Dynamic connectedness among energy markets and EUA carbon index: the role of GPR and VIX

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Abstract

Energy raw materials are the basis of the productive and economic system. From this consideration emerges the need to examine in more detail how various uncertainty indices interact with the dynamic of spillovers connectedness among energy markets. The TVP-VAR model is used to investigate the connectedness among US, European, and Indian oil and gas markets. Following, the wavelet decomposition technique is used to capture the dynamic correlations between uncertainty indices (GPR and VIX) and connectedness indices. First, the results indicate that energy market spillovers are time-varying and crisis-sensitive. Second, the time-frequency dependence among uncertainty indices and connectedness indices is more marked and can change with the occurrence of unexpected events and geopolitical conflicts. Moreover, the VIX index shows a positive dependence on total dynamic connectedness in the mid-long term, especially with the occurrence of crisis events. While the GPR index has only a limited and long-term effect. The analysis of the interdependence among connectedness of each market and the uncertainty indices is more heterogeneous. Political tensions and geopolitical risks are, therefore, causal factors of energy prices. Given their strategic and economic importance, policy makers and investors should establish risk warning mechanism and try to avoid the transmission of spillovers as much as possible. This, in order to ensure a stable piece of energy products and prevent the negative impact of geopolitical risks on energy security and economic activities, as recent events (e.g. Russia-Ukraine war) have highlighted.

Keywords: Energy markets, Geopolitical risk, Volatility connectedness, TVP-VAR

JEL Classification: C58, G15, Q02, Q41

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1 Introduction

Commodity and energy markets have been the engine of economic development and have allowed many countries to increase their success. In this way, economic, commercial and socio-cultural interdependence between various nations has been fostered. In fact, oil and gas are key determinants of energy security, energy geopolitics and the international political economy. These dynamics have been undergone changes when socioeconomic and climate events, and geopolitical tensions have made their effects on the markets, especially energy markets, produced sudden variation in direction. Geopolitical risk can be defined as the probability that events of a political, social, or military nature occurring in one state could potentially jeopardize the stability of a country, region, or even the global economy. So geopolitical risk is a global risk that goes beyond geographical borders and specific economic sectors and that implies the failure of global governance. For these reasons it is inevitable that this risk will have a considerable impact on international financial markets (Choi 2024; Fiorillo et al. 2024; Salisu et al. 2022; Zhou et al. 2020), with a corresponding effect on energy commodity price volatility. This is corroborated by the plethora of studies that have addressed this issue. The correlation between geopolitical risk and the variability of energy commodity prices was fully confirmed following the outbreak of the Russia-Ukraine conflict in 2022; this global energy crisis has disrupted the financial and energy markets (Manelli et al. 2024).

In recent years, the academic literature on geopolitical risk and its implications for energy markets has been expanded by a substantial number of contributions examining various aspects of this topic. One area of research that has emerged is the examination of the relationship between geopolitical risk and energy commodity prices (Lee et al. 2021a; Liang et al. 2020; Plakandaras et al. 2019; Qin et al. 2020; Tiwari et al. 2021). Gong et al. 2022 posit that geopolitical risk is the primary factor contributing to instability in the energy market. They assert that geopolitical risk significantly affects the dynamics of energy product supply and demand, leading to heightened volatility in energy prices. Additionally, the authors highlight that at the macroeconomic level, countries with emerging economies have exerted a pronounced influence on energy commodity demand and price volatility. In their research work, Abdel-Latif et al. 2020 relate three variables: financial liquidity, oil prices and geopolitical risk. The authors confirm the existence of a self-sustaining cycle. Specifically, a negative oil price shock leads to an increase in geopolitical risk and a decrease in global financial liquidity. Conversely, a positive shock to geopolitical risk leads to an increase in oil prices. Abid et al. 2023 conclude that there is a relationship between geopolitical risk and the prices of five commodities (energy, precious metals, agriculture, industrial metals and livestock products) when analyzing the data from 2013 to 2023. All commodities demonstrate responsiveness to geopolitical risk shocks, with energy products exhibiting greater sensitivity than the others. Additionally, Mo et al. 2024 highlight the heightened susceptibility of the energy sector to geopolitical risk, in comparison to non-energy sectors. In a research work, Bompard et al. 2017 developed a survey methodology for evaluating a country's energy security, encompassing both external supply and the reliability of its internal infrastructure. The application of the analytical model to the Italian context, a country with a low level of energy self-sufficiency, revealed the high sensitivity of the crude oil market to shocks caused by geopolitical risks. This finding underscores the strategic importance of energy diversification for risk reduction. In their study, Liu et al. 2019 examine the impact of serious geopolitical risk on the forecasting of oil future volatility. Their econometric analysis substantiates the hypothesis that geopolitical risk, particularly serious geopolitical risk, gives rise to fluctuations in oil market prices. Moreover, they find that the presence of serious geopolitical risk, which contains valuable information about oil price volatility, is capable of generating superior economic profits. Further studies have addressed the topic either by considering traditional energy markets or by focusing on a single country. In fact, in their analysis of the relationships between geopolitical risk, the traditional energy sector (coal, oil and gas) and the carbon market, Jiang et al. 2024 suggest that geopolitical risk exerts a more significant influence on other markets in the medium to long term, whereas in the short term, this impact is more variable. Additionally, a distinctive feature of the carbon market emerges, whereby it appears to exert a greater influence on geopolitical risk than vice versa. A study on the combined impact of Chinese economic policy uncertainty and Chinese geopolitical risk on the global commodities market was conducted by Hu et al. 2023. The analysis revealed that from 2006 to 2023, Chinese commodity prices were influenced by shocks in economic policy and geopolitical risk. Notably, the latter also had a significantly positive impact on commodity prices during the global financial crisis. Furthermore, about the Chinese economic context, the study by Meng et al. 2024 adopts a contrasting approach, examining the impact of natural resource volatility on geopolitical risk. The authors conclude that geopolitical risk is asymmetrically influenced by natural resource volatility and propose that policymakers should prioritize the adoption of renewable energy sources, invest in the extraction of natural resources and reduce oil imports to mitigate geopolitical risk. Finally, an intriguing contribution to the discourse was suggested by Jiao et al. 2023 who concentrated on the indirect mechanisms through which geopolitical risk exerts an influence on oil prices. The transmission modes of geopolitical risk are divided into two categories: micro media (demand, supply and speculative behavior) and macro media (global economy). The analysis yielded the following results: oil prices are influenced by geopolitical risk through supply and demand dynamics, with the effect being amplified in periods of high geopolitical tensions due to the speculative behavior assumed by investors.

