peace, which can be influenced by energy availability and prices in different regions. For example, disruptions in natural gas supplies could trigger regional geopolitical tensions, affecting these sub-indexes. Oil prices, such as WTI and Brent, are key indicators of geopolitical instability, as significant changes in these prices can reflect events such as conflicts in the Middle East or economic sanctions on large producers. These events often have a direct impact on GPRA and GPRT indexes. Conversely, the UK_NatGas commodity futures influence the GPR and GPRA more than the GPRT, and the SP_GCE influences the GPR and GPRT more than the GPRA.

The UK_NatGas and HB_NatGas seem to have no similar influence on the GPR, GPRA, and GPRT indexes. The UK_NatGas may influence GPR and GPRA more than GPRT for several reasons. Natural gas is a crucial energy commodity, and the UK significantly depends on it for domestic consumption and its industries. Therefore, fluctuations in the UK_NatGas commodity futures prices can directly impact the country's economy and, consequently, the perception of geopolitical risk, aligning with Zakeri et al. (2023). Issues relating to energy security and UK energy policy may be more directly related to the categories included in the GPRA, such as war initiation and escalation of war, than those in the GPRT, such as nuclear threats and terrorism.

On the other hand, the HB_NatGas commodity futures influence GPRA and GPRT more than GPR. Fluctuations in HB_NatGas prices may reflect changes in production, supply, and demand in the US, which may have more direct implications for regional and global geopolitics events. The US plays a significant role in geopolitical affairs, and events or policies that affect US natural gas production and trade can directly influence risk perceptions regarding geopolitical threats, including escalation of war and terrorist acts. Furthermore, natural gas is a global commodity, and changes in HB_NatGas prices can influence international energy market dynamics, thus impacting the categories included in GPRA and GPRT.

Notes: (i) lighter red corresponds to lower TE levels and darker red to higher levels of TE; (ii) ** depicts the significance of the causality at a 5 % level; (iii) on the top heatmap – panel a), the geopolitical risks transmit information (influence) the energy commodities and indexes; (iv) on the heatmap below – panel b), the GPR index and its sub-indexes (GPRA and GPRT) receive information (are influenced) from the energy commodities and indexes, i.e., the energy commodities transmit information (influence) the GPR and it sub-indexes.

Heatmaps are useful tools that provide an image of the results. However, we calculated the NET TE to assess better what energy commodities and indexes are net influencers or influences. The results are presented in Fig. 6. Blue means that the energy commodities and indexes are net-influenced, while red means that energy commodities and indexes are net influencers. The reference is the column on the left side of the heatmaps. From the heatmap on the top (Fig. 6 – panel a)), it can be easily seen that most of the GPR and its sub-indexes (GPRA and GPRT) are net influenced by the energy commodities and indexes. On the other hand, the heatmap below (Fig. 6 – panel b)) highlights that most of the energy commodity futures and clean energy indexes are net influencers of the GPR and its sub-indexes.

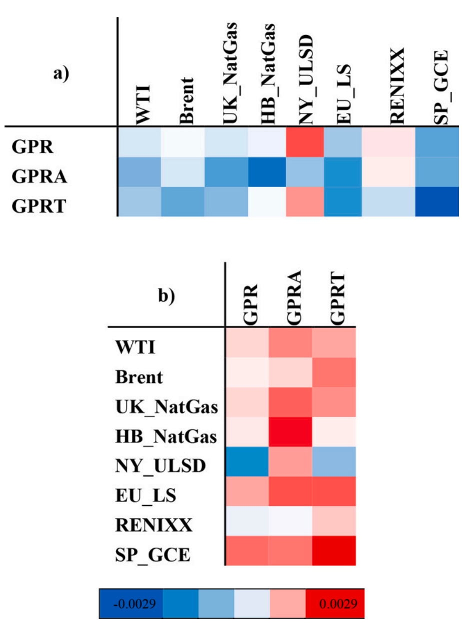

Fig. 6. Heatmaps for net transfer entropy (NET TE).

Note: Positive and negative NET TE values are represented in red and blue, respectively. The red color indicates that the commodity or index is a net influencer, while the blue color indicates that it is net-influenced.

