JEL Classification: C32; F3; G12; Q43
Keywords: Volatility indices; Green markets; Fossil energy markets; TVP-VAR Model; Connectedness

The Effects of Global Volatility Indices on Green and Fossil Energy Markets

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Abstract

Uncertainties cause significant fluctuations in financial markets. Energy markets are more susceptible to uncertainties because of their strategic importance. This paper examines connectedness among various implied volatility indices (stock, oil, gold, currency), green markets (green stocks, bonds), and fossil energy commodities (natural gas, oil, heating oil, gasoline) from November 2, 2012, to July 25, 2023, by employing Chatziantoniou et al. (2023)'s TVP-VAR model. We use Broadstock et al. (2022)'s Minimum Connectedness Portfolio technique to construct optimal portfolio weights and hedge ratios. Our findings reveal moderate interdependence, with an increase during the pandemic. Short- and long-term factors are equally significant in this connectedness. All volatility indices are volatility transmitters, while energy markets are recipients. We provide important implications for investors interested in energy markets and aiming at constructing optimal hedging strategies, as well as for policymakers aiming to develop policies to stabilize energy prices and increase the effectiveness of green markets.

1. Introduction

Global volatility indices are indicators of fluctuations in financial markets, and these indices are increased by greater risk and uncertainty in financial markets. Over the last two decades, significant fluctuations in financial markets have been caused by trade tensions between the US and China, the COVID-19 pandemic, and the Russia-Ukraine conflict. In addition, the increase in global inflation, changes in the FED's interest rate policy, and fear of recession have further increased volatility. The recent increases in global risk and uncertainties and their significant effects on global markets

https://doi.org/10.32065/CJEF.2025.03.02

We sincerely thank the two anonymous reviewers for their comments and suggestions, which have significantly improved the quality of our paper.

This article was supported by the Scientific Research Projects Coordination Unit of Dokuz Eylül University within the scope of the Research Universities Support Program (ADEP) by the Council of Higher Education (YÖK). Project Number: 2022-2908.

motivated us to examine the impacts of global volatility indices on energy markets. This paper focuses on energy markets, which are critical to economic growth. In addition to fossil energy, it examines green energy markets because of the increasing use of renewable energy sources.

Many factors are influencing the growing transition from fossil to green energy for sustainable economic growth, such as the growing instabilities in financial markets (Li et al., 2023; Yu and Guo, 2022; Zhang and Razzaq, 2022), unpredictable fluctuations in fossil fuel prices (Ari et al., 2022; Shinwari et al., 2022) and energy security (Ainou et al., 2023; Aized et al., 2018; Ibrahiem and Hanafy, 2021). In addition, environmental and climate change concerns (Dincer, 1999; Khan et al., 2022; Omri and Nguyen, 2014) have triggered this transition towards more sustainable development.

The transition from an industrialized past to a sustainable future has led to the emergence of environmental, social, and governance (ESG) principles and sustainable development goals (SDGs), which are now the focus of attention of governments, businesses, and individuals (Işık et al., 2024e). There is a close relationship between ESG and SDGs. While ESG represents firm and microeconomic-based sustainability, SDG addresses sustainability from a more general perspective. ESG now takes into account macroeconomic variables, and this ensures integration between these variables and provides a holistic perspective on sustainability (Işık et al., 2024c). The significant long-term positive influence of ESG practices on economic growth significantly supports a sustainable economy (see Işık et al., 2024d). Greater renewable energy use reduces energy dependency and uncertainty in energy markets because it is less sensitive to external factors and fossil fuel price fluctuations. This aligns with the United Nation's SDG7 (Affordable and Clean Energy), aiming to improve the share of clean energy by 2030 (Işık et al., 2024b). In addition, increases in renewable energy consumption decrease CO2 emissions, indicating the potential benefits of incentivizing and investing in renewable sources (Işık et al., 2024a). Since fossil fuel use increases the risks of climate change and global warming, encouraging renewable energy usage is directly linked to SDG13 (Climate Action), which promotes urgent action to combat climate change and its impacts.