A second area of research concerns the role played by geopolitical risk in the functioning mechanisms of financial markets (Albulescu et al. 2019; Bouras et al. 2019; Bouri et al. 2021; Chiu et al. 2015; Guo et al. 2021; Mensi et al. 2018). From this perspective, it becomes evident that the existence of highly integrated and globalized financial markets gives rise to a considerable risk contagion phenomenon, which serves to exacerbate the instability of international economic and financial systems (Forbes et al. 2021). Indeed, a substantial body of empirical evidence demonstrates that geopolitical risk exerts a pronounced influence on financial markets, affecting both financial liquidity and investor behavior (Su et al. 2019).

Zheng et al. 2023b examine the interrelationship between geopolitical risk and diverse segments of the financial market, encompassing both short-term and long-term perspectives. These include the stock market, bond market, foreign exchange market, and crude oil market. The findings suggest that the oil market is more closely associated with geopolitical risk than other markets. In the same field, Alqahtani et al. 2021 examine the impact of oil prices and geopolitical risks on equities in the Gulf Cooperation Council (GCC) countries. The results of the analysis demonstrate that local geopolitical risk exerts a significant negative influence on the stock markets of the surveyed countries. Furthermore, equity markets exhibit sensitivity to fluctuations in oil prices, except for Qatar, where global geopolitical risk has a detrimental impact.

In the wake of the recent upheavals in Europe (the Russian invasion of Ukraine) and the Middle East (the war between Israel and Palestine, with subsequent spillovers into Lebanon and Syria), and the concomitant rise in global tensions, the literature on geopolitical risk has witnessed a surge in contributions seeking to ascertain the extent and direction of the impact of geopolitical risk induced by wars on energy markets. In a similar vein, Khan et al. 2024 investigate the impact of geopolitical risk on the performance of global commodities, contextualizing their analysis within the broader temporal framework of the ongoing conflicts, namely the Russia-Ukraine war and the Israeli-Palestinian conflict. The study demonstrates a low interconnection between geopolitical risk and commodity prices in the pre-crisis periods. Additionally, it indicates a heterogeneous reaction of commodities to geopolitical shocks, which are perceived as very positive. This highlights the necessity for diversified investment strategies. Conversely, during crisis periods, there are significant opportunities for investors to diversify their portfolios, as commodities demonstrate considerable resilience to shocks, both positive and negative, that arise from geopolitical tensions. A similar analysis of geopolitical risk during conflicts was conducted by Wang et al. 2022, who focused specifically on the impact on systematic commodity risk during the conflict between Russia and Ukraine. The data confirm a notable increase in spillover indices during the conflict and an increase in the volatility of commodity markets. It is also possible to include in this line of research contributions that have analyzed the implications of geopolitical risk in situations that are not overt conflicts, but which are characterized by tension between different states. In particular, the subject of geopolitical risk and the political relations between two states, specifically China and the United States, was addressed by Mignon et al. 2024. The authors examined two indicators, the Political Relationship Index (PRI) and the Geopolitical Risk Index (GPR), with the objective of understanding the relationship between these two factors. The analysis demonstrates that an improvement in political relations between states and an increase in geopolitical risk are both associated with higher oil prices. The authors conclude that political tensions are related to consumer expectations, while geopolitical risk is related to energy market expectations.

Our research stems from the growing importance of global geopolitical risks and their effects on economic and financial markets. It is well known how geopolitical tensions predict global oil price volatility, and the effects that they cause on energy markets, (Lee et al. 2021b; Zhang et al. 2023). Considering the importance of energy markets our study attempts, for the first time, to analyze how are the various uncertainty indices interrelated with the dynamic connectedness among different oil and gas markets? How does mutual interdependence manifest itself? Therefore, this article will try to answer these questions.

The reminder of this paper is organized as follows. Section 2 presents the methodology; section 3 outlines the data used and shows our empirical findings; and section 4 offers study's conclusions and implications.

2 Empirical methodology

2.1 TVP-VAR model

In order to accurately examine the transmission mechanism of energy markets, a dynamic connectedness TVP-VAR model (Chatziantoniou et al. 2021) is chosen. This model roots dynamic connectivity measures (Diebold et al. 2014) on the results of a TVP-VAR with time-varying covariances (Koop et al. 2014). This methodology allows not to lose observations and to choose the window size in a non-arbitrary way. The TVP-VAR model is as follows:

$$\begin{aligned} x_t &= \Phi_t x_{t-1} + \varepsilon_t \\ \varepsilon_t|\Omega_{t-1} &\sim N(0, \Sigma_t) \end{aligned} \tag{1}$$

$$\begin{aligned} vec\Phi_t &= vec(\Phi_{t-1}) + \xi_t \\ \xi_t|\Omega_{t-1} &\sim N(0, \Xi_t) \end{aligned} \tag{2}$$

where ,Ω_{t-1} illustrates all available information until time $t-1$, x_t and x_{t-1} are $m \times 1$ dimensional vectors, Φ_i and Σ_t are $N \times N$ coefficient matrices, and ε_t, is the vector of the error terms.
To calculate the generalised forecast error variance decomposition (GFEVD) (Koop et al. 1996; Pesaran et al. 1998) the time-varying parameters model is transformed, using the Wold representation theorem, in a TVP-VMA which is represented as follows:

$$x_t = \sum_{i=1}^{p} \Phi_{it} x_{t-i} + \varepsilon_t = \sum_{j=1}^{\infty} \Lambda_{jt} \varepsilon_{t-j} + \varepsilon_t \tag{3}$$