Dutta and Dutta (2022) analyzed the impact of GPR on renewable energy ETFs. They found that increased GPR leads to a shift towards clean energy, reducing market volatility. This result suggests that clean energy indices can act as influencers in the context of geopolitical risks, which our findings also indicate. Exceptions to the referred are the NY_ULSD and RENIXX, with the former being a net influencer of GPR and GPRT and the second a net influencer of GPR and GPRA. The results demonstrate that energy markets feel risk first, which can then be measured by the GPR index or its sub-indexes, which are influenced by energy prices. Economically, the fact that the GPR index and its sub-indexes are net-influenced by the energy sector could mean that energy markets are less sensitive to geopolitical events, which could signify a lower energetic dependence between countries and regions. Our results are aligned with Jin et al. (2023), who found that three energy markets (namely, the West Texas Intermediate crude oil futures, heating oil futures and natural gas futures) exert a *net* transmitting effect on geopolitical risk.

This study reveals the interconnectedness of energy markets with geopolitical risks and underscores actionable insights for different market participants. For example, they can use the NET TE results to predict price shifts and volatility spikes, optimizing investment strategies during geopolitical crises. Policymakers can interpret these dynamics to draft contingency plans that buffer domestic markets from external geopolitical shocks. At the same time, renewable energy advocates could advocate for policies that reduce the susceptibility of clean energy investments to international conflicts.

5.2.2. *Dynamic analysis*

To identify the time-varying dynamics of the TE and net TE, we apply the sliding windows approach considering consecutive windows of 500 observations, i.e., we estimate 3632 TEs for each pair under analysis.

In Fig. 7, it is possible to see the evolution of the NET TE between the Brent and the GPR index, as well as between Brent and both GPRA and GPRT indexes (we made similar analysis for all the commodities and indexes used. Due to space constraints, they are not displayed, but they are available upon request). On these graphs, a positive value of the NET TE (in red) means that the net information flow is from Brent to the GPR and its sub-indexes. For example, the graph on the top left means that $TE_{Brent \to GPR} > TE_{GPR \to Brent}$. On the other hand, a negative value (in blue) of the NET TE means that net information flow is from Brent to the GPR and its sub-indexes. For example, on the graph on the top left means that $TE_{GPR \to Brent} > TE_{Brent \to GPR}$.

Between 2009 and 2012, Brent was a net influencer of the GPR and its sub-indexes, and there are no very different patterns between the GPR and its sub-indexes. During this period, several events, such as China's growing demand for energy, international sanctions imposed on Iran due to its nuclear program, and the Arab Spring, among others, contributed to high pressure on oil prices and to keep the prices of energy sector commodities at relatively high levels, which may justify the evidence found.

Between mid-2012 and the beginning of 2014, the GPR proved to be a net influencer of Brent, which is not the case for its sub-indexes GPRA and GPRT. During this period, tensions worsened in the Middle East,