The recent rapid growth in green investments includes those of companies that provide or support environmentally friendly products and practices, and green financing to support such investments.[1] Due to the shifts in the preferences of individuals, businesses, and governments from fossil to green investment and financing, there has been a growing tendency toward socially responsible and environmentally friendly practices. This growing trend of investors (firms) demanding (supplying) newly emerged instruments is increasing the number of these instruments, which now include green energy firm stocks (distributor, supplier, manufacturer, etc.), green and blue bonds, green sukuk, sustainability-linked, environmentally friendly,

[1] Green financing consisting of debt and equity financing. Global borrowing by issuing green bonds and equity funding through initial public offerings targeting green projects swelled to $540.6 billion in 2021 from $5.2 billion in 2012. Green bonds accounted for 93.1% of total green finance globally between 2012 and 2021. In 2021, global green bond issuance stood at $511.5 billion, compared with $2.3 billion in 2012. (Reuters, 2022)

and ESG-linked instruments. Despite the importance of green instruments (green energy stocks and green bonds) and traditional energy commodities (natural gas, oil, heating oil, and gasoline) alongside volatility indices (stock, oil, gold, and currency), there is a lack of studies on the implied volatility-energy related instruments nexus (see literature review section). This deficit is our motivation for examining the interactions among financial instruments and market volatilities. This study aims to uncover their volatility transmission mechanism in both short and long terms and has implications for the allocation of assets in the portfolio based on their hedging effectiveness.

Energy stocks are risky assets, so investors will reduce their position in energy stocks with increasing expected volatility in stock markets. This may decrease oil and natural gas-producing companies' stock prices and potentially fossil energy prices (Jubinski and Lipton, 2013; Lin et al., 2019; Sari et al., 2011). The rise in expected volatility brings uncertainty to financial markets. Energy prices may decline due to the expected economic slowdown during uncertain periods (Punzi, 2019). In addition, from the demand side, high volatility expectations in oil prices may direct investors towards a substitute product, such as natural gas. On the supply side, increasing crude oil prices can result in higher natural gas production as an alternative. As a result, this increase in natural gas supply may decrease its price (Atil et al., 2014; Villar and Joutz, 2006). High oil prices may also drive up the cost-competitiveness of companies using green energy, which may positively impact green stock prices. However, the uncertainty caused by high anticipated volatility in foreign exchange and gold markets may negatively affect the green stock market. Gold has been used to indicate upcoming inflation and hedge currency risk, but high volatility expectations in gold prices may lead to unsafe investment conditions (Gokmenoglu and Fazlollahi, 2015, p. 479). The stock market can be impacted by expected fluctuations in exchange rates, especially if businesses have not taken steps to protect themselves fully (Badshah et al., 2013). In this regard, the theoretical linkage of volatility indices can be shown via two channels (Fousekis, 2024; Li, 2022). The first was developed by Kodres and Pritsker (2002) and is known as financial contagion (cross-market rebalancing). In this channel, the transmission mechanism is triggered by investors' reaction to a shock in one market, which spreads across another market by reallocating their portfolios. The second is Trevino (2020)'s social learning. In this theory, contagion is triggered by investors' fear of a crisis due to a shock in one market spreading to others.

This paper analyzes the connectedness among green markets (encompassing stocks in solar, wind, geothermal, bio/clean fuels, and water, as well as green bonds), energy commodities (natural gas, oil, heating oil, and gasoline) and global volatility indices (such as the Chicago Board of Exchange's (CBOE) S&P 500 volatility (VIX), crude oil (OVX), gold (GVZ), and Eurocurrency (EVZ)). We specifically focus on the influence of these volatility indices on energy markets. We employ the vector autoregressive model with a time-varying parameter (TVP-VAR) frequency connectedness approach to capture short-term and long-term interactions. Additionally, we utilize portfolio and hedging effectiveness techniques to determine weights of optimal portfolios and hedge ratios for portfolio managers and investors holding energy securities. Our data spans November 2, 2012, to July 25, 2023, including significant global events, such as the pandemic and the Russian-Ukraine conflict, both of which triggered substantial energy price fluctuations.