Since the aim of the analysis is to examine the dynamic connectedness among energy markets, it is possible to detrmine diffrent connectedness indices. The total connectivity index (TCI) measures the total information spillover in a system and expresses the average amount of the share of variance of the forecast error of a variable explained by all other variables. The equation of TCI is:

$$C_t^g(K) = \frac{\sum_{i,j=1,i\neq j}^{m} \tilde{\Psi}_{ij,t}^g(K)}{m} \tag{4}$$

The total directional connectedness TO others describes how much a shock in variable i is able to influence all other variables j. The equation of TO is:

$$C_{i\to j,t}^g(K) = \frac{\sum_{j=1,i\neq j}^{m} \tilde{\Psi}_{ji,t}^g(K)}{\sum_{j=1}^{m} \tilde{\Psi}_{ji,t}^g(K)} \tag{5}$$

Similarly, the total directional connectedness FROM others describes how much variable i receives from shocks in all other variables j. The equation of FROM is:

$$C_{i\leftarrow i,t}^g(K) = \frac{\sum_{j=1,i\neq j}^{m} \tilde{\Psi}_{ij,t}^g(K)}{\sum_{j=1}^{m} \tilde{\Psi}_{ij,t}^g(K)} \tag{6}$$

The net total directional connectedness (NET) measures the difference between the total directional connectedness TO others and the total directional connectedness FROM others. It indicates the net contribution of the variable i to the system. The equation of NET is:

$$C_{i,t}^g = C_{i\to j,t} - C_{i\leftarrow i,t}^g \tag{7}$$

When $C_{i,t}^g > 0$ the variable i is defined a net trasmitter because it is influencing all other variables more than being influenced by them. Otherwise, when $C_{i,t}^g < 0$ the variable i is defined a net receiver.

2.2 Wavelet coherence analysis

After the TVP-VAR analysis that allows to identify the transmission mechanism within the energy markets, the wavelet coherence analysis (WTC) is employed to examine the interdependence between the latter and the uncertainty indices. WTC analysis is found on the Fourier transform that expresses the information related only to the frequency (Sun et al. 2020). Unlike this one WTC analysis examines the dependence between two variables in both time and frequency. In order to perform the WTC, the time series have to assume the structure of a continuous wavelet transform (CWT). CWT of time series x_t is obtained by transferring the basic wavelet function to an original time series x_t. The CWT function is:

$$W_x(a,b) = \int_{-\infty}^{+\infty} x(t)\frac{1}{\sqrt{a}}\psi\frac{t-b}{a}dt \tag{8}$$

where a captures the information of the wavelet dilation and b that about its position. The Wavelet coherence (WTC) equation as formulated by Torrence et al. 1998 is as follows:

$$R^2(a,b) = \frac{|S(s^{-1}W_{xy}(a,b))|^2}{S(s^{-1}|W_x(a,b)|^2)S(s^{-1}|W_y(a,b)|^2)} \tag{9}$$

where S is the smoothing parameter that refer to both time and frequency, $R^2(a,b)$ can take values between 0 and 1, and the more the value tends to 1, the greater the interdependence between the two variables.

The phase difference indicates the direction of the dependence between two time series and it is represented by the following formula:

$$\varphi_{xy}(a,b) = \tan - \left(\frac{\Im\{S(s^{-1}Wxy(a,b))\}}{\Re\{S(s^{-1}Wxy(a,b))\}} \right) \tag{10}$$

Where $\Im$ and $\Re$ are imaginary and real part, respectively. The phase difference allows to obtain the relationships of lead and lag of the variables. It is indicated by the black arrows on the wavelet choerence graphs. Concretely, a phase difference equal to zero indicates the same trend of the examined time-series. The arrows point to the right (or to the left) where the two variables are in phase (or anti-phase) or are positively (or negatively) correlated. If the arrows point to the top right the first variable leads the second. Otherwise, if they point to the bottom left the second variable is ahead. Instead, when they point vertically upwards they indicate that the first variable is ahead and, on the contrary, when they point vertically downwards, they indicate that the first variable is behind.

3 Findings

This study aims to analyze the dynamic connection of returns between energy markets. It is based on a dataset consisting of returns related to oil and natural gas futures prices. To which is added the S&P Carbon Credit EUA index (Eua) used as a benchmark of the performance of carbon emission markets. The indices related to this last market have become increasingly important following the adoption of measures aimed at limiting CO_2 emissions and, hence, the use of fossil energy sources. Consequently, we collect the daily futures prices quotes of the main oil and natural gas market indices such as WTI, Brent, MCX Crude oil index (MCX Oil), Henry Hub natural gas (NG), ICE Dutch TTF natural gas (TTF) and MCX natural gas index (MCX Gas). As can be seen, the analyzed indices refer to different geopolitical areas. In particular the three main energy markets are considered: the US, European and Indian. In fact, these are among the main countries that consume energy raw materials and therefore represent a significant sample of the relevant market. To these are added two indices that measure uncertainty such as the geopolitical risk index (GPR) constructed by Caldara et al. 2022 and the volatility index (VIX). The GPR allows to quantify the economic effects caused by the manifestation of geopolitical risks, while the VIX measures the sentiment of American stock market and therefore is usually used as a measure of volatility expectations. The data cover the period from 3 November 2014, to 31 October 2024.