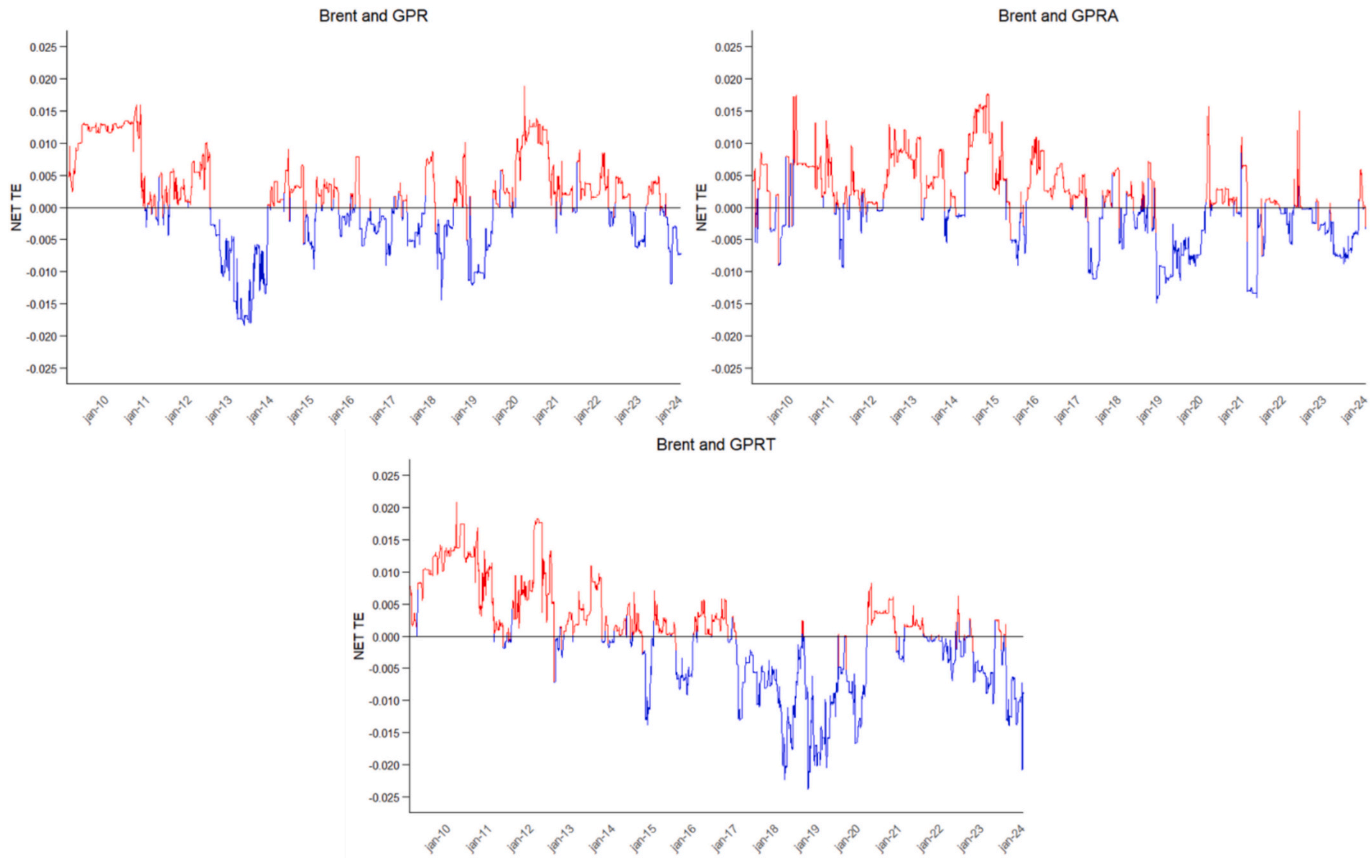

Fig. 7. Time evolution of the NET TE between Brent and the GPR index (on the top left) and its sub-indexes GPRA (on the top right) and GPRT (on the bottom).

especially concerning Iran's nuclear program and the conflict in Syria, with the potential to interrupt oil production in the region. These geopolitical events may have been captured by the GPR index (more general than the GPRA and GPRT), thus influencing investors' perceptions of geopolitical risk and, in turn, Brent prices.

Between 2017 and 2020, the GPRT was revealed to be a net influencer of Brent. This result aligns with previous studies showing that the GPR index, particularly the GPRT, is associated with short-term oil futures price volatility (Liu et al., 2024) and that increases in GPRT significantly affect the long-run volatility of Brent crude oil prices (Mei et al., 2020), supporting the notion that the GPRT index impacts Brent prices. In this period, various geopolitical events occurred, such as the escalation of tensions between the US and North Korea (with a peak in 2017), tensions in the Middle East (especially between Saudi Arabia and Iran), the increase in large-scale military maneuvers (e.g., those carried out by Russia near its borders), and various terrorist attacks (on public places, military installations and civilian targets) in multiple countries around the world (e.g., the UK, Spain, Austria, France). These events may justify the net influencer behavior of the GPRT, considering the news categories covered by this index.

Notes: (i) the analysis involves a sliding windows approach based on a window size of 500 observations; (ii) positive values of NET TE are traced in red, meaning Brent is a net influencer of the GPR and its sub-indexes during the periods signaled; (iii) negative values of NET TE are traced in blue, and mean that the Brent is a net influenced by the GPR or its sub-indexes, i.e., GPR or its sub-indexes are net influencers of Brent.