We found volatility transmission from global volatility indices to energy markets increasing during high uncertainty periods. Furthermore, both short-term and long-term factors equally influence this connectedness. All these volatility indices are the dominant volatility transmitters, while the energy markets are mainly net receivers. As expected, VIX is the most significant transmitter, followed by oil, gold, and eurocurrency. The results from the minimum connectedness portfolio highlight that the average investment in natural gas, geothermal stock, and green bonds leads to reductions in volatility. Our results provide policymakers with important implications for reducing the negative impacts of global market risks, stabilizing energy prices, and promoting sustainability. Our results also provide critical guidance for investors and fund managers seeking strategies to diversify and hedge their investments across green and fossil energy markets.

This paper contributes to the literature by expanding the available data and introducing a novel technique. Specifically, first, we use a comprehensive dataset, incorporating an expanded range of fossil energy, such as natural gas, oil, gasoline, and heating oil, and green energy stock markets, such as wind, solar, water, geothermal, and bio-clean sectors. In addition, we include green bonds as an integral part of the green market analysis. This makes this study the first to investigate the influence of implied volatility indices on fossil and green energy stock markets across such a broad spectrum. Second, we employ the novel TVP-VAR frequency connectedness approach, avoiding observation loss and enabling robust parameter estimation even with outliers. Short- and long-term connectedness provides policymakers and investors with more comprehensive insights than previous studies. Finally, our paper provides an analysis of hedging effectiveness and portfolio strategies for constructing efficient portfolios.

The paper is organized as follows: Following the introduction, Section 2 presents the related literature and highlights the gaps addressed by this study. Section 3 gives the data and the methodology; Section 4 discusses the findings. Lastly, Section 5 presents the conclusding remarks.

2. Literature Review

The related literature has been summarized into two parts. The first strand is constructed on the studies related to the various volatility indices and includes only the spillover and connectedness framework. There are relatively few studies on different implied volatility indices, and a previously noted gap in the literature, according to Andrada-Félix et al. (2018), Cagli and Mandaci (2023), Dutta et al. (2020a), and Maghyereh et al. (2016), is in the area of spillover, connectedness, and hedging opportunities of implied volatility indices. The interlinkages among these shape the allocation of assets in the portfolio diversification and hedging opportunities, and provide insights for investors and policymakers into how cross-market information transmission occurs. Studies in this area include Liu et al. (2013), who examined market volatility indices representing stock, oil, gold, and eurocurrency from 2008 to 2012. Oil was found as a net receiver from other indices, but this connection was short-lived. Considering bond uncertainty, Andrada-Félix et al. (2018) investigated the period from 2008 to 2017 and found that bond and oil uncertainties were mainly receivers while the currency was the transmitter. In a more recent study, Fousekis (2024) investigated the period from 2017 to 2023 and found asymmetric, time-varying, and event-dependent relations. Regarding their transmission mechanism, oil acted as a net receiver, as previously mentioned. Nevertheless, there are different and even contradictory results. For instance, exploring bi-directional relations, Naeem et al. (2024) showed that oil acted as a volatility transmitter to the stock market in the 2008 financial crisis, but in other periods, currency acted as a net receiver of volatility; in contrast, Fousekis (2024) found that currency had neutral characteristics. In contrast to those results, Awartani et al. (2016) examined a broader set of implied volatility indices, including oil, equity, exchange rate, and other commodities, and they found that oil was the highest contributor to bidirectional spillover. From a different perspective, Antonakakis et al. (2020b) examined hedging opportunities between various assets' implied volatility indices regarding oil and recommended a portfolio allocation giving the highest share to the oil volatility index. Moreover, including a novel uncertainty index, COVOL, Xu et al. (2023) depicted the heterogeneous roles of oil, currency, and gold while showing the precise role of the stock uncertainty index as a risk transmitter. Another study by Cagli and Mandaci (2023) confirms the volatility transmission role of stock uncertainty; this study includes the cryptocurrency uncertainty index. They found that oil uncertainty was a net receiver, unlike Xu et al. (2023)