To analyze the connection between energy markets and S&P Eua index, we utilize the first differentiated series of logarithms:

$$y_{i,t} = ln(p_{i,t}) - ln(p_{i,t-1}) \tag{11}$$

Figure 1: Daily closing prices

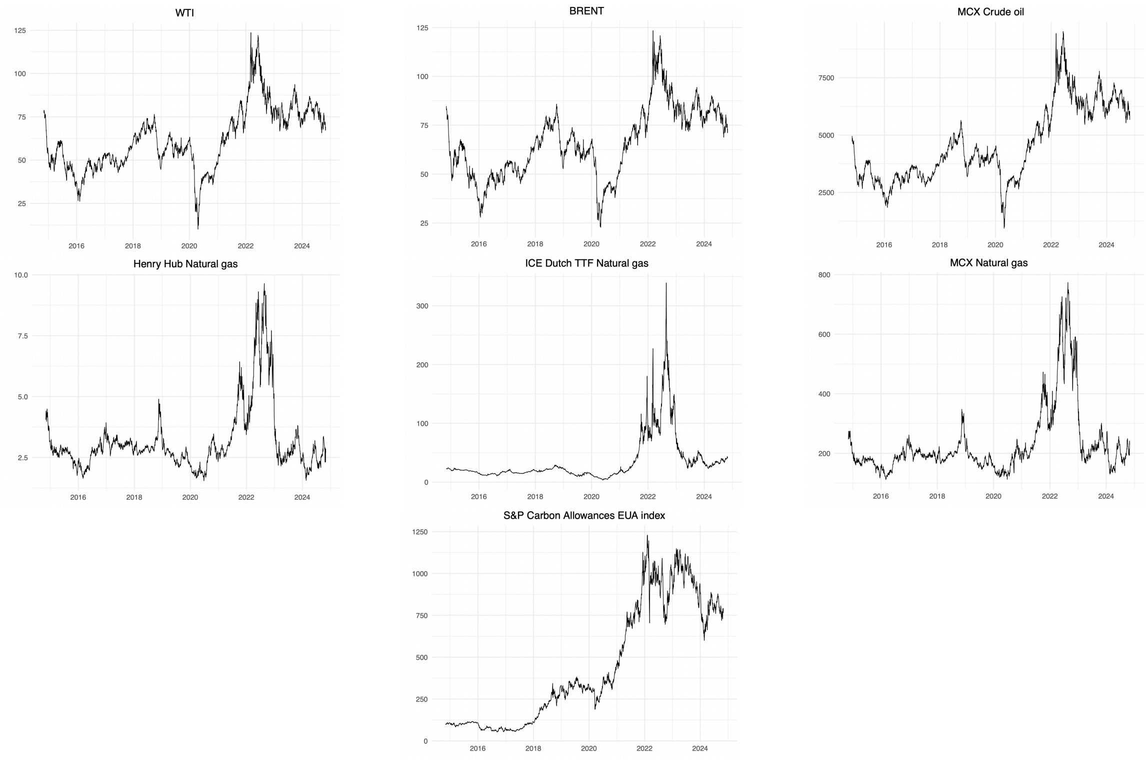


Figure 1 illustrates the trend of the historical series. Notably, it is observed how the oil and gas markets follow similar trends. Regarding the former, after the peak detected during the pandemic, a strong subsequent co-movement is noted, and in particular during the war between Russia and Ukraine. Regard the gas market, plot show a certain synergy between the NG and MCX Gas. Instead TTF shows heterogeneous movements that diverge significantly until the 2022 energy crisis, when they anticipate and exacerbate the price peaks that occur during the year. A separate discussion deserves the S&P Carbon Credit EUA index which shows continuous growth starting from 2018 and exacerbated before the energy crisis of 2022.

Table 1: Descriptive statistics

	Wti	Brent	MCX Oil	Natural Gas	TTF	MCX Gas	Eua
Min	-0.6016	-0.3118	-0.3457	-0.1944	-0.3524	-0.2091	-0.1923
Median	0.0015	0.0015	0.0000	-0.0003	-0.0005	-0.0005	0.0008
Mean	-0.0006	-0.0000	0.0000	-0.0001	0.0002	-0.0001	0.0008
Max	0.3331	0.2353	0.3189	0.2273	0.4127	0.2226	0.1516
Standard Deviation	0.0329	0.0256	0.0292	0.0369	0.0471	0.0373	0.0298
Skewness	-2.2121	-0.9550	-0.5375	0.2326	0.3769	0.2122	-0.4343
Kurtosis	64.2300	18.5368	24.7287	4.3591	9.6039	3.3022	4.2731
ADF test	-12.567*	-12.564*	-12.801*	-12.458*	-12.963*	-12.648*	-13.858*
JB test	407748***	34154***	60259***	1888.5***	9125.1***	1088.9***	1868.7***
PP test	-2486.7*	-2433.7*	-2450.5*	-2589.5*	-2242.7*	-2443.7*	-2500.6*

Note: *, **, *** indicate significance at 10%, 5%, 1% respectively.

Table 2: Correlation

	Wti	Brent	MCX Oil	Natural Gas	TTF	MCX Gas	Eua
Wti	1						
Brent	0.9011***	1					
MCX Oil	0.7334***	0.7842***	1				
Natural Gas	0.0831***	0.1017***	0.0747***	1			
TTF	0.1077***	0.1370***	0.1128***	0.1107***	1		
MCX Gas	0.0583**	0.0932***	0.1138***	0.7617***	0.1247***	1	
Eua	0.1712***	0.1817***	0.1643***	0.0677***	0.1811***	0.0624**	1

Note: *, **, *** indicate significance at 10%, 5%, 1% respectively.

In turn, as can be seen in table 1 which presents the statistical description of the returns, all means and medians have values around 0. Furthermore, the standard deviation is higher for gas markets than for the others, with the TTF showing the highest value. All oil markets and EUA index show a negative skewness, they are left-skewed distributions. Instead, all gas markets are right-skewed distributions. Moreover, all series are significantly leptokurtic; the kurtosis are greater than 3. The Jarque-Bera test significantly rejects the hypothesis of normality as all variables exhibit a clear leptokurtosis and fat tails. The results of the unit-root test, ADF test, and Phillips-Perron stationarity test confirm that all returns are stationary at the 1% significance level. In conclusion, as shown in table 2 the unconditional correlations between oil markets are highest (with values above 0.7), while the correlation between gas markets and between gas, oil and Eua markets is moderately high (with values around 0.2).