One of the TE properties is its additivity. Thus, it is possible to calculate the mean NET TE. Considering this property and to better understand (visualization and interpretation) the information, we constructed yearly-based heatmaps based on the whole set of TE estimated. Fig. 8 displays the yearly evolution of the NET TE between GPR and the energy commodity futures and indexes analyzed. We made a similar

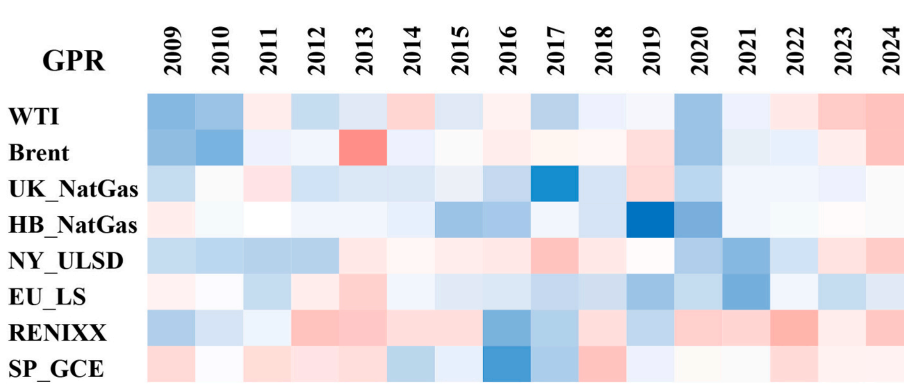

Fig. 8. Yearly evolution of the NET TE between GPR and the energy commodity futures and indexes analyzed.

analysis for the GPRA and GPRT. However, due to space constraints, the results are not displayed; they are available upon request. The changing colors allow us to identify interesting time-varying patterns in several cases.

Brent and RENIXX were revealed to be the most influenced by geopolitical risk, while UK_NatGas was shown to be the least influenced by this risk. These results are aligned with the results of Ganepola et al. (2023), Mgadmi et al. (2024) and Zakeri et al. (2023), with the former showing that while geopolitical events influence natural gas prices in the UK, other unique factors also play a significant role in electricity price fluctuations. This finding suggests that UK_NatGas may be less influenced by geopolitical risks than other factors. The GPRA was to be the most influential geopolitical risk index of the energy commodities and clean energy indexes studied, while the GPRT was the least influential. Thus, geopolitical acts influence the energy markets more than geopolitical threats. The GPRA was a more informative index for the different players in this market compared to the GPR and GPRT indexes. Regarding commodities in the energy sector, commodities traded in the EU markets were more influenced by geopolitical risk than those traded in the US market. The exception is natural gas commodities, which are more influenced by the US market. The clean energy indexes were the most influenced by the GPRA and the GPR, which could mean that these markets are more sensitive to geopolitical risk than commodities in the energy sector. On the other hand, the clean energy indexes were the least influenced by the GPRT, meaning that in situations where geopolitical threats are frequent, these indexes can be a hedge for investors. The clean energy indexes are net influencers of the GPRT during almost all the analyzed periods, aligned with Su et al. (2021).

Although the ESDC began in 2009, it became clear that some EU countries faced significant financial difficulties in paying off their sovereign debts. The crisis intensified in 2010, when Greece revealed the true extent of its fiscal crisis, with a much larger budget deficit than initially presented. This crisis reached a critical point in 2011, with concerns about the ability of countries like Greece, Portugal, Ireland, Spain, and Italy to repay their debts. This situation led to a series of financial bailouts and austerity plans. In 2011, the Arab Spring (which began in 2010) and the civil war in Syria also peaked. All these events may justify the evidence that in 2011, the GPR became a net influencer of commodities such as WTI, HB_NatGas, UK_NatGas, and even clean energy indexes.

Notes: (i) on the top left cell of the heatmap is represented the basis index, i.e., the GPR in this case; (ii) the blue color means that the GPR is net influenced by the energy commodities and indexes on the rows. On the other hand, the red color means that the GPR is a net influencer.

The GPR is a net influencer of the renewable energy indexes most of the time. However, the same does not happen with the energy commodities analyzed, which contradicts what was expected because crude oil commodities and natural gas commodities are generally more directly affected by geopolitical events due to the strategic importance of these kinds of commodities to the global economy, its established market infrastructure, and its interconnectedness with the energy. The GPR and GPRA are net influencers, particularly for WTI and Brent since 2022, which may reflect the conflict between Russia and Ukraine, aligning with the findings of Jin et al. (2023). It is curious to observe that at the beginning of the analyzed period (2009–2010), GPR and GPRT were strongly influenced by almost all of the energy commodity futures and clean energy indexes, which may reflect the consensus achieved during the Copenhagen Conference.