The second strand includes studies investigating the nexus between implied volatility indices and financial instruments. In this regard, some studies focus on the relationship between implied volatility indices and green bonds (e.g., Lin and Su, 2023; Pham and Do, 2022; Xu et al., 2024), energy markets (e.g., Cochran et al., 2015; Geng et al., 2021), clean energy (e.g., Çelik et al., 2022; Dutta, 2017; Wang et al., 2022). For instance, both Pham and Do (2022) and Xu et al. (2024) depicted the weak connectedness between green bonds and implied volatility indices; however, the latter study emphasized the short-term characteristic of the transmission. The subfield of this literature consists of implied volatility indices and newly emerging instruments, such as green energy firm stocks, green bonds, and sustainability-linked and socially responsible assets. For example, using various volatility indices, Lucey and Ren (2023) investigated the risk transmission among green bonds, sustainability-linked indices, fossil energy instruments, carbon and energy futures, and drivers of connectedness. Their results indicated that the energy commodity futures and green bonds were the risk receivers. Moreover, Shahid et al. (2023) examined the clean energy equities, commodity implied volatility indices, and socially responsible stocks for the UK, EU, US, and global markets from 2013 to 2022. They suggested that commodity-implied volatilities could be reduced by adding clean energy equities to portfolios. Using different socially responsible investment tools, Elsayed et al. (2024) found that clean energy stocks and green bonds offer hedging opportunities. Considering sustainable equity market indices and global common and implied volatility indices, Xu et al. (2025) showed that the stock volatility index acted as a transmitter. This study examined green instruments such as green energy stocks, green bonds, and energy commodities, including natural gas, oil, heating oil, and gasoline, alongside volatility indices representing stock, oil, gold, and currency markets. Thus, not only is the topic underexplored in the literature, but also, the relevant studies use varying data and methodologies, leading to widely differing results.

3. Methodology and Data

In our paper, we initially employ the time-varying vector autoregression (TVP-VAR) frequency connectedness of Chatziantoniou et al. (2023). This approach integrates Baruník and Křehlík (2018) and Antonakakis et al. (2020a), which enables us to estimate the connectedness in the time and frequency domains. We follow Diebold and Yilmaz (2012, 2014) (DY) to find the time domain measures.[2]

The original DY connectedness approach allows us to model volatility spillovers from variance decomposition with a simple rolling window-based generalized (covariance stationary *N*-variable) VAR model (Diebold and Yilmaz, 2012). Variance decompositions enable us to compute assets' *own variance shares* and (volatility) *spillovers* across assets, breaking down the *H*-step (i.e., forecast horizon) *forecast error variances* of each variable into components associated with different system-wide shocks (Diebold and Yilmaz, 2009; 2012). Based on the framework, it is possible to calculate the total, directional, and net volatility spillovers from the variance decompositions. The total connectedness index (TCI) can be defined as the impact of volatility shock spillovers across the variables on the total forecast error variance. The directional and net spillovers identify volatility receivers and transmitters in the system, where for volatility receivers (transmitters), the magnitude of gross volatility shocks exceeds those received (transmitted) from (to) all other variables.[3] Chatziantoniou et al. (2023) provide a novel approach for decomposing the above-defined connectedness measures into frequencies, referring to the short—and long-term investment horizons.

The TVP-VAR model-based methodology offers refined connectedness measures by incorporating a time-varying coefficient and variance–covariance structure. This framework is highly effective in managing outliers (Chatziantoniou et al., 2023) and eliminates the need for arbitrarily setting a window size, unlike standard rolling-window VAR model-based connectedness approaches (Diebold and Yilmaz, 2012; 2014), thereby preventing the loss of observations (Antonakakis et al., 2020a). These features provide significant advantages, particularly given that the sample dataset captures key events such as the COVID-19 outbreak. The framework still necessitates stationary time series throughout the analysis and the absence of missing observations. Following Chatziantoniou et al. (2023) and Cagli (2023), we break down the measure of time connectedness into two distinct frequencies, short-term (1-5) and long-term (5-Inf) periods, which allows a more detailed understanding of the interrelationship.

In the second step, we use Broadstock et al.'s (2022) Minimum Connectedness Portfolio (MCoP) technique, which utilizes the previously explained pairwise

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[2] For robustness purposes, we also use aggregated measures proposed by Gabauer and Gupta (2018). This connectedness provides a holistic approach in terms of the effect of variables in an aggregate manner. The results are similar to those obtained from the TVP-VAR frequency framework; thus, to conserve space, we do not report the results obtained from aggregated connectedness measures; these are available upon a reasonable request.