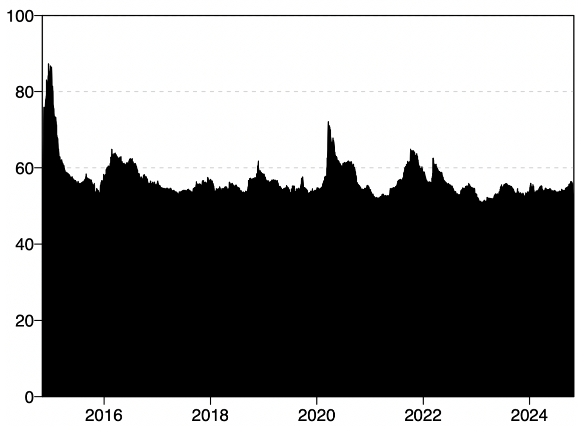
Table 3: Averaged dynamic connectedness table

	WTI	Brent	MCX Oil	Natural Gas	TTF	MCX Gas	Eua	FROM
Wti	34.86	30.64	28.31	1.32	1.49	1.13	2.25	65.14
Brent	30.90	35.13	27.16	1.48	1.83	1.19	2.31	64.87
MCX Oil	30.14	28.10	35.29	1.30	1.72	1.31	2.14	64.71
Ng	1.77	1.83	1.90	52.13	2.42	38.14	1.80	47.87
TTF	3.31	3.37	3.28	3.36	75.77	2.46	8.45	24.23
MCX Gas	1.55	1.56	1.86	38.40	2.15	52.87	1.62	47.13
Eua	4.54	4.42	4.15	2.43	8.50	2.10	73.86	26.14
Contribution To others	72.21	69.92	66.67	48.29	18.11	46.33	18.57	340.09
Inc.Own	107.07	105.04	101.96	100.42	93.88	99.19	92.43	cTCI/TCI
NET directional connectedness	7.07	5.04	1.96	0.42	-6.12	-0.81	-7.57	56.68/48.58
NPDC transmitter	6.00	5.00	4.00	3.00	1.00	2.00	0.00	

Notes: Results are based on a TVP-VAR(0.99,0.99) model with lag length of order 3 (BIC) and a 10-step-ahead forecast.

We start our discussion by analyzing the total dynamic connectedness (TCI) and net return (NET) between energy commodity markets and Eua index. Table 3 shows that the main shock transmitter is the WTI followed by Brent, MCX Oil and NG, while the net shock recipients are the Eua index followed by TTF and MCX Gas. This is confirmed by the pairwise net directional transmission dominance value which for these last three markets shows negative values equal to -7.57, -6.12, and -0.81, respectively. Furthermore, the TCI explains that on average the co-movement of energy markets, and therefore the risk equality of the entire network, is 56.68%, which in turn means that on average 48.58% ($= 56.68\% \cdot \frac{6}{7}$) of the variance of the forecast error of a market return can be explained by the influence of the returns of all other markets. The results suggest that the Eua index is the largest recipient of the system, i.e. it is dominated by other energy markets, as is logical given the type of linkage that it has with traditional energy markets. This indicates that price changes in the Eua index have a limited role and lower propensity to transmit shocks to the other markets in the system. Instead, oil markets emerge as the main sources of shocks, (Adekoya et al. 2021a; Chen et al. 2024). Then, dynamic total connectedness captures the temporal variation of the TCI for the entire period of study.

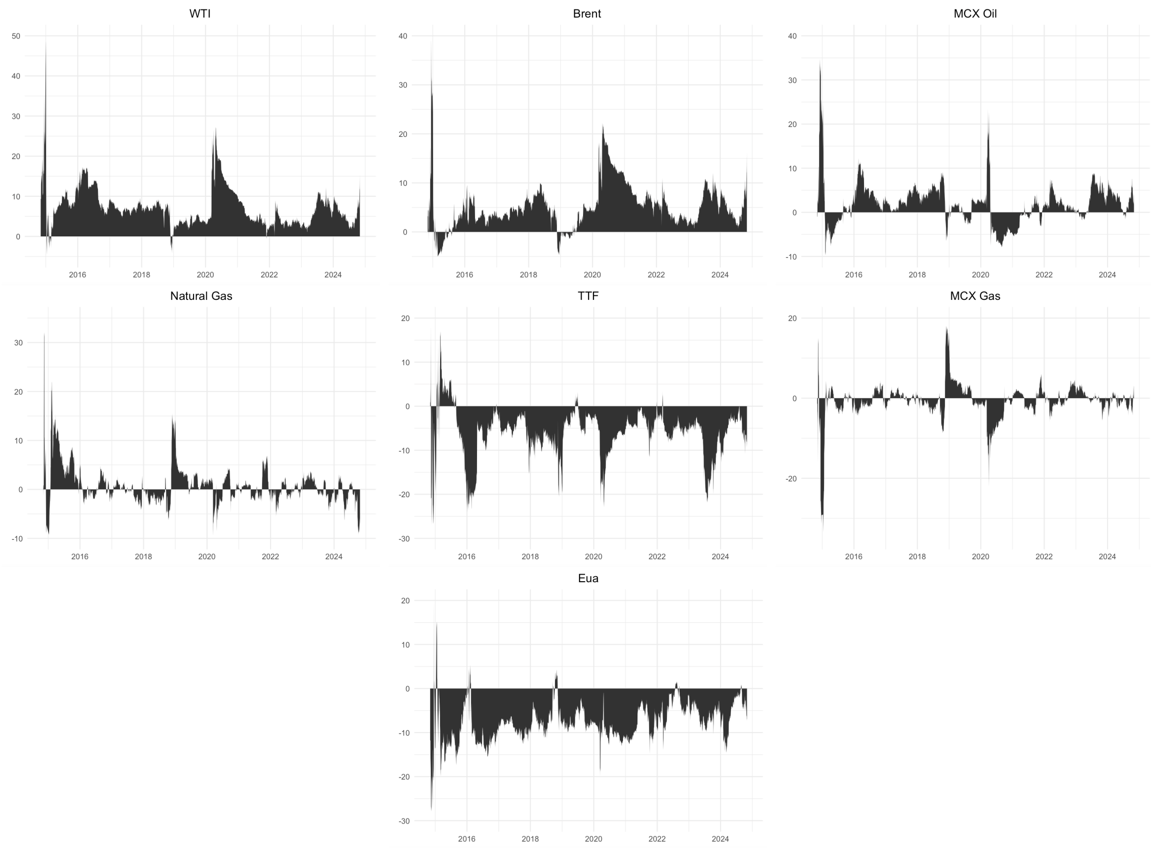
Figure 2: Dynamic total return spillover