In 2023, the GPRA was a net influencer for all commodities in the energy sector —except for WTI and the clean energy indexes. The intensification of tension between Russia and Ukraine and the trade disputes between the US and China can be possible explanations for this evidence. In 2023, there were also signs of a new financial crisis (e.g., the collapse of Silicon Valley Bank and the takeover of Credit Suisse Bank) and a global recession, which may explain why in 2023, geopolitical risk indexes became influencers in the energy sector. Most of these events will take place in 2024, which may also justify the influence of these indexes on the energy markets considered.

6. Conclusions

In this study, we investigate the dynamics of energy markets (crude oil and natural gas commodities and clean energy) and the geopolitical risk, focusing on long-range autocorrelation, serial dependence, and market efficiency evolution over time. Our goal is to identify the influencer and the influenced between energy commodities and geopolitical events. All the applied approaches allow the evaluation of the dynamics in the energy sector, including non-linear relationships.

The DFA uncovered evolving patterns in market efficiency over time, particularly during significant geopolitical and economic events such as the COVID-19 pandemic and the Russia–Ukraine conflict. Energy commodities like WTI and Brent exhibited changes in behavior amidst crises, suggesting sensitivity to geopolitical and economic factors. The findings from the DFA and EI indicate the potential for forecasting price fluctuations, which raises questions about weak-form market efficiency. This result is consistent with the research conducted by Demiralay et al. (2020) and Roy et al. (2023). Investors and portfolio managers can use the insights provided to adjust their investment strategies, considering varying levels of efficiency and persistence across different commodity futures of energy. Regulators and policymakers may benefit from understanding the factors contributing to market inefficiencies to implement appropriate measures to enhance market transparency and stability.

The directional dependence analysis using TE highlighted complex relationships between energy commodities, clean energy indexes, and geopolitical risk. Although there exists a bi-directional relationship between geopolitical risks and the energy commodity futures and clean energy indexes [aligned with Su et al., 2021], generally (in both static and dynamic ways), energy markets were found to influence or anticipate the GPR, as well as its sub-indexes (GPRA and GPRT), with certain commodities and energy indexes exerting more influence on geopolitical risk indexes than others. Furthermore, the size and the asymmetry of directional information transmission vary over time, in line with Gong et al. (2021). Our results lead us to conclude another interesting thing, i.e., threats and acts do not have a similar effect on the energy sector [aligned with Qin et al., 2020], with the GPRA playing a more important role as a net influencer than GPRT. The dynamic analysis of NET TE also allowed us to conclude another interesting thing, i.e., while GPR and GPRA are net influencers of both clean energy indexes during almost all the analyzed periods, the same does not happen with the GPRT. This result could mean that geopolitical acts directly impact clean energy markets more than geopolitical threats, which aligns with Gong and Xu (2022). Thus, investors in clean energy should consider the asymmetric effects of geopolitical risk on their investment decisions on clean energy.

Our research has uncovered important implications for various stakeholders in the energy market. Energy market participants can utilize our insights on market efficiency to create customized risk management strategies tailored to specific commodity behaviors during times of crisis. By understanding the directional dependencies we have identified, policymakers can work towards enhancing market stability by implementing regulations that help mitigate the impact of geopolitical risks on energy markets. For example, recognizing the increased sensitivity of clean energy indexes to geopolitical risks can lead to the development of more effective policy frameworks to stabilize these markets during periods of uncertainty.

Furthermore, financial institutions can benefit from our findings by using them to develop predictive models that can anticipate changes in market dynamics, which can help enhance portfolio diversification strategies and hedging approaches and ultimately lead to more effective risk management practices. Indeed, our research provides valuable insights that a wide range of stakeholders can apply to improve decision-making and enhance overall market performance.

The GPR index is derived from the frequency of geopolitical risk phrases in the US, UK and Canadian media, but it does not reflect the media coverage in other countries. This situation may lead to neglecting some critical geopolitical events, which may be identified as a limitation of this study and a possible explanation for the weak net information from the geopolitical risk indexes to the energy sectors.

For financial market participants, our results about directional and pairwise information flow could be used for risk management and hedge strategy. For example, financial institutions could use linkage results to forecast energy future market trends and improve their hedging performances. In addition, changes in the patterns of the information flow are connected with some periods when extreme events or crises occur.

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CRediT authorship contribution statement

Dora Almeida: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Paulo Ferreira:** Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Andreia Dionísio:** Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Faheem Aslam:** Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

None.