[3] To conserve space and avoid repeating the original papers' content, we refer the reader to the papers by Diebold and Yilmaz (2009, 2012, 2014) and Chatziantoniou et al. (2023) for additional technical explanations of the framework. Furthermore, for the averaged connectedness table schematic we use in the subsequent section (i.e., Table 2 in this paper), we refer the "connectedness table schematic" documented in *Table 1* of Diebold and Yilmaz (2014:120) and *Table 2* of Cocca et al. (2024).

connectedness indices derived from the connectedness framework. The main aim of constructing such a portfolio is to minimize the interactions between variables, thus creating an investment tool that reduces mutual influence among assets.

We obtain daily data of various green energy (sub) sector indices, the green bond index, and the prices of different fossil energy commodities. The green energy stock (sub)sectoral indices include solar (SOL), wind (WND), geothermal (GEO), bio/clean fuels (BIO), and water (WAT), as well as the green bonds index (BND). Fossil energy commodities include oil (OIL), natural gas (NGS), heating oil (HOI), and gasoline (GAS). In addition, we collect daily data on the Chicago Board of Exchange's (CBOE) S&P 500 volatility (VIX), crude oil (OVX), gold (GVZ), and Eurocurrency (EVZ) global volatility indices to see a more comprehensive network. VIX serves as an uncertainty index proxy for stock markets; OVX and GVZ represent implied volatility indices for oil and gold, respectively; and EVZ is used as a proxy for the currency market.

All data is extracted from Thomson Reuters DataStream, except the S&P Green Bond index, which is obtained from its website. The study period spans from November 2, 2012, to July 25, 2023. All data is denominated in USD. Following Forsberg and Ghysels (2007), Evrim Mandacı et al. (2020), and Mandaci and Cagli (2021), we compute the volatility series of green and fossil energy commodities by transforming raw price series into their *absolute* natural logarithm forms. The uncertainty measures are converted into their natural logarithmic forms. Figure 1 shows the movements in the volatility series, indicating that asset volatility exhibited a similar trend during the pandemic.

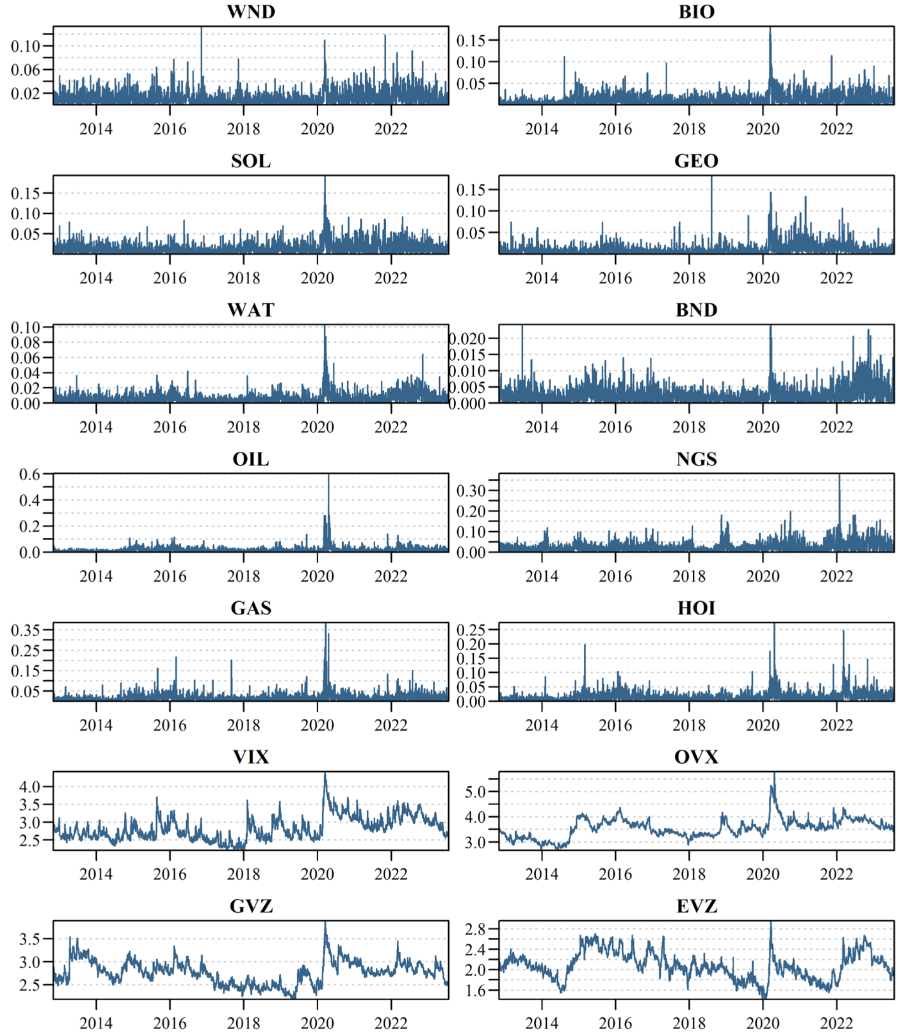
The descriptive statistics of the converted series to volatility are displayed in Table 1. Based on Jarque and Bera (1980), it can be inferred that at the 1% significance level, the normality is not supported for any series, i.e., the volatility series does not follow a normal distribution. According to Elliott et al.'s (1996) unit root test, the findings indicate that the series is stationary at the 1% significance level. Furthermore, Fisher and Gallagher's (2012) serial correlation (*Q*) test results reveal that autocorrelation exists in all series at a 1% significance level, validating the usage of the TVP-VAR connectedness framework with heteroscedastic variance–covariances, in line with Balcilar et al. (2021) and Chatziantoniou et al. (2023), Cagli (2023).