At this point, we focus our attention on the analysis of the total dynamic connectedness (TCI), which provides the interconnectedness of the network over time. Figure 2 shows how the total dynamic return connectedness is variable over time, but always above 40%, indicating, thus, a solid interconnectedness between energy markets and Eua index. Significantly, the total dynamic return connectedness reaches values greater than 60% in 2014 - at the beginning of the analysis period – in 2020, and in 2022. This adapts with periods of tension in the commodity markets, pandemic and Russia-Ukraine war. These very strong connections denote how in times of significant crisis and uncertainty the interconnectedness between energy markets is significantly consolidated. This may be because in the presence of unlooked-for and uncertain events investors are more cautions in diversifying their portfolios and less willing to take risk, this causes a greater interconnectedness between markets (Adekoya et al. 2021b).

Figure 3 represents the dynamic connectedness of the net directional returns among energy markets. A

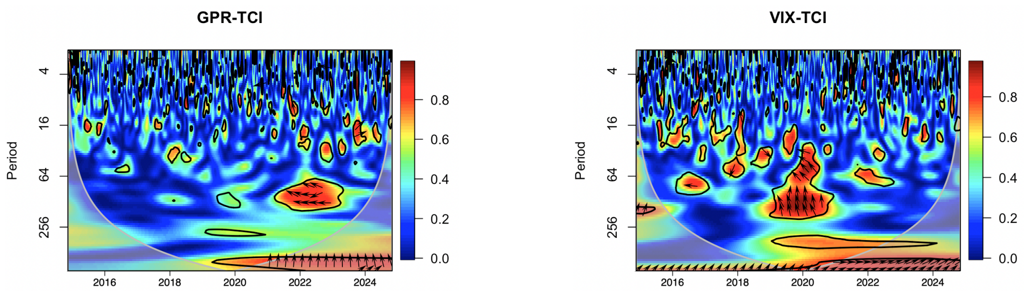
Figure 3: Dynamic net directional return connectedness



positive value indicates that the information spillover is positive and, thus the related market behaves as a net transmitter. On the other hand, a negative value signals a negative information spillover which indicates that the market is a net receiver. The oil markets, markedly WTI and Brent, are the main transmitters of information to other markets. While the gas markets, to a greater extent TTF, and Eua index receive information from other markets for the entire period analyzed. The MCX Oil market, the NG and MCX Gas alternate positive net spillover values with negative, indicating, in this way, how the role played by these markets is not always that of transmitter or receiver. Analyzing in more detail the Indian oil markets, MCX Oil, this one with a prevalence of positive values tends to follow the footsteps of the US and European ones, functioning mainly as a transmitter.

In summary, in terms of yield connectedness, the WTI and Brent crude oil markets act as a net transmitter of spillover, with very high percentage in late 2014 and after 2020. Instead, TTF gas market and Eua credit index function as a net receiver. Furthermore, the WTI market has the toughest dominant role in the connectedness among oil markets, indicating that US crude oil market has the utmost influence on the other markets. While TTF gas market emerges as the most significant information receiver, suggesting its limited influence on other markets. Additionally, as partly already highlighted, unexpected and significant events, such as pandemic, can amplify the performance connectedness among energy commodity markets.

Figure 4: Dynamic total return connectedness and uncertinty indices (GPR, VIX)



Note: The horizontal axis represents the time scale, while the vertical axis indicates different frequency bands. The bold black outline denotes the 5% significance level, determined through Monte Carlo simulations. The presence of a light black contour around the cone of influence is attributed to edge effects.

Following the analysis of the dynamic connectedness of the return among energy markets, we analyze the way in which the uncertainty indices, the geopolitical risk index (GPR) and the VIX index, influence the dynamic connectedness systems. In this regard, the analysis of the wavelet coherence is used in order to verify the presence of dependence among the dynamic total connectedness and the already mentioned uncertainty indices. The dependence is measured in terms of time and frequency. Figure 4 exhibit the results of the wavelet coherence among GPR and VIX and the dynamic total connectedness. The horizontal axis indicates the time scale, and the vertical axis the different frequency bands. A strong co-movement among the dynamic total connectedness and the uncertainty indices is represented by the red regions.

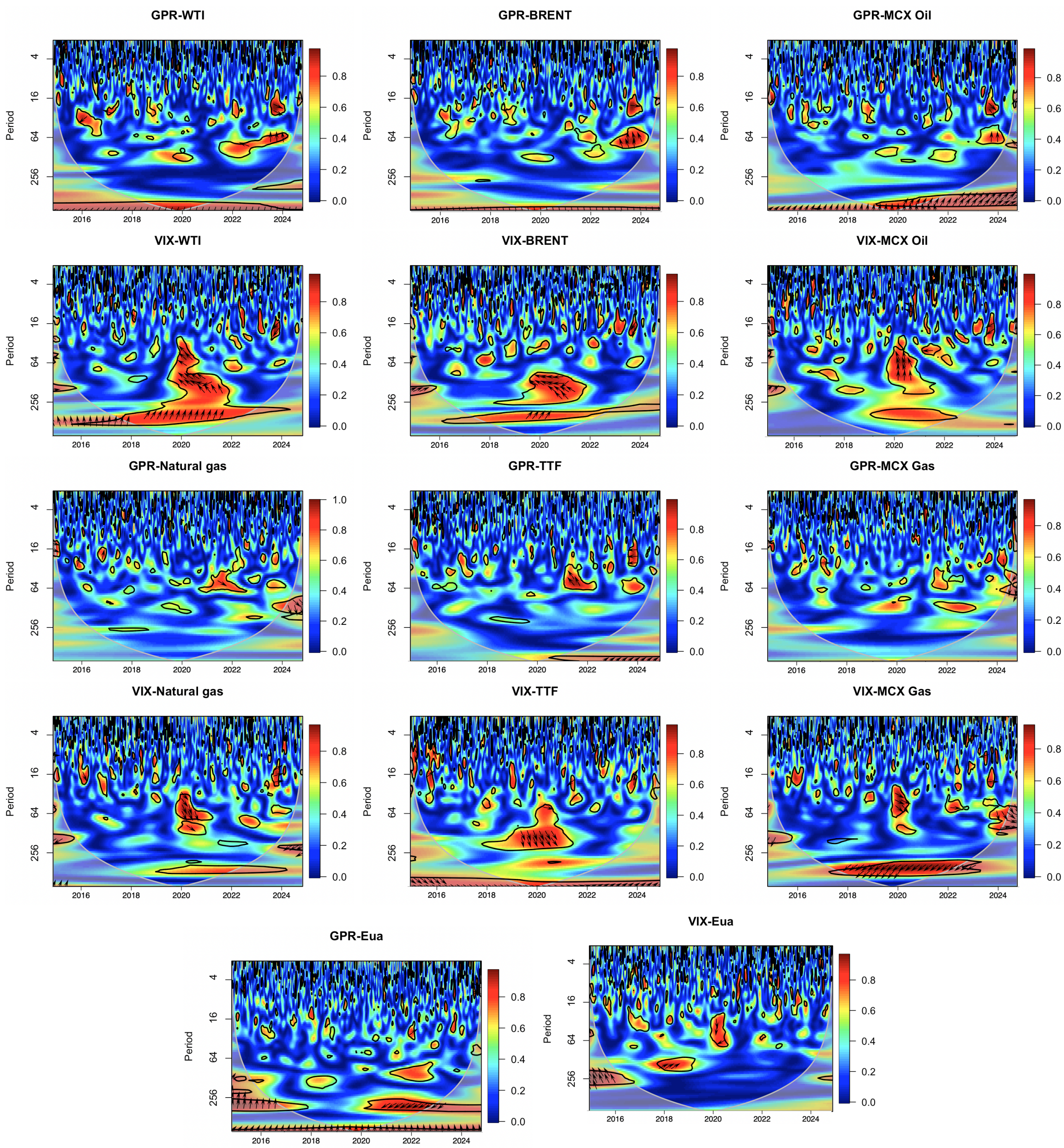
First of all, it emerges how there is a lower dependence among dynamic total connectedness and GPR. In fact, the relationship between GPR-TCI shows the presence of few red regions from 2022 onwards, and these are concentrated in the medium-long term, with a frequency of 64 and over 256 days. Of greater interest appears the relationship VIX-TCI, in which the red region with strong coherence are larger, but always concentrated mainly in the medium – 16 to 256 days – and in the long term – over 256 days.

A further consideration concerns the fact that significant events that radically change the previous situation, such as pandemic and Russia-Ukraine war, determine an increase in intensity of the dependence between TCI and uncertainty indices. In fact, the dependence among TCI and VIX is greater in the medium term during pandemic and in the long-term during Russia-Ukraine conflict. Instead, there is a long-term dependence among TCI and GPR only after 2022. These results may be due to the fact that during the two periods uncertainty and geopolitical risk increased. In fact, during pandemic with the lockdown of economic activities, energy prices recorded a drastic decrease. Instead, during the war the tension recorded on these markets, with particular emphasis on the gas markets, produced sudden increases in its prices. Furthermore, the two events, albeit with different modalities, affected global supply chains and particularly in energy markets (Li et al. 2023), with interruptions in supply or the presence of higher costs (Zheng et al. 2023a).

In summary, the GPR-TCI relationship shows how in the medium term the two variables are negatively correlated. A different scenario emerges from the analysis of the relationship between dynamic total connectedness and VIX, which shows a positive dependence in the medium and long term with the VIX which anticipates the dynamic total connectedness. This indicates that the return spillovers within the energy markets tend to increase when the VIX increases in the medium-long term.

So far, the analysis carried out indicates the way in which the uncertainty indices interact with the dynamic total return connectedness of the energy markets. At this point, to have a more in-depth understanding of the individual markets, we analyze the dependence among the uncertainty indices and the dynamic connectedness of the net total return that each market has with them. Figure 5 indicates the changing characteristics of this relationship. A first distinction concerns the dissimilar behaviors of the GPR and VIX indices. In fact, if we consider the three oil markets analyzed, it emerges that the positive relationship between these and the GPR is limited to the long term and to a few areas of the medium term but after 2022. In the opposite order, the relationship between the three oil markets and the VIX index is greater than the GPR. In the VIX-WTI graph, large red areas can be seen throughout the long term with extensive spills over in the medium term in the aftermath of the pandemic. Furthermore, if in the long term the VIX be ahead the WTI, in the medium term the arrows pointing to the left indicate a negative correlation. Similar conclusions, although the red areas are smaller, can be drawn for the VIX-Brent relationship. Also, in this case we note red areas in the long term and a large negative correlation in the medium term between pandemic and the war years. Analyzing the VIX-MCX Oil relationship we note a presence of small red areas in the short term and a marked correlation in the medium-long term but only during pandemic with the VIX ahead of the MCX Oil. Moving on to the analysis of the GPR and the gas markets, we note how for all three markets lone occasionally red areas appear in the short term. Moreover, these are concentrated after 2020. If we analyze the relationship with the VIX the conclusions change. In the VIX-NG we note a relationship in the medium term during the pandemic and a negative correlation at the beginning of the period and at the end. More marked relationships with occasional red areas in the short term are found in the VIX-TTF graphs. In this, a large red area emerges in the medium term between 2019 and 2021 with the TTF ahead of the VIX. In the long term,

Figure 5: Dynamic net return connectedness for each market and uncertainty indices (GPR, VIX)



it is noted that until 2018 the TTF is ahead of the VIX, it goes back during the pandemic, and then moves forward again during the war. Looking at the connectedness VIX-MCX Gas we note an intense connection for almost the entire long term that also spills over into the medium term during pandemic with the MCX Gas ahead the VIX. Furthermore, there is a large red area in the medium term between 2023 and 2024. Finally in the analysis of GPR-Eua we note the presence of connections in the long term with the GPR ahead. In the medium term up to 2017 it sees the GPR ahead, and the EUA ahead after 2020. The VIX-Eua graph indicates more occasional red areas. The connectedness it is not consistent in the various time scales since the arrows point in different directions in the diagram, with the presence of positive correlations alternating with negative ones.