Appendix A. Appendix

Table A1
Description of the data and symbols used, and rationale for selecting each variable.

Variable	Symbol	Description	Rationale
NYMEX Light Sweet Crude Oil Electronic Energy Future	WTI	It tracks the electronic futures contract for light sweet crude oil traded on the New York Mercantile Exchange (NYMEX). It reflects the market expectations and price movements of this benchmark oil.	It is a widely recognized benchmark for crude oil prices in the U.S. and is critical for global oil market trends. It also provides insights into North American energy markets and their role in price discovery.
ICE Europe Brent Crude Electronic Energy Future	Brent	It represents the electronic futures contract for Brent crude oil traded on the Intercontinental Exchange (ICE) Europe. It is a benchmark for pricing two-thirds of the world's internationally traded crude oil supplies.	It represents the benchmark for two-thirds of internationally traded crude oil and is indispensable for understanding global oil market movements and intercontinental price interactions. It reflects intercontinental price interactions and trends in the international crude oil market.
Intercontinental Exchange UK NBP Natural Gas Electronic Monthly Energy Future	UK_NatGas	It reflects the electronic futures contract for UK National Balancing Point (NBP) natural gas traded on the Intercontinental Exchange (ICE) and provides a reference for natural gas prices in the UK.	It is a key regional indicator for natural gas pricing in Europe and essential for understanding European energy market dynamics and their role in the broader energy landscape.
NYMEX Henry Hub Natural Gas Electronic Energy Future	HB_NatGas	Tracks the electronic futures contract for natural gas traded at the Henry Hub in Louisiana on NYMEX and serves as a benchmark for natural gas pricing in the United States.	It is the benchmark for natural gas pricing in the USA and captures the dynamics of North American natural gas markets, complementing the European perspective provided by UK_NatGas.
NYMEX NY Harbor ULSD Electronic Energy Future	NY_ULSD	It represents the electronic futures contract for ultra-low sulfur diesel (ULSD) traded on NYMEX and reflects market expectations and price movements for diesel fuel in the New York Harbor region.	It provides insights into the downstream energy market, representing price movements of diesel fuel, which is critical for understanding regional refined energy product pricing.
ICE Europe Low Sulfur Gasoil Energy Future	EU_LS	Tracks the electronic futures contract for low sulfur gasoil traded on ICE Europe and provides a benchmark for pricing middle distillates in Europe	It offers an analysis of European refined energy product price dynamics, which is essential for understanding regional market trends.
RENIXX - Renewable Energy Ind. Index	RENIXX	It tracks the performance of the world's 30 largest renewable energy companies listed on stock exchanges, reflecting the overall performance and trends within the renewable energy industry.	Highlights global trends and growth potential in the renewable energy sector, focusing on the performance of major renewable energy companies.
S&P Global Clean Energy Index	SP_GCE	An index that comprises companies involved in clean energy production and related technologies and reflects the performance of the clean energy sector globally.	It reflects diversification within the clean energy sector and its sensitivity to external shocks, providing a balanced view of the clean energy industry alongside RENIXX.
Geopolitical risk index	GPR	Measures the level of geopolitical risk in various regions or countries, assessing factors such as political instability, conflicts, and economic uncertainties that could impact global markets and investments. It reflects automated text-search results of the electronic archives of 10 newspapers (six from the US, three from the UK, and one from Canada). The index is calculated by counting the number of articles related to adverse geopolitical events in each newspaper (as a share of the total number of news articles), and the search is organized into eight categories.	It captures external influences on global energy markets, encompassing various geopolitical factors affecting market dynamics.
Geopolitical acts index	GPRA	A GPR subindex that includes words belonging to categories six to eight, i.e., the beginning of the war, escalation of the war, and terror acts, respectively	It provides granularity by focusing on the immediate and direct impacts of geopolitical events, such as acts of war and terrorism, on energy markets.

(*continued on next page*)

Table A1 (*continued*)

Variable	Symbol	Description	Rationale
Geopolitical threats index	GPRT	A GPR subindex that includes words belonging to categories one to five, i.e., war threats, peace threats, military buildups, nuclear threats, and terror threats, respectively.	It provides granularity by focusing on forward-looking geopolitical risks, including military buildups and potential conflict, offering an anticipatory perspective on market risks.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.108113.

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