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Reconceptualizing the interplay between geopolitical index, green financial assets and renewable energy markets: evidence from the machine learning approach

Received 26 September 2023
Revised 2 January 2024
Accepted 29 January 2024

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Abstract

Purpose – In an era marked by heightened geopolitical uncertainties, such as international conflicts and economic instability, the dynamics of energy markets assume paramount importance. Our study delves into this complex backdrop, focusing on the intricate interplay the between traditional and emerging energy sectors.

Design/methodology/approach – This study analyzes the interconnections among green financial assets, renewable energy markets, the geopolitical risk index and cryptocurrency carbon emissions from December 19, 2017 to February 15, 2023. We investigate these relationships using a novel time-frequency connectedness approach and machine learning methodology.

Findings – Our findings reveal that green energy stocks, except the PBW, exhibit the highest net transmission of volatility, followed by COAL. In contrast, CARBON emerges as the primary net recipient of volatility, followed by fuel energy assets. The frequency decomposition results also indicate that the long-term components serve as the primary source of directional volatility spillover, suggesting that volatility transmission among green stocks and energy assets tends to occur over a more extended period. The SHapley additive exPlanations (SHAP) results show that the green and fuel energy markets are negatively connected with geopolitical risks (GPRs). The results obtained through the SHAP analysis confirm the novel time-varying parameter vector autoregressive (TVP-VAR) frequency connectedness findings. The CARBON and PBW markets consistently experience spillover shocks from other markets in short and long-term horizons. The role of crude oil as a receiver or transmitter of shocks varies over time.

Originality/value – Green financial assets and clean energy play significant roles in the financial markets and reduce geopolitical risk. Our study employs a time-frequency connectedness approach to assess the interconnections among four markets' families: fuel, renewable energy, green stocks and carbon markets. We utilize the novel TVP-VAR approach, which allows for flexibility and enables us to measure net pairwise connectedness in both short and long-term horizons.

Keywords Contagion risk, Green financial assets, Renewable energy markets, Russia–Ukraine conflict, COVID-19, Cryptocurrency carbon emission, TVP-VAR, SHAP

Paper type Research paper

The authors extend their appreciation to the Deanship of Scientific Research at King Khalid University for funding this work through large group Research Project under grant number RGP2/154/44.

Arab Gulf Journal of Scientific Research
Emerald Publishing Limited
e-ISSN: 2536-0051
p-ISSN: 1985-9899
DOI 10.1108/AGJSR-09-2023-0458

1. Introduction

In recent years, the integration of markets has experienced significant growth and transformation, primarily driven by technological advancements, financial integration, globalization and increased openness (Liu, Razzaq, Shahzad, & Irfan, 2022). This integration has brought numerous benefits, enabling the efficient exchange of goods, services and capital across borders. Energy resources are vital in fostering industrial development and driving national economic growth (Zhu, Ding, & Chen, 2022). However, excessive energy consumption and its resulting environmental pollution have become pressing concerns. Furthermore, the emergence of climate change, particularly global warming, has posed a shared challenge for humanity (Kim, 2015). Carbon emissions are the primary contributor to global warming, necessitating global awareness and concerted efforts to promote green and low-carbon development.

Recognizing this situation, countries worldwide have highlighted the importance of energy conservation, emission reduction and the pursuit of carbon peaking and carbon neutrality goals (Nan, Huo, You, & Guo, 2022; Stoll, Klaaßen, & Gallersdörfer, 2019; Truby, Brown, Dahdal, & Ibrahim, 2022). These measures aim to control pollution emissions effectively, enhance the utilization of clean energy sources and facilitate sustainable development. As a result, green finance has gained prominence as a means to promote sustainability and combat climate change.

However, amidst these global efforts, the recent COVID-19 pandemic and the ongoing conflict between Russia and Ukraine have presented new challenges. Some economies, faced with immediate economic concerns and uncertainties, have prioritized investments less concerned with climate change and sustainable development (Lorente, Mohammed, Cifuentes-Faura, & Shahzad, 2023). Therefore, the proportion of renewable energy consumption concerning total energy consumption is a crucial factor significantly influencing carbon dioxide emissions. Consequently, to effectively combat the dangerous effects of global warming, it is imperative to swiftly and sufficiently invest in renewable energy sources while increasing investments in green financial assets (Zhao, Gozgor, Lau, Mahalik, Patel, & Khalfaoui, 2023). The recent COVID-19 pandemic and the Ukraine–Russia conflict have increased financial market volatility, resulting in spillover effects across markets (Le, 2023). The conflict between Russia and Ukraine has brought attention to the impact of geopolitical risk on fuel markets. Certain assets served as a safe against this type of risk, resulting in them experiencing positive effects from the tensions (Long, Demir, Będowska-Sójka, Zaremba, & Shahzad, 2022). Geopolitical risk refers to the potential danger of political events such as war, terrorism and tensions between countries, including the possibility of these events becoming more severe or escalating (Caldara & Iacoviello, 2022). Nevertheless, there is a growing public apprehension about the painful ramifications of climate change, including its impact on various aspects such as production, human livelihood, economic expansion and national security.

Green financial assets, renewable energy markets, the geopolitical risk index and cryptocurrency carbon emissions are critical factors in the complex interplay of energy and financial markets amid geopolitical and environmental challenges. Green assets drive investment in sustainable practices, while renewable markets implement these assets, reducing fossil fuel reliance and addressing climate change. The geopolitical risk index reflects how international tensions affect markets, impacting energy prices and investment flows. Meanwhile, cryptocurrency emissions present a dual issue: increasing energy demand and incentivizing sustainable energy for blockchain technologies. These elements interact intricately, with geopolitical events potentially disrupting the alignment of economic growth and environmental sustainability. Understanding these dynamics is vital for stakeholders to navigate the economic and ecological landscape effectively.

The recent COVID-19 pandemic and the ongoing conflict between Russia and Ukraine have prompted some economies to prioritize investments that are less concerned with climate change and sustainable development (Lorente *et al.*, 2023). However, some companies are still considering green investments not only as a means to achieve social and environmental goals but also to improve their financial returns. Recent studies have shown that investing in sustainable and environmentally friendly projects can enhance financial performance. These concerns have sparked worries regarding the potential diversion of resources from green finance initiatives. Recent studies have shown that investing in sustainable and environmentally friendly projects can result in positive financial performance. As the world faced unprecedented challenges, the disruptions caused by the pandemic and geopolitical tensions have created a ripple effect across various sectors, including energy and sustainability (Long *et al.*, 2022; Zhao *et al.*, 2023; Jin, Zhao, Bu, & Zhang, 2023; Aloui, Hamida, & Yarovaya, 2021; Sharif, Aloui, & Yarovaya, 2020). Managing and measuring these outbreaks and monitoring ongoing crises have become imperative to ensure the stability and resilience of the markets. Establishing effective systems to detect and warn of emerging concerns is crucial for timely decision-making and mitigating potential risks. Therefore, this paper addresses these pressing issues by comprehensively analyzing the time-frequency connectedness between the COVID-19 pandemic, geopolitical uncertainties and energy and green markets.

Furthermore, we seek to investigate the relative importance of each element in shaping market dynamics, employing advanced and mixed machine-learning approaches. Our study fills a crucial gap by analyzing the complex relationships among carbon, fuel, clean energy markets, cryptocurrency emissions and geopolitical risk areas underexplored with sophisticated methodologies. Post-COVID-19 shifts in energy use, fossil fuel price fluctuations and renewable energy interest underscore the need for integrated analysis. The traditional models fail to capture these dynamic interrelations, especially under rapid geopolitical and environmental changes. Our innovative approach offers more profound insights into how these factors interplay, aiding in understanding complex market dynamics and informing energy economics and policymaking in a digitally transforming, environmentally conscious world.

This study offers an extended and comprehensive analysis of the interplay between the COVID-19 pandemic, geopolitical uncertainties and energy and green markets. By exploring the time-frequency connectedness and assessing the relative importance of each element, we aim to contribute significantly to the existing literature on carbon, fuel and clean energy markets. Our study fills a notable gap in the literature by investigating the magnitude and direction of return spillovers and the resulting connectedness across these markets. Using the novel time-varying parameter vector autoregression (TVP-VAR) frequency connectedness approach, we can conduct a more informative analysis of spillovers under different market states, including bear, normal and bull market conditions. This methodology improves the prediction accuracy of the time-series models (Huang, Chen, Xu, & Xia, 2023).

The structure of the paper is as follows: Section 2 presents a comprehensive review of the relevant literature. Section 3 outlines the methodology employed in the study, while Section 4 describes the data used. In Section 5, the empirical results are discussed in detail. Finally, Section 6 provides the conclusion.

2. Literature and related works

Much research has been dedicated to exploring the relationship between energy and geopolitical risk in the existing body of literature. For instance, Zhang, Wang, and Li (2023) empirically investigated the asymmetric spillover effects between geopolitical risk and oil price volatility across six major regions, including the Middle East and North America. Their study shed light on the potential spillover effects between geopolitical risk and oil price volatility. Similarly, Zheng, Zhao, and Hu (2023) found that geopolitical risk substantially negatively impacts the price volatility of various commodities. They specifically observed that geopolitical risk increases the price volatility of coal, iron ore and crude oil futures while decreasing the price volatility of gold. However, their analysis failed to include copper futures, a vital commodity in the energy sector. Future studies should consider including copper futures to provide a more comprehensive understanding of the impact of geopolitical risk on energy markets. Another stream of empirical studies has extended this research by introducing environmental issues and climate change to analyze geopolitical risks and energy markets. Zhao *et al.* (2023) examined the effects of geopolitical risks on renewable energy demand and found that geopolitical risks reduce the need for renewable energy and threaten climate change mitigation policies. However, their study did not adequately address the potential interaction between geopolitical risks and other factors influencing renewable energy consumption, such as government policies and technological advancements. Future studies should consider incorporating these factors for a more comprehensive analysis.

Similarly, Jin *et al.* (2023) provided empirical evidence of the dynamic spillover relationships among geopolitical risk, climate risk and energy markets from an international perspective. However, their study primarily focused on energy futures prices, such as crude oil, heating oil and natural gas, without considering the broader renewable energy sector.

The third strand of literature has examined the interrelations and risk transmission between emerging technology, fuel energy markets and carbon emission issues. For instance, Su, Qin, Tao, and Umar (2020) studied the causal relationship between Bitcoin and oil prices, providing valuable insights into the interconnectedness of these markets. Dogan, Madaleno, Taskin, and Tzeremes (2022) and Dogan, Majeed, and Luni (2022) investigated the causal relationship between Bitcoin, clean energy and carbon emissions allowances. Their results showed evidence of a revolving causal association between Bitcoin and clean energy and emission allowances. Tiwari, Abakah, Le, and Leyva-de la Hiz (2021) examined the relationship and dynamics between artificial intelligence (AI) and carbon prices during the era of the Fourth Industrial Revolution. Their findings revealed a time-varying Markov tail dependence structure and dynamics between AI and carbon prices. Chen and Xu (2022) examined the influence of cryptocurrencies on the fluctuation of China's carbon prices, particularly during the COVID-19 period. Their research findings demonstrated a significant explanatory power of cryptocurrencies with the carbon market, as determined by the nonparametric causality-in-quantiles method. Furthermore, the study reveals that cryptocurrencies can be a viable hedging option for the carbon market across various investment horizons, as indicated by the quantile coherency approach. Dogan, Madaleno *et al.* (2022) examined the relationship between green finance and five types of renewable energy (biofuels, fuel cells, geothermal, solar and wind) using the TVP-VAR method on daily indexes. They found that connectedness between these sectors varies over time and is affected by economic events, with wind being the primary transmitter of shocks to green finance. Their research suggests that green finance generally receives more shocks from renewable energies, especially during the COVID-19 pandemic, highlighting its potential as a safe haven for investment diversification. In the same context, Dogan, Luni, Majeed, and Tzeremes (2023) focused on the critical role of the energy transition and carbon markets in combating global warming and promoting sustainability. The TVP-VAR method examined the interactions between global carbon and renewable energy sources like wind, solar, geothermal, biofuel and fuel cells. Results reveal solar and biofuel as primary shock transmitters to global carbon, with notable variations during economic and health crises like COVID-19. Madaleno, Taskin, Dogan, and Tzeremes (2023) explored the link between rare earth minerals, clean energy and carbon emissions using daily stock data and advanced models. Their results show that the interaction between rare earths and renewables varies with market conditions and time, with rare earths often being net receivers in the short term. Kyriazis, Papadamou, Tzeremes, and Corbet (2023) examined the potential of cryptocurrencies as a hedging tool for major market indices, focusing on different market conditions. Analyzing the MSCI World index and its sectors, it finds limited causal links at lower quantiles in some industries, noting substantial nonlinear impacts on volatility, especially during significant price fluctuations. The findings suggest cryptocurrencies are emerging as comparable hedging assets to traditional ones, offering protection against extreme market variations for portfolios, including MSCI constituents. Nations often compete with each other to gain advantages during the transition process. Scholars have argued that the rapid growth of the renewable energy sector may introduce a new dimension of geopolitical risks (Jin *et al.*, 2023; Zhao *et al.*, 2023). Renewable energy development requires access to resources, such as land, potentially leading to geopolitical tensions among countries. These tensions often arise concerning economic aid and potential access to European Union rights. Therefore, studying the interrelation between geopolitical tensions, climate change and the energy markets is crucial as it yields substantial outcomes for the literature, managers and policymakers.

To thoroughly examine the interactions between geopolitical risk, carbon emissions and the energy sector, it is necessary to integrate these elements into a more comprehensive framework. Such a framework should consider various aspects, including the geopolitical implications of renewable energy development, the impact of carbon emissions on global politics and the interplay between energy markets and climate change. By adopting this holistic approach, researchers can provide valuable insights for academia and policymakers.

3. Data and methodology

a. TVP-VAR frequency

The TVP-VAR-based connectedness approach has been shown to effectively address some of the limitations of the rolling-window VAR methodology, such as the potential loss of observations and the sensitivity of parameters to outliers. For these reasons, this paper employs a newly developed process known as the TVP-VAR frequency connectedness approach proposed by Chatziantoniou, Gabauer, and Gupta (2021). The outline of the TVP-VAR(p) can be described as follows:

$$x_t = \Phi_{1t}\, x_{t-1} + \Phi_{2t}\, x_{t-2} + \ldots + \Phi_{pt}\, x_{t-p} + \epsilon_t \; \epsilon_t \sim \mathrm{N}(0,\Sigma_t) \tag{1}$$

The TVP-VAR(p) model is composed of y_t and ε_t, which are $N \times 1$ vectors, Σ_t, which is the $N \times N$ time-varying variance-covariance matrix and Φ_{it}, $i = 1, \ldots, p$, which represent the $N \times N$ time-varying VAR coefficient (Chatziantoniou *et al.*, 2021).

Using the matrix lag-polynomial $\Phi(L) = [I_N - \Phi_{1t}L - \ldots - \Phi_{pt}\, L^p]$ and the Wold representation theorem, the stationary TVP-VAR process can be expressed as a TVP-VMA(∞) model, in which $x_t = \Psi(L)\varepsilon_t$ and $\Phi(L) = [\Psi(L)]^{-1}$. Since $\Psi(L)$ contains infinite lags, it is estimated by computing Ψ_h at $h = 1, \ldots, H$ horizons.

The generalized forecast error variance decomposition (GFEVD) can be computed using the TVP-VMA coefficients Ψ_h. The GFEVD represents the impact of a shock in variable j on variable i regarding its forecast error variance. Mathematically, it can be expressed as:

$$C_{ijt}(H) = \frac{\left(\sum t\right)_{ij}^{-1} \sum_{h=0}^{H} \left((\Psi_h \varepsilon_t)_{ijt} \right)^2}{\sum_{h=0}^{H} \left(\Psi_h \varepsilon_t \acute{\Psi}_h \right)_{ii}} \tag{2}$$

$$\widetilde{C_{ijt}}(H) = \frac{C_{ijt}(H)}{\sum C_{ijt}(H)} \tag{3}$$

$\widetilde{C_{ijt}}$ (H) denotes the amount by which the jth variable contributes to the variance of the forecast error of the i^{th} variable at the H^{th} horizon. Using equations (2) and (3), we can calculate various connectedness measures, which include:

Net pairwise directional connectedness:

$$NPDC_{ijt}(H) = \widetilde{C_{ijt}}(H) - \widetilde{C_{jit}}(H) \tag{4}$$

The $NPDC_{ijt}$ (H) indicates that variable j has a greater (or lesser) influence on variable i than the reverse.

Total directional connectedness TO others:

$$TO_{it}(H) = \sum\nolimits_{i=1, i \neq j}^{N} \widetilde{C_{jit}}(H) \tag{5}$$

The TO_{it} (H) measure quantifies the extent to which a perturbation in the variable i is transmitted to all other variables j in the system.

Total directional connectedness FROM others:

$$FROM_{it}(H) = \sum\nolimits_{i=1, i \neq j}^{N} \widetilde{C_{ijt}}(H) \tag{6}$$

It measures the impact of perturbations in all other variables j on variable i.

Net total directional connectedness:

$$NET_{it}(H) = TO_{it}(H) - FROM_{it}(H) \tag{7}$$

The value of $NET_{it}(H)$ is obtained by subtracting the total directional connectedness from other variables toward variable i $(FROM_{it}(H))$ from the total directional connectedness from variable i towards other variables $(TO_{it}(H))$. This value represents the net impact that variable i has on the volatility transmission network, indicating whether it is a net transmitter or receiver of shocks. When $NET_{it}(H)$ is greater (or less) than zero, it suggests that the variable i has a more substantial influence on all other variables j and vice versa, meaning that it is a net transmitter (or receiver) of shocks.

Total averaged connectedness index:

It quantifies the average influence exerted by a disturbance in one variable on all others, thereby assessing the extent of interconnection within the network and gauging market risk (Chatziantoniou *et al.*, 2021).

$$TACI_t(H) = N^{-1} \sum_{i=1}^{N} TO(H) = N^{-1} \sum_{i=1}^{N} FROM(H) \tag{8}$$

b/connectedness in the frequency domain.

By integrating the TVP-VAR connectedness framework with the spectral representation of variance decompositions presented in the BK-18 model, we can analyze the interdependence of transformed prices among the variables of interest within the frequency domain.

The frequency response function is as follows:

$$\Psi\left(e^{-iw}\right) = \sum_{h=0}^{\infty} e^{-iwh}\,\Psi_{\mathrm{h}}, \text{where } \mathrm{i} = \sqrt{-1} \tag{9}$$

Let ω denote the frequency at which we examine the spectral density of variable y_t. The spectral density of y_t at frequency ω can be characterized as the Fourier transform of the TVP-VMA(∞) model.

$$\mathrm{S_y}\,(\omega) = \sum_{h=-\infty}^{\infty} E\left(y_t y'_{t-h}\right)e^{-iwh} = \Psi\left(e^{-iwh}\right)\,\varepsilon_t\,\Psi'\left(e^{+iwh}\right) \tag{10}$$

The computation of the frequency generalized forecast error variance decomposition (GFEVD) involves combining the spectral density and the GFEVD.

$$\mathrm{C_{ijt}}(\omega) = \frac{(\varepsilon_t)_{jj}^{-1}\left|\sum_{h=0}^{\infty}\left(\Psi(e^{-iwh}\varepsilon_t\right)_{ijt}\right|^{2.}}{\sum_{h=-\infty}^{\infty}\left(\Psi(e^{-iwh})\varepsilon_t(\Psi(e^{iwh})\right)_{ii}} \tag{11}$$

$$\widetilde{C_{ijt}}\,(\mathrm{H}) = \frac{C_{ijt}\,(\omega)}{\sum C_{ijt}\,(\omega)} \tag{12}$$

We then, aggregate all frequencies falling within a specified range of interest.

$\widetilde{\theta}_{ijt}(d) = \int_a^b \widetilde{\theta}_{ijt}(\omega)\,d\omega$, where d = (a, b): a, b ∈ (−π, π), a < b, Afterward, we can proceed with the computation of various frequency connectedness measures, which offer insights into the transmission of effects within a specific frequency range, denoted as “d”.

$$NPDC_{ijt}\,(d) = \widetilde{C_{ijt}}\,(d) - \widetilde{C_{jit}}\,(d) \tag{13}$$

$$TO_{it}\,(d) = \sum\nolimits_{i=1,i\neq j}^{N}\widetilde{C_{jit}}\,(d) \tag{14}$$

$$FROM_{it}\,(d) = \sum\nolimits_{i=1,i\neq j}^{N}\widetilde{C_{ijt}}\,(d) \tag{15}$$

$$NET_{it}\,(d) = TO_{it}\,(d) - FROM_{it}\,(d) \tag{16}$$

Therefore, CN (H) = $\sum_d CN(d)$

The function CN(·) = [NPDC, TO, FROM, NET and TACI] represents the connectedness of the above measures. It signifies that when we aggregate all the frequencies of the frequency connectedness measure, it yields the connectedness measure in the time domain.

b. eXtreme Gradient Boosting: XGBoost

XGBoost is a robust tree-boosting algorithm introduced by Chen and Guestrin (2016). This algorithm is widely used due to its modularity and effectiveness in classification tasks (Nobre & Neves, 2019). It has gained widespread popularity and is renowned for its modularity and efficacy in various classification tasks (Nobre & Neves, 2019). The algorithm terminates when a specific stopping criterion is satisfied, such as reaching the maximum number of iterations or when the improvement in the objective function falls below a predefined threshold

(Nobre & Neves, 2019). One of the significant advantages of XGBoost is its high customizability, as it offers a wide range of hyperparameters that can be fine-tuned to enhance the algorithm's performance (Dai, Huang, Zeng, & Zhou, 2022).

c. SHAP (SHapley additive exPlanations)

The SHAP approach is a valuable tool for interpreting machine learning models, and it is rooted in the concept of Shapley values derived from the cooperative game theory. The primary objective of Shapley values is to quantify each player's contribution in a cooperative game. Lundberg, Erion, and Lee (2018) proposed a method to measure feature importance using Shapley values. In simpler terms, a Shapley value denotes the average contribution of a feature instance across all possible coalitions (Lin & Gao, 2022). This study uses the previous section's data to train an XGBoost model that predicts oil prices based on these features.

d. Data

This research paper examines a daily dataset consisting of several economic indicators. These indicators encompass fuel market prices such as crude oil (WTI), natural gas (NG) and coal, carbon prices, renewable energy and green markets (NASDAQ OMX Wind (GRNWIND), GRNGEOX (NASDAQ OMX Geothermal TR), GRNBIO (NASDAQ OMX Bio/Clean Fuels), WilderHill Clean Energy ETF (PBW)), geopolitical risk index (GPR) and the energy consumption index of the largest cryptocurrencies (Bitcoin (BTC) and Ethereum (ETH) selected based on market capitalization). The construction of the geopolitical risk index developed by Caldara and Iacoviello (2022) is derived from automated text-search queries conducted on the digital archives of ten prominent newspapers [1]. The dataset covers the period from December 1, 2017 to February 15, 2023. This timeframe was meticulously selected to encompass the most critical phases of market volatility and geopolitical developments associated with the Russo–Ukrainian war, ensuring the inclusion of a comprehensive pre-war period for baseline comparison, the onset of the conflict and subsequent market reactions. To account for any potential non-stationarity and ensure our analysis's robustness, we have conducted unit root tests using the Phillips and Perron method and have taken the necessary steps to differentiate the data accordingly. To address the issue of non-stationarity in the variables, we conduct a unit root test using KPSS and the Zivot–Andrews unit root test. The test results confirm the nonstationarity of the variables. Therefore, we take the first log difference of the series, which represents the percentage change in these variables over time. The pattern observed in these series is depicted in Figure 1, and the logs differenced of the data are presented in Figure 2.

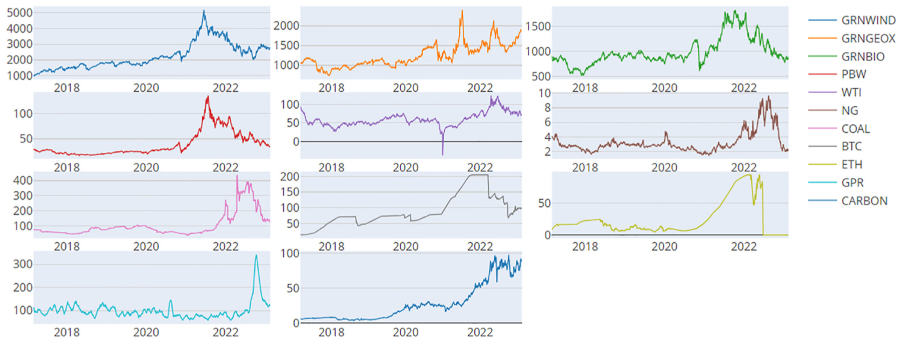
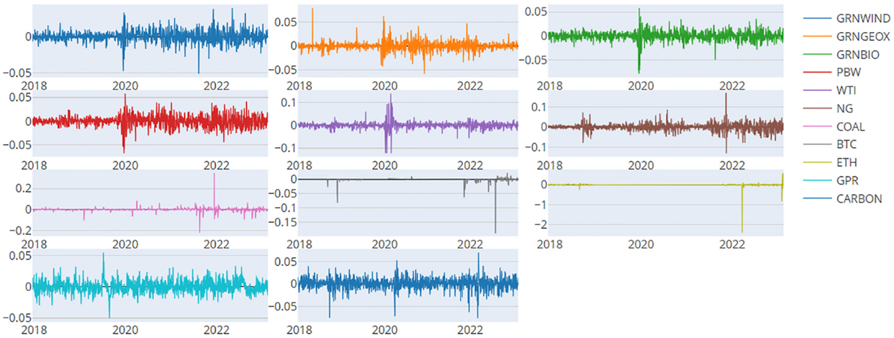


Figure 1.
The dataset

Source(s): Created by authors



Source(s): Created by authors

Figure 2. The transformed dataset

Table 1 presents the descriptive statistics for fuel, carbon, green markets, geopolitical and carbon emission indices. The research period encompasses a total of 1,886 observations. Following standard practices in empirical research, the study presents descriptive statistics and distribution properties of the transformed values. The analysis in Table 1 reveals that, on average, the returns of all the studied markets are positive, except for the GRNBIO markets. Notably, the standard deviations of these series are generally low. Furthermore, fuel and carbon markets exhibit the most considerable variances, making them the riskiest choices among the considered markets for investors during the selected sample period. It is worth mentioning that this paper finds all of the series' distributions to be highly leptokurtic, as indicated by the kurtosis values. Compared to a normal distribution, these variables exhibit a shape with fatter tails, suggesting that they do not follow a normal distribution, as Jarque and Bera (1980) argued. Based on the ERS unit root test of Elliott, Rothenberg, and Stock (1996), these variables are statistically stationary at a 1% significance level. As we delve into the analysis, it is crucial to highlight some key insights offered by these descriptive statistics. Positive and negative returns among the assets indicate a potential give-and-take relationship. This suggests the likelihood of significant volatility spillovers and interconnectedness among the assets, which we will further explore in the next section. Furthermore, it is essential to note that the data series exhibits non-normal distributions, with negative and positive skewness and high kurtosis values, indicating that the data has heavy tails, is skewed to the right or left and displays excess kurtosis. These characteristics imply the presence of nonlinearity, structural breaks and regime changes in the data. Consequently, relying solely on the linear models that assume constant parameter estimation would yield findings lacking originality and reliability for informing appropriate policy formulation and investment decisions. Furthermore, we used the KPSS and the Zivot–Andrews unit root test for a more comprehensive understanding of the properties of the time series. The results of these tests confirm that the series are stationary and adequately account for structural breaks, giving evidence of the robustness and accuracy of the TVP-VAR model's inferences.

Consequently, considering the abovementioned features, we propose utilizing the TVP-VAR frequency connectedness approach. This method finds all the mentioned characteristics and provides a more comprehensive analytical framework by accommodating time-varying parameters and nonlinearity in the data (Chatziantoniou *et al.*, 2021). Therefore, we have strong evidence to support a TVP-VAR approach with time-varying frequency interlinkages among these studied markets.

Table 1. Descriptive statistics results for the daily return data

	Mean	SD	Skewness	Kurtosis	JB	ERS	KPSS	Zivot–Andrews unit root test
CARBON	0.00067	0.01261	−0.729	4.56	1800.046***	−7.672***	0.1066*	−21.764***
WTI	0.00063	0.01489	1.243	24.865	49047.019***	−11.526***	0.1223*	−24.5516***
NG	0.00024	0.01892	0.741	11.471	10507.032***	−18.186***	0.1543*	−24.183***
COAL	0.00026	0.01518	4.621	182.043	2,609,544***	−16.836***	0.2153*	−20.2828***
GRNWIND	0.00011	0.00795	0.110	3.726	1094.189***	−18.172***	0.0624*	−21.5201***
GRNGEOX	0.00017	0.00946	0.233	9.219	6691.975***	−16.052***	0.0468*	−21.6974***
GRNBIO	−5.038e−05	0.0101	−1.372	11.238	10511.5***	−16.532***	0.049*	−20.7433***
PBW	6.587e−05	0.01138	−0.335	3.053	767.366***	−17.651***	0.2416*	−21.3962***
BTC	0.00066	0.00912	−15.698	299.011	7,099,642***	−15.384***	0.291*	−23.0178***
ETH	0.00153	0.07397	−21.838	669.339	35,337,646***	−15.361***	0.2383*	−22.7091***
GPR	0.00029	0.00999	0.257	1.245	142.514***	−10.213***	0.0591*	−19.2759***

Source(s): Created by authors

4. Empirical results and discussion

In the empirical part, we first examine the outcomes regarding total net connectedness and net pairwise connectedness. This analysis allows us better to understand each market's significance in our proposed system. It is important to highlight that every market has the potential to function as either a net shock transmitter or a net shock receiver. The econometric technique widely utilized to analyze interconnectedness is the one proposed by Diebold and Yilmaz (2012). This methodology tracks contagions within a predetermined network, aiming to mitigate the adverse effects of specific economic shocks. However, one drawback of the original approach is its reliance on an arbitrarily chosen rolling window size for time-varying connectedness. Several alternative methods have been suggested to overcome this limitation. For instance, Chatziantoniou *et al.* (2021) have proposed a novel approach built upon the valuable insights from the previous work of Baruník and Křehlík (2018) and Antonakakis, Chatziantoniou, and Gabauer (2020), by using the mean-squared prediction error of the rolling-window VAR to determine the optimal window size. By leveraging the essence of their research, we aim to efficiently incorporate their findings and methodologies to study the interlinkages among energy markets (fuel, renewable, green and carbon markets) and indices (geopolitical and cryptocurrency energy consumption measurements).

In the next step, we justify the importance of geopolitical tensions in increasing crude oil market volatility using the SHAP approach.

4.1 Total average dynamic connectedness

Tables 2 and 3 display the outcomes of the total average connectedness between energy green markets, with and without geopolitical risk and cryptocurrency energy consumption proxies. Meanwhile, Tables 4–7 present the results of the short-run (1–5 trading days) and long-run (5 or more trading days) components, respectively.

Tables 2 through 7 highlight the intrinsic volatility of a specific market, indicated by the diagonal elements, which represent the impact of its own shocks. Additionally, the tables elucidate the Intermarket dynamics in two ways: firstly, by showing how each market contributes to the volatility of others, detailed in the off-diagonal elements in the "FROM" section and secondly, by illustrating the influence of various external variables on the volatility of the market in question, as depicted in the off-diagonal elements in the "TO" section. This comprehensive layout describes both internal and external factors affecting market volatility.

In these tables, the row values show how much each market contributes to the forecast error variance of a specific market, while column values indicate a market's impact on others. We calculate the total average connectedness, excluding geopolitical and climate factors, revealing market interrelations. The diagonal values in Table 2 show the most robust connections, representing each market's relationship with itself. The off-diagonal values display interesting patterns of intermarket influence. On average, 16.44% of the forecast error variance in global financial markets is due to inter-market shocks, while the rest is due to unique market factors. Green energy stocks, barring PBW, are the primary volatility transmitters, with COAL following. Conversely, CARBON is the leading volatility receiver, with fuel energy assets next.

The considerable level of volatility transmission observed during the geopolitical tensions caused by the recent Russia–Ukraine conflict aligns with the findings of Ha and Nham (2022), Huang *et al.* (2023) and Le (2023). These studies gave evidence of a considerable transmission of volatility between fuel and renewable energy markets.

Incorporating geopolitical and cryptocurrency consumption data, as shown in Table 3, we observe that nearly 23% of the forecast error variance in global markets is due to shocks, climate and geopolitical risks. The remaining 77% is attributed to unique market factors.

Table 2. Total averaged volatility connectedness without geopolitical and climate change proxies

	GRNWIND	GRNGEOX	GRNBIO	PBW	WTI	NG	COAL	CARBON	FROM
GRNWIND	78.78	6.34	7.70	2.00	1.39	1.47	1.60	0.71	21.22
GRNGEOX	5.70	75.46	10.59	2.07	2.58	1.47	1.31	0.83	24.54
GRNBIO	6.85	11.03	74.50	1.87	1.46	1.56	1.92	0.81	25.50
PBW	3.38	2.89	3.53	85.50	1.28	1.09	1.04	1.29	14.50
WTI	1.47	2.92	1.57	1.01	86.84	3.32	2.13	0.74	13.16
NG	1.53	1.82	1.51	1.06	3.01	87.61	2.30	1.16	12.39
COAL	2.05	1.60	1.50	0.91	2.07	2.17	88.57	1.13	11.43
CARBON	1.24	0.81	1.40	1.36	1.28	1.20	1.48	91.24	8.76
TO	22.21	27.41	27.80	10.29	13.05	12.28	11.78	6.68	131.50
NET	1.00	2.87	2.30	−4.21	−0.11	−0.12	0.35	−2.08	16.44

Source(s): Created by authors

Table 3. Total averaged volatility connectedness with geopolitical and climate proxies

	GRNWIND	GRNGEOX	GRNBIO	PBW	WTI	NG	COAL	BTC	ETH	GPR	CARBON	FROM
GRNWIND	73.64	5.75	7.18	1.67	1.08	1.05	1.30	3.70	2.52	1.24	0.88	26.36
GRNGEOX	5.05	69.04	9.67	2.16	2.91	1.10	1.84	2.53	3.00	1.70	1.00	30.96
GRNBIO	6.39	9.87	68.13	1.98	2.16	1.10	2.24	1.65	4.43	1.24	0.82	31.87
PBW	2.73	2.46	3.71	74.96	2.39	1.50	2.30	2.42	3.14	2.82	1.57	25.04
WTI	1.07	2.23	1.97	1.54	74.54	2.13	3.41	3.60	6.08	2.23	1.19	25.46
NG	1.41	1.31	1.33	1.61	1.93	80.57	2.06	5.19	2.18	1.24	1.17	19.43
COAL	1.77	2.12	1.98	1.89	3.90	1.96	75.88	1.58	5.20	2.57	1.14	24.12
BTC	0.56	0.52	0.40	0.50	0.60	0.39	0.20	87.67	8.13	0.39	0.63	12.33
ETH	0.98	1.49	1.19	0.65	0.94	0.70	0.60	8.12	84.18	0.44	0.71	15.82
GPR	1.68	1.10	1.36	2.69	3.07	1.66	2.16	3.54	4.53	77.14	1.06	22.86
CARBON	1.12	1.01	1.46	1.63	2.34	1.07	1.55	4.18	3.01	1.20	81.45	18.55
TO	22.75	27.86	30.25	16.31	21.32	12.68	17.67	36.52	42.22	15.07	10.16	252.79
NET	−3.61	−3.10	−1.63	−8.73	−4.14	−6.75	−6.45	24.18	26.40	−7.78	−8.40	22.98

Source(s): Created by authors

Table 4.
The averaged return connectedness in the short run (1–5), without geopolitical and climate indicators

	GRNWIND	GRNGEOX	GRNBIO	PBW	WTI	NG	COAL	CARBON	FROM
GRNWIND	48.85	3.23	3.99	0.98	0.73	1.03	1.05	0.47	11.50
GRNGEOX	3.63	51.07	6.80	1.14	1.74	1.14	0.85	0.51	15.81
GRNBIO	4.20	6.93	49.76	1.01	0.92	1.22	1.37	0.54	16.19
PBW	1.61	1.42	1.52	56.07	0.82	0.73	0.65	0.78	7.54
WTI	0.92	1.91	0.88	0.61	58.51	1.93	1.27	0.41	7.94
NG	1.19	1.30	1.02	0.65	2.28	60.63	1.40	0.76	8.60
COAL	1.19	0.93	0.98	0.62	1.24	1.28	55.79	0.82	7.06
CARBON	0.69	0.49	0.85	0.82	0.78	0.81	0.99	60.77	5.43
TO	13.43	16.21	16.05	5.84	8.51	8.14	7.59	4.29	80.07
NET	1.93	0.40	−0.14	−1.70	0.57	−0.46	0.53	−1.14	10.01

Source(s): Created by authors

Table 5. The averaged return connectedness in the short run (1–5), with geopolitical and consumption indicators

	GRNWIND	GRNGEOX	GRNBIO	PBW	WTI	NG	COAL	BTC	ETH	GPR	CARBON	FROM
GRNWIND	45.61	2.93	3.83	0.74	0.57	0.67	0.85	0.32	0.56	0.68	0.52	11.68
GRNGEOX	3.20	47.22	6.14	1.15	1.67	0.67	1.11	0.30	1.07	0.86	0.60	16.80
GRNBIO	3.88	6.31	45.72	1.12	1.45	0.75	1.50	0.17	0.89	0.63	0.56	17.27
PBW	1.23	1.13	1.63	48.89	1.57	1.00	1.42	0.32	0.54	1.47	0.91	11.21
WTI	0.57	1.55	1.10	0.99	49.85	1.19	2.08	0.32	0.72	1.46	0.64	10.60
NG	0.93	0.72	0.90	1.05	1.34	55.00	1.21	0.54	0.60	0.74	0.76	8.78
COAL	1.01	1.35	1.09	1.10	2.28	1.14	47.55	0.16	0.66	1.34	0.74	10.86
BTC	0.07	0.07	0.06	0.05	0.06	0.08	0.02	12.53	0.15	0.07	0.16	0.81
ETH	0.43	0.78	0.54	0.38	0.41	0.37	0.25	0.29	22.20	0.14	0.22	3.80
GPR	0.63	0.68	0.66	1.10	1.38	0.68	0.97	0.19	0.48	39.13	0.49	7.27
CARBON	0.67	0.62	0.79	0.92	1.24	0.72	0.97	0.32	0.37	0.57	54.04	7.19
TO	12.63	16.15	16.74	8.59	11.99	7.27	10.39	2.92	6.03	7.97	5.59	106.27
NET	0.95	−0.65	−0.53	−2.62	1.38	−1.51	−0.47	2.11	2.23	0.70	−1.60	9.66

Source(s): Created by authors

Table 6.
The averaged transformed prices connectedness in the long run (5-inf)

	GRNWIND	GRNGEOX	GRNBIO	PBW	WTI	NG	COAL	CARBON	FROM
GRNWIND	29.94	3.11	3.71	1.02	0.65	0.44	0.55	0.24	9.72
GRNGEOX	2.07	24.39	3.78	0.93	0.84	0.33	0.46	0.32	8.73
GRNBIO	2.65	4.11	24.74	0.86	0.54	0.35	0.54	0.27	9.31
PBW	1.77	1.47	2.00	29.43	0.46	0.36	0.38	0.51	6.96
WTI	0.54	1.01	0.69	0.40	28.33	1.39	0.85	0.33	5.22
NG	0.35	0.53	0.49	0.41	0.73	26.98	0.91	0.39	3.79
COAL	0.86	0.67	0.52	0.29	0.83	0.89	32.78	0.32	4.37
CARBON	0.55	0.32	0.55	0.55	0.49	0.39	0.49	30.47	3.33
TO	8.79	11.20	11.74	4.44	4.54	4.14	4.18	2.39	51.43
NET	−0.93	2.47	2.44	−2.51	−0.68	0.34	−0.18	−0.94	6.43

Source(s): Created by authors

Table 7. The averaged transformed prices connectedness in the long run (5-inf), with proxies

	GRNWIND	GRNGEOX	GRNBIO	PBW	WTI	NG	COAL	BTC	ETH	GPR	CARBON	FROM
GRNWIND	28.03	2.81	3.35	0.92	0.50	0.39	0.45	3.39	1.95	0.56	0.36	14.68
GRNGEOX	1.84	21.83	3.53	1.01	1.23	0.43	0.73	2.23	1.93	0.84	0.40	14.16
GRNBIO	2.50	3.56	22.40	0.87	0.70	0.35	0.73	1.48	3.54	0.61	0.26	14.61
PBW	1.50	1.33	2.08	26.08	0.82	0.51	0.88	2.11	2.59	1.35	0.66	13.83
WTI	0.50	0.68	0.88	0.55	24.69	0.95	1.33	3.28	5.37	0.77	0.54	14.85
NG	0.47	0.59	0.43	0.56	0.59	25.57	0.86	4.65	1.59	0.50	0.41	10.65
COAL	0.76	0.77	0.89	0.80	1.62	0.83	28.33	1.42	4.54	1.24	0.40	13.26
BTC	0.49	0.45	0.34	0.44	0.54	0.31	0.18	75.14	7.98	0.33	0.47	11.52
ETH	0.55	0.72	0.65	0.27	0.53	0.33	0.34	7.83	61.98	0.29	0.50	12.02
GPR	1.05	0.42	0.70	1.59	1.70	0.98	1.20	3.34	4.05	38.02	0.57	15.59
CARBON	0.44	0.38	0.67	0.71	1.10	0.35	0.58	3.86	2.64	0.62	27.41	11.36
TO	10.12	11.71	13.51	7.71	9.33	5.41	7.28	33.60	36.19	7.11	4.56	146.52
NET	−4.57	−2.45	−1.09	−6.12	−5.52	−5.24	−5.98	22.07	24.17	−8.48	−6.80	13.32

Source(s): Created by authors

Data indicates that Bitcoin and Ethereum's energy consumption moderately affects shock transmission and volatility in other markets. The considerable effect of geopolitical risks on volatility transmission aligns with the results of several studies, such as Boungou and Yatié (2022) and Le (2023).

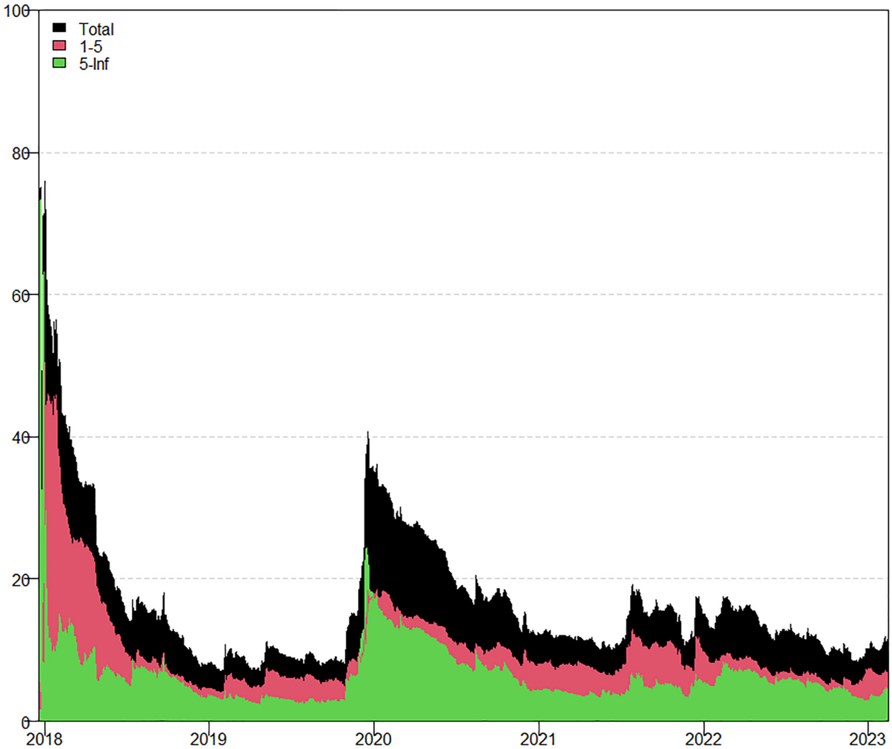
Furthermore, the frequency decomposition analysis shows that short-term volatility transmission in Table 4 accounts for most Intermarket volatility connectedness (10.01 %), while long-term transmission in Table 6 accounts for a smaller portion (6.43 %). Besides the renewable energy markets (GRNWIND and GRNGEOX), crude oil has the most significant impact on transmitting effects and volatility of shocks to other markets in the system. Conversely, the renewable energy markets (GRNBIO and PBW), Natural Gas and CARBON are net recipients of these shocks in the short-term horizon (Table 3). The Natural Gas, GRNGEOX and GRNBIO are considered volatility transmitters. However, the other markets under study are regarded as shock receivers in the long term (Table 6). Based on the frequency bands, volatility transmission associated with geopolitical indicators in Tables 5 and 7 is primarily propelled in short-term horizons. Similarly, a long-term volatility transmission related to cryptocurrency consumption is predominantly involved. These findings align with previous studies conducted by Chen, Xu, and Peng (2022) and Huang *et al.* (2023), which also documented a long-term pattern of volatility transmission. These results suggest that the global pandemic and geopolitical tensions may have caused a fundamental change in investor expectations, leading to an increase in long-term uncertainty and systemic risk.

4.2 Total dynamic connectedness

For a better understanding of the influence of the Russia–Ukraine conflict on these interconnections across the network of markets, we lead a more dynamic analytical framework that considers the changing nature of the TACI over time (depicted with black color) and reflects how the roles of the studied markets within the network evolve illustrated in Figure 3. The dominance of low-frequency response to shocks primarily drives the total volatility spillover, which aligns with the findings of Huang *et al.* (2023). In addition, we noticed a sharp increase in TACI in late December 2019, coinciding with the COVID-19 epidemic spreading rapidly worldwide, causing turmoil in the global financial market. Although COVID-19 continues to pose a threat, there has been a downward trend in total volatility transmission since its peak in March 2020. Finally, there has been a noticeable upward trend in the dynamic volatility transmission since February 2022, which may be related to market uncertainty caused by the Russia–Ukraine conflict.

4.3 Net total directional volatility connectedness

In the forthcoming analysis, our primary focus will be on the outcomes of net connectedness, offering insights into whether a given market can be classified as a net shock transmitter or a net shock receiver. Figure 4 illustrates the dynamic evolution of the directional volatility spillover and reveals several insights. In late 2017 and the beginning of 2018, Crude oil, Natural Gas and the Green stocks (GRNWIND and GRNGEOX) markets experienced a volatility transmission to other markets. However, CARBON, COAL, PNB and GRNBIO markets are regarded as net recipients of shocks during this period as they are mainly affected by the short-run volatility. Furthermore, the net directional volatility connectedness varies explicitly over time. After the outbreak, the green stocks (GRNBIO and GRNGEOX) gradually shifted back to transmitters of the long-run volatility, lasting more recently. However, the other markets under study evolved between net recipients and net transmitters of volatility, especially after the Russia–Ukraine conflict. The frequency decomposition results also indicate that the long-term components serve as the primary source of directional



Source(s): Created by authors

Figure 3.
Total dynamic connectedness without proxies

volatility spillover, suggesting that volatility transmission among green stocks and energy assets tends to occur over a more extended period.

Our primary focus lies on the effect of geopolitical risk by analyzing the impact of the Russia–Ukraine conflict. We draw attention to the connections between GPR and markets under study, as illustrated in Figure 5. During this period, the geopolitical indicator appears to significantly impact the volatility of renewable energy stocks in the short horizon (GRNWIND and GRNBIO) and long-term run (PBW and GRNGEOX). This effect is less considerable for the other markets in the short run (WTI and COAL) and long-term horizons (CARBON and NG), as indicated in Figure 5. These findings are consistent with previous research Dogan, Madaleno *et al.* (2022) and Dogan, Majeed *et al.* (2022), who found evidence of a causal association between both clean energy and emission allowances with Bitcoin.

4.4 SHAP (SHapley additive exPlanations) results

Thus far, we have observed a pronounced level of volatility interconnectedness among green, renewable and fuel energy markets. Natural Gas is the primary recipient of shocks, and renewable energy stocks and oil are the primary transmitters. Now, our focus shifts to examining the role of geopolitical risks and cryptocurrency energy consumption, increasing each market's volatility.

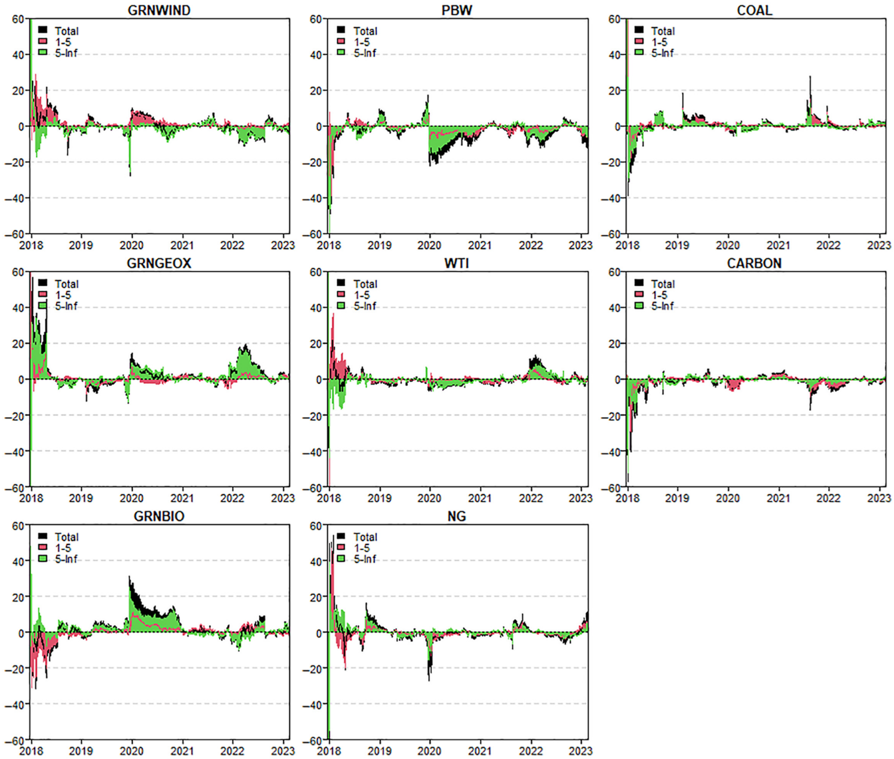


Figure 4.
Net total directional volatility connectedness

Source(s): Created by authors

The findings in Figures 6–13 confirm the spillover results and show that geopolitical risks and cryptocurrency energy consumption are significant indicators for all markets and negatively influence other markets.

4.5 Discussion

In light of our findings, discussing the broader economic implications and the underlying theoretical constructs that inform our analysis is imperative. The observed patterns of total net connectedness and pairwise connectedness among various markets provide profound insights into shock transmission and reception dynamics. Notably, the significant role of green energy stocks and fossil fuel assets in this interconnected network underscores the influence of energy markets on global financial stability. These patterns are not merely empirical observations but are deeply rooted in the economic theories of market behavior and risk contagion. The prevalence of volatility transmission during heightened geopolitical tensions, such as the Russia–Ukraine conflict, aligns with views of uncertainty and investor sentiment affecting market dynamics. Furthermore, the methodological approach adopted by Diebold and Yilmaz (2012) and its enhancements by subsequent researchers offer a robust framework for understanding these complex relationships. By incorporating these theoretical perspectives, our discussion contextualizes the empirical findings within the broader economic discourse. It provides a scaffold for future research to build upon, particularly in exploring the nuanced roles of geopolitical and climate risks in shaping market behavior.

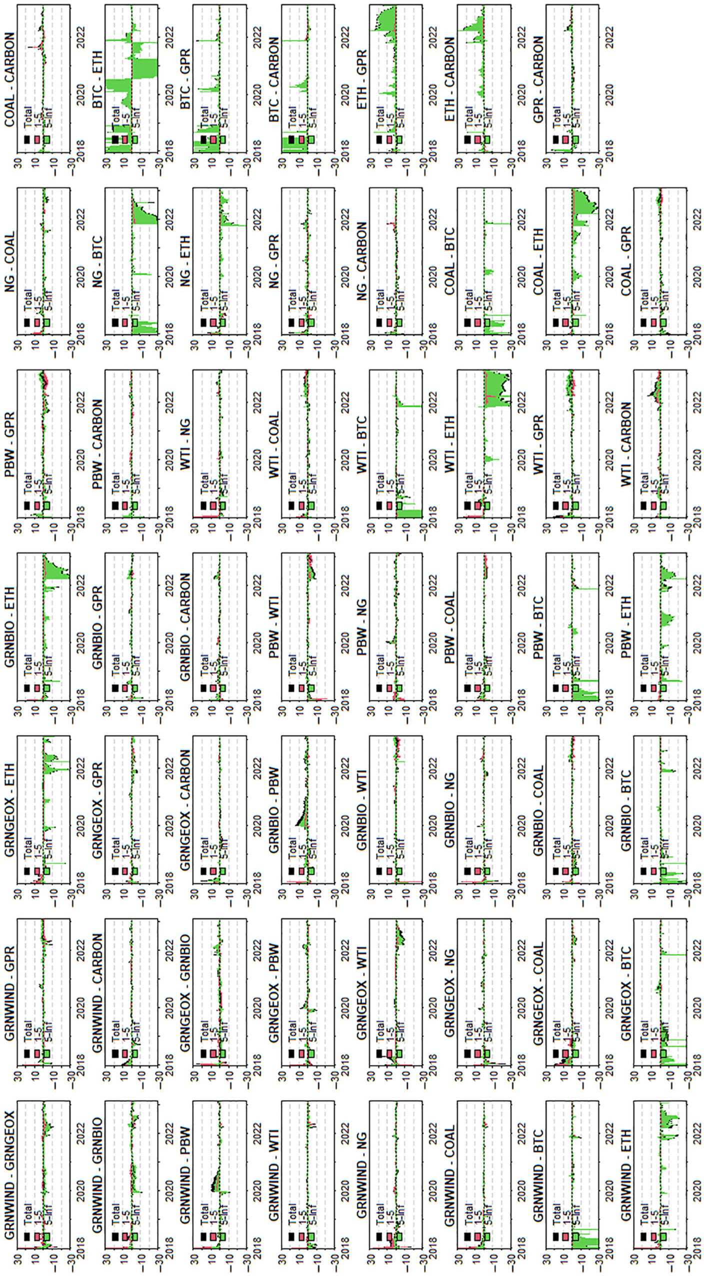


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Figure 5.
Net pairwise directional connectedness

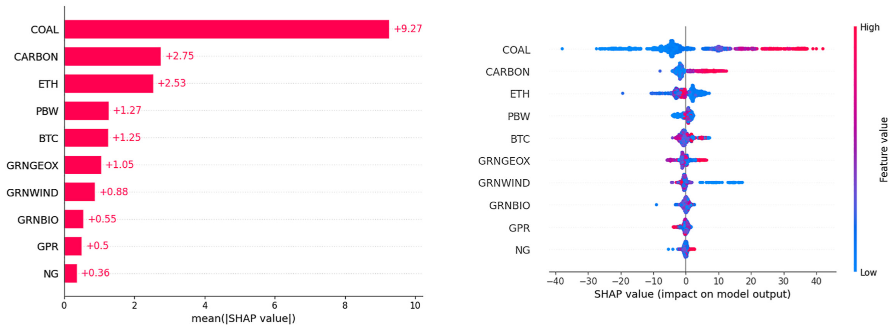

Figure 6.
SHAP values for WTI

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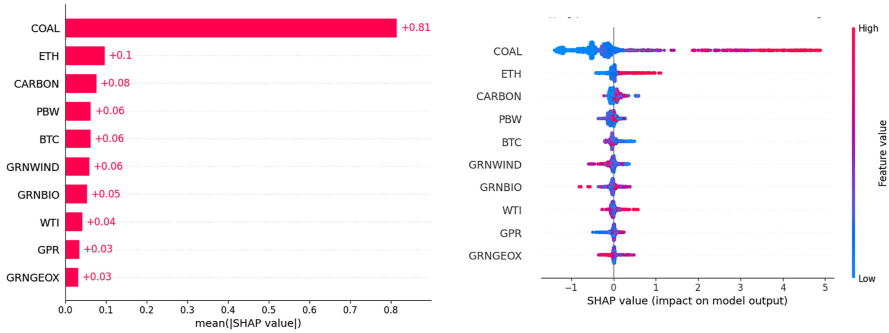

Figure 7.
SHAP values for NG

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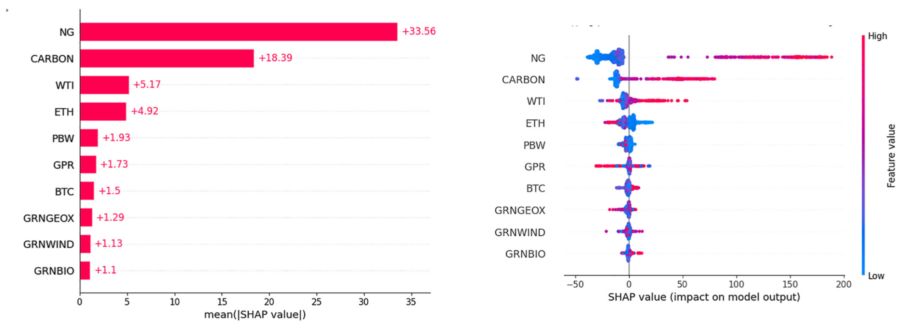

Figure 8.
SHAP values for COAL

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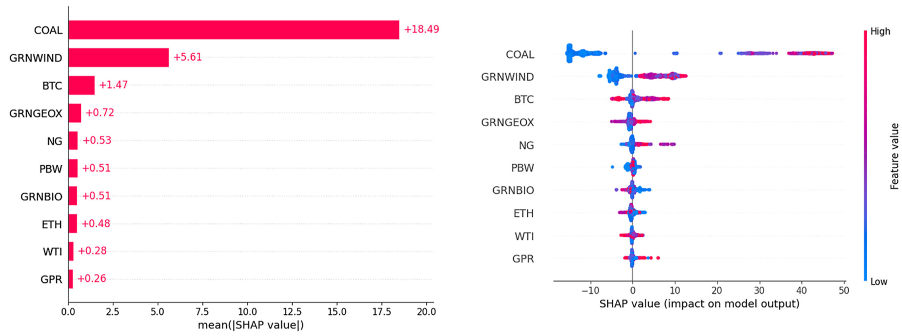

Source(s): Created by authors

Figure 9.
SHAP values for CARBON

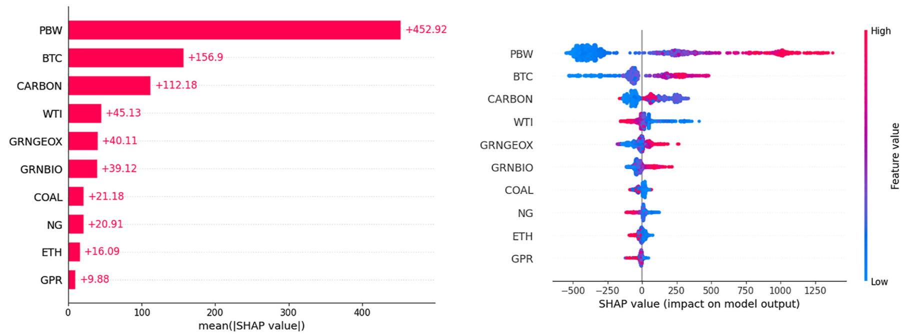

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Figure 10.
SHAP values for GRNWIND

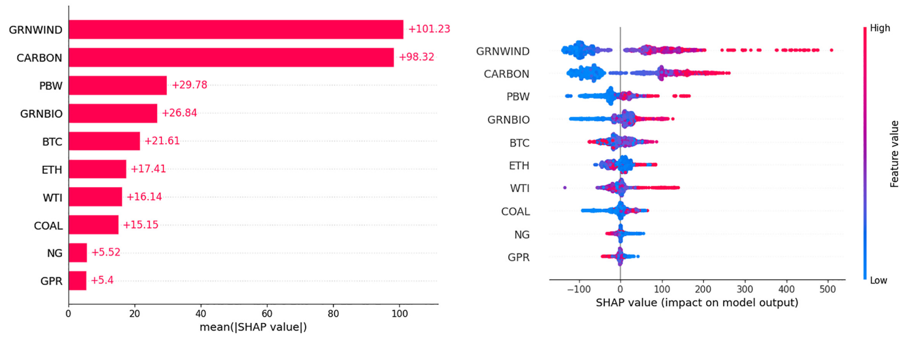

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Figure 11.
SHAP values for GRNGEOX

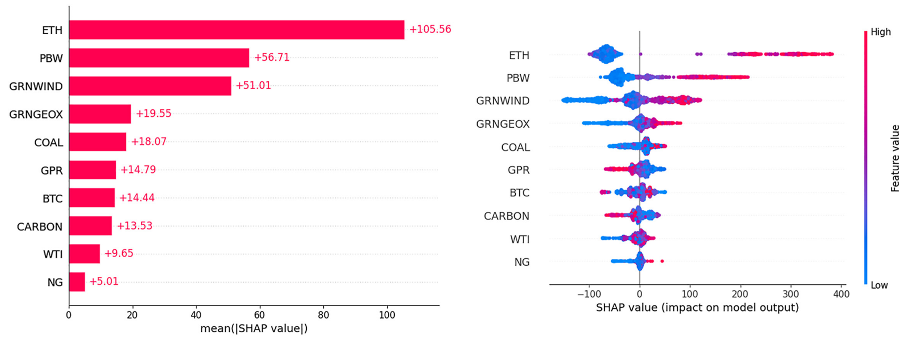

Figure 12.
SHAP values for GRNBIO

Source(s): Created by authors

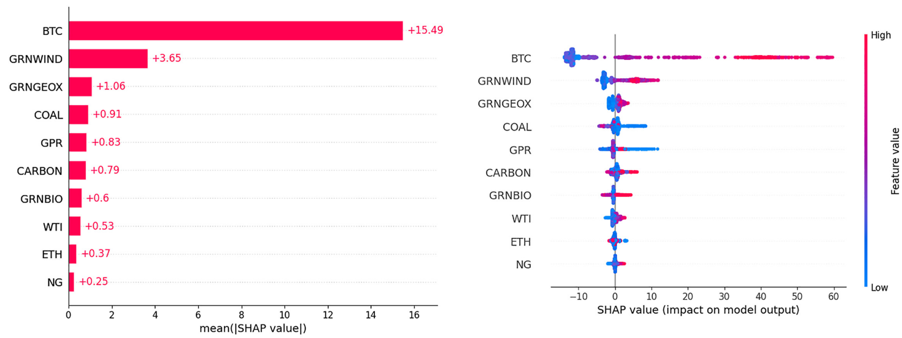

Figure 13.
SHAP values for PBW

Source(s): Created by authors

5. Conclusion and implications

Our research paper employs a time-frequency connectedness approach to assess the interconnections among four markets' families: fuel, renewable energy, green stocks and carbon markets. We utilize the TVP-VAR approach, following the methodology of Chatziantoniou *et al.* (2021), which allows for flexibility and enables us to measure net pairwise connectedness in both short and long-term horizons. Our results indicate that the interconnectedness among the studied markets is relatively significant. These findings suggest that our network is exposed to elevated market risk, with the COVID-19 pandemic and geopolitical risks playing a motivating role in the time-varying system-wide interlinkages. Furthermore, we find empirical evidence highlighting the dominance of renewable energy markets except for the PBW as volatility transmitters in the other markets. In contrast, CARBON emerges as the primary net recipient of volatility, followed by fuel energy assets. The frequency decomposition results also indicate that the long-term components serve as the primary source of directional volatility spillover, suggesting that volatility transmission among green stocks and energy assets tends to occur over a more extended period. The SHAP results show that the green and fuel energy markets are negatively connected with geopolitical risks (GPR). The results obtained through the SHAP analysis confirm the novel TVP-VAR frequency connectedness findings, indicating that clean energy markets can serve as a safe haven against GPR during the Russian invasion. The estimates of pairwise connectedness consistently indicate that fuel and energy markets respond to related shocks from other markets while also influencing those markets. Overall, geopolitical risks and cryptocurrency energy consumption are robust indicators to predict these markets' volatility.

This research uses a time-frequency connectedness framework alongside TVP-VAR and SHAP models to highlight the complex relationship between geopolitical risk, green financial assets and renewable energy markets. Our findings confirm the vital role of green investments and renewable markets in mitigating volatility due to geopolitical uncertainties, offering essential insights for stakeholders and policymakers focused on sustainable growth and stability. While our methodology is robust, it may not fully capture the complexity of geopolitical risks and market dynamics and concentrates on specific markets. Future research should expand market coverage, employ alternative models for a more comprehensive view and investigate the long-term impacts of policy and technology changes to understand these relationships further and bolster sustainable economic strategies against geopolitical uncertainties.

Our study significantly advances theoretical knowledge by detailing the interconnectedness between clean and dirty energy markets and the impact of crises like COVID-19 and the Russia–Ukraine conflict on their dynamic relations. By calculating net pairwise connectedness, we offer insights into how these markets interact, especially under uncertain events, providing valuable information for investors and authorities on potential contagion effects. Practically, our findings are vital for investors and policymakers, shedding light on spillover effects and market linkages. Understanding these connections helps in crafting strategies to mitigate market vulnerabilities and manage portfolio investments effectively. We highlight the heightened interlinkages during crises, showing how shocks in one market can ripple through the network, crucial for investment and policy decisions. Our research aids policymakers in understanding the broader impacts of market dynamics on public welfare, emphasizing the importance of recognizing and addressing the spillover effects of risk and uncertainty between the markets.

Note

1. This index is retrieved in daily frequencies from this link: https://www.matteoiacoviello.com/gpr.htm

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