From the considerations carried out it can be concluded that the strong coherence among uncertainty indices and return connectedness for each markets occurs mostly in turbulent periods, such as pandemic and Russia-Ukraine war. These findings are consistent with Tran et al. 2023, who documented that following increases in the VIX index, investors, having pessimistic expectations and overreacting, tend to increase selling. This leads to lower returns and increased market volatility. Unlike the VIX, GPR involve conflict and more complex relationships (Raheem et al. 2023) modifying various aspects of global economic interactions and producing long-term consequences such as disruption in supplies.

3.1 Robustness checks

The time-varying connectedness dynamics provide important insights into the transmission mechanism of returns in energy markets. Robustness checks of the TVP-VAR estimate were performed using alternative windows and forecast horizons.

Figure 6 shows the dynamic spillover index lines resulting from these robustness checks, with the 150-day window/5-day forecast horizon results shown as the blue line, the 150-day window/15-day forecast horizon results shown as the red line, the 250-day window/5-day forecast horizon results shown as the green line and, the 250-day window/15-day forecast horizon results shown as the yellow line. This analysis allows us to test the stability of our results across model specifications. Therefore, the results reveal a parallel and similar trend in terms of dynamic connectedness, even if different alternatives of rolling window and forecast horizon are used. It is evident that these are uniform in various periods and market conditions. In fact, the different line tends to overlap and are not completely remarkable. This consistency supports the robustness of our results regarding fluctuations in interconnectedness and spillovers among energy markets.

Figure 6: Dynamic total return spillover with different rolling windows and forecast horizons

Note: TCI 1: 150-day window/5-day forecast horizon; TCI 2: 150-day window/15-day forecast horizon; TCI 3: 250-day window/5-day forecast horizon; TCI 4: 250-day window/15-day forecast horizon.

4 Conclusion

In this study, we examined the energy markets of different types of crude oil and natural gas. To have a better understanding of the energy market, in addition to those traditional markets we added the carbon market. This market is important not only for the growing attention paid to the environmental policies aimed at reducing carbon emissions but above all for the close relationship and integration between CO_2 emissions and the use of traditional energy sources such as crude oil and natural gas. The aim of this study was to examine over and above the integration and the potential contagion risk of energy markets. The variable investigated are: WTI, Brent, MCX crude oil, Henry Hub Natural Gas, Ice Dutch TTF gas, MCX gas and S&P Carbon Allowances EUA index. Finally, we seek to determine whether net connectedness among energy markets is driven by political uncertainty and risk. It has been widely demonstrated that external uncertainty influences the fluctuations of financial and commodity markets (Bahloul et al. 2018; Gozgor et al. 2016). In this study, we provide new evidence of how the geopolitical risk (GPR) and uncertainty index (VIX) interact with dynamic connectedness between energy commodity markets. To this end, by applying the dynamic connectedness approach based on a TVP-VAR model in the spirit of Chatziantoniou and Gabauer (2021) we compute the dynamic return connectedness among energy markets. After that, we employ the wavelet coherence methodology to investigate and measure the existence and dependent relationships between uncertainty indices (GPR and VIX) and the dynamic connectedness within energy markets. Compared to previous studies, our results provide new and valuable insights.

First, the time domain analysis indicates a strong interaction within energy markets with a total spillover index exceeding 50% throughout the period and reaching significantly high levels of around 60-80% on some occasions.

Second, the main crude oil markets, (WTI and Brent), are net transmitters of spillover while the TTF gas and Eua markets function as net receivers. The other markets, MCX Oil, NG and MCX Gas, alternate periods in which they are net receivers and periods in which they are net transmitters of spillover. The

WTI oil market has the most powerful dominant role in connectedness among energy markets, signaling its strong effect on the other markets, while the Eua index stands out as the most significant receiver of information, suggesting its limited influence. Furthermore, the results suggest that dynamic connectedness is highly dependent on exogenous shocks and is very sensitive to global events, like pandemic and Russia-Ukraine war. Then we analyzed the intensity of co-movement among the examined variables and different uncertainty indices (GPR and VIX) to identify actual interaction. In this context, the most influential uncertainty index on connectedness is VIX that shows a positive dependence on dynamic total connectedness in the medium and in the long term, while GPR mainly has a negative relationship in the long term.

Third, the connectedness among VIX and each market is mainly seen in the mid-long term with notable spillovers into the mid-term in the aftermath of the pandemic. While, for the GPR the connectedness is more limited and concerns only the long-term. The only exception is S&P Carbon Allowances Eua index where it is more marked and concerns also the mid-term. Furthermore, over time, the uncertainty indices have changed roles and differing from one market to another. In fact, it can be noted how, within the same market, the correlation among connectedness and uncertainty index is both positive and negative at different time scales (the arrows point in different directions). Isolated events could help explain these changes over time. In particular, amplified uncertainty about the potential effects of pandemic and Russia-Ukraine war on economic activity potentially help explain the prevalence of long-term connectedness.

Finally, the results of our analysis support policy makers and investors. Given that the energy market connectedness shows differentiated interactions across both the different uncertainty indices (GPR and VIX) and different time scales, it is useful for policy makers to be able to distinguish the sources from which shocks originate and the different time horizons. Furthermore, since information spillovers interact across different markets, investors should incorporate the transmission mechanism and the dependency relationship between uncertainty and energy market connectedness. This is to understand how geopolitical risk impacts prices in order to be able to forecast prices based on changes in geopolitical risk and adapt their asset allocation and hedging strategies accordingly in light of specific geopolitical event.

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