Table 1 Descriptive Statistics of Volatility Series

	Mean	Variance	Skewness	Excess Kurtosis	JB	ERS	Q(20)	Q2(20)
WND	0.012***	0.000	2.504***	11.980***	18947.810***	-14.750***	419.956***	204.312***
BIO	0.014***	0.000	3.592***	25.927***	81335.510***	-9.403***	1502.893***	2223.160***
SOL	0.015***	0.000	2.739***	15.492***	30343.405***	-15.502***	938.682***	1436.211***
GEO	0.011***	0.000	3.773***	25.595***	80019.959***	-10.868***	1227.598***	364.659***
WAT	0.007***	0.000	3.887***	29.456***	104296.152***	-12.576***	2489.696***	2816.205***
BND	0.003***	0.000	2.554***	11.223***	17085.987***	-12.041***	865.867***	608.895***
OIL	0.018***	0.001	8.886***	153.339***	2677744.032***	-12.511***	2223.493***	575.082***
NGS	0.025***	0.001	3.214***	23.222***	65241.085***	-10.075***	1144.695***	542.013***
GAS	0.018***	0.000	6.032***	65.780***	502594.813***	-13.679***	1012.916***	606.242***
HOI	0.016***	0.000	4.339***	38.045***	171113.346***	-9.265***	1467.621***	319.925***
VIX	2.822***	0.108	0.864***	1.020***	452.203***	-5.251***	20955.237***	20818.601***
OVX	3.553***	0.145	0.667***	2.268***	778.102***	-3.528***	24607.364***	24086.809***
GVZ	2.768***	0.065	0.238***	0.132	27.356***	-4.516***	22611.013***	22227.533***
EVZ	2.081***	0.070	0.167***	-0.383***	29.107***	-4.202***	23048.898***	22690.917***

Notes: ***, **, and * symbolize significance levels at 1%, 5%, and 10%, respectively. Jarque and Bera (1980) normality test, Elliott et al. (1996) unit root test, and the Fisher and Gallagher (2012) weighted portmanteau tests statistics are abbreviated as *JB, ERS*, and *Q*, respectively.

Figure 1 Volatility Series



4. Empirical Results

We calculate volatility connectedness among variables using the TVP-VAR frequency connectedness approach of Chatziantoniou et al. (2023). For reasons of parsimony and better forecasting, the model's lag length is determined as one, according to the Schwarz Information Criterion (SIC), with a forecast horizon of ten days. The parsimony of the SIC is mentioned in Chatziantoniou et al. (2022, p. 2); Granger and Jeon (2004, p. 1238). On the frequency bands, we investigate the connectedness in short (1-5) and long (5-Inf) terms, respectively.

Table 2 presents the average connectedness results in both time and frequency domains. While the off-diagonal values show the spillover between variables, the diagonal values indicate each item's own shock. The net directional connectedness is shown in the penultimate part of each panel. A positive (negative) value means that it transmits (receives) a net shock.

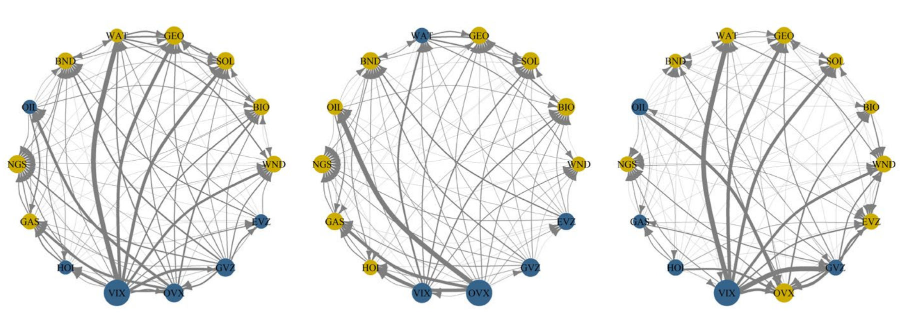
Panel A displays time connectedness, while subsequent panels depict frequency connectedness in the short (1-5) and long (5-Inf) terms. In the first panel, the corrected total connectedness index (cTCI) is calculated as 40.37%, indicating a moderate level of dependence among variables, which aligns with the study of Song et al. (2019). The model explains around 40 percent of the variations in the network. The total connectedness shown in the subsequent panels is almost equally influenced by short-term (20.15%) and long-term (20.22%) dynamics. The diagonal measures in the table represent the idiosyncratic shocks, calculated at approximately 60%. Moreover, the pairwise spillover measures are reported off-diagonally in Table 2. According to Panel A, the largest average pairwise spillover between the fossil energy commodities, from crude oil to heating oil, is 19.65%. The sequence includes spillovers between heating oil and crude oil, crude oil and gasoline, and heating oil and gasoline, respectively, at 19.15%, 14.71%, and 14.59%. The high spillover in the fossil market aligns with the results of Umar et al. (2022). The lowest average pairwise spillover is from natural gas to gasoline, with 0.53%. Our net spillover measures diverge from Reboredo and Uddin (2016) and He et al. (2021), but align with Fu et al. (2022), revealing that all volatility indices, crude oil, and heating oil act as volatility transmitters, while all green assets are volatility receivers.

Panels B and C of Table 2 show the average short- and long-term connectedness, respectively. The primary transmitter in the system is VIX in both the time and long-term frequency domains. All green variables serve as net shock receivers in both time and frequency domains, except water in the short term. Among these, the dominant net receivers in the system are geothermal (-7.07%) and solar (-6.21%). Furthermore, all fossil energy variables except natural gas act as net shock transmitters. The findings of Geng et al. (2021) differ from our network dynamics results in frequency, but they align with natural gas's role as a volatility receiver. The roles of the green bond as a net receiver and VIX as a net transmitter are consistent with the results of Elsayed et al. (2022) and Lundgren et al. (2018). Our results on the effects of VIX and OVX on energy markets align with Ji et al. (2018) and Saeed et al. (2021). In addition, VIX has a more vital impact on renewable energy compared to fossil energy. Oil was found to act as a transmitter, in line with Bouri et al. (2021). The visual illustration of the network can be seen in Figure 2. In the short term, the transmission direction for oil and heating oil changes to the receiver, while water becomes a transmitter. In the long-term, the transmission direction for gasoline shifts to a transmitter, while OVX and EVZ become receivers compared to the average total time connectedness.

After presenting a general overview in terms of the average measures of the results obtained from the connectedness framework, we shift our focus to the findings of the dynamic analysis structure, the crucial output of the econometric framework. Dynamic analysis enables the observation of changes in the connectedness structure over time, which is derived from statistical tests. This allows tracking of the evolution of connectedness over time, capturing fluctuations in market interactions and transmission mechanisms, enabling the econometric demonstration of how financial markets' mutual influence before or after significant socio-economic events, such as the COVID-19 outbreak, geopolitical tensions, or shifts in monetary policies. Examining the time-varying structure allows the identification of periods of heightened volatility transmission and of markets that act as major volatility transmitters or receivers at different times. To illustrate this, Figures 3 and 4 display the econometric findings related to the dynamic structure, highlighting shifts in market connectedness across different time horizons.

Figure 3 represents the dynamic structure of the time and frequency connectedness measures over time. The overall cTCI is shown in the black-shaded area, and the short- and long-term connectedness indices are shaded in red and green, respectively. The impact of frequency dynamics on the time domain measures is almost identical; however, the long-term connectedness is slightly more dominant in the total connectedness. TCI reaches its peak at the beginning of the sample period. The early rise of the index is possibly related to the persistent concerns about the global economy after the global financial crisis, the debt crisis, trade tensions, and invasions/conflicts. Markets gradually stabilized around the halfway point of the sample period (2016-2019), and during this time, the connectedness measures converged closer to their long-term averages. However, a significant spike is observed in early 2020, coinciding with the COVID-19 outbreak. This surge in short- and long-term frequency connectedness underscores the pandemic's substantial impact, leading to increased volatility spillovers across asset classes. Our findings add credibility to the results of prior studies (e.g., Armeanu et al., 2023; Bouri et al., 2021; Foglia and Angelini, 2020; Wang et al., 2022), which document an intensified interconnectedness between volatility measures and energy markets during the pandemic. Furthermore, the post-pandemic period exhibits persistent volatility fluctuations, pointing out structural shifts in market dependencies influenced by evolving macroeconomic conditions, policy interventions, and investor sentiment (Assaf et al., 2021; Chen et al., 2023; Jiang and Chen, 2022; Man et al., 2024; Wu and Liu, 2023).

Figure 2 Time and Frequency Connectedness Network



Notes: The outcomes stem from a TVP-VAR model with one lag determined by the SIC. The network on the left depicts the average total time connectedness. The networks in the middle and right show short (1-5) and long (5-Inf) terms, respectively. The more prominent nodes indicate the extent of transmission/reception. Thicker arrows represent the more substantial impact of the source variable on the target variable. Blue nodes show that the variables act as net transmitters, while yellow nodes indicate that the variables act as net receivers.

Figures 4 illustrates the net directional connectedness across all domains, capturing their roles as either net transmitters or receivers of volatility over time. The pre-pandemic period exhibits relatively stable patterns of net connectedness, except during the very beginning of the sample period, during 2012-13. Before the pandemic, green assets such as wind (WND), geothermal (GEO), and solar (SOL) consistently acted as net receivers of volatility, with limited changing roles as receiver or transmitter. In contrast, fossil energy assets, such as heating oil (HOI), natural gas (NGS), and gasoline (GAS), had relatively stable and limited net directional connectedness. The VIX primarily acted as a net receiver of long-term shocks while transmitting short-term volatility for a limited time in the early sample period.

However, the post-pandemic period reveals intensified volatility spillovers, with several key changes in market dynamics. Notably, VIX experienced substantial spikes in net connectedness, becoming a dominant volatility transmitter, which aligns with Bouri et al. (2024) and Ji et al. (2018)'s emphasis on the crucial role of financial uncertainties in propagating systemic risk. This finding additionally aligns with Lundgren et al. (2018) and Elsayed et al. (2022)'s discovery that financial stress and uncertainty indices serve as primary shock transmitters, particularly in times of crisis. Throughout the later stages of the sample, VIX solidified its role as a dominant long-term volatility transmitter, consistent with the findings of Ji et al. (2018) and Saeed et al. (2021), who documented the pronounced impact of financial uncertainties on energy markets.

OVX, GVZ, and EVZ are among those that transmit volatility to the system, although to a lesser degree than VIX, confirming the results of Bouri et al. (2024), which highlight the influential role of oil market uncertainty. Fossil energy markets exhibited nuanced behavior, with oil generally transmitting long-term uncertainty, a finding supported by Reboredo (2015) and Naeem et al. (2021), who demonstrated a persistent yet moderate linkage between oil prices and clean energy markets. Oil (OIL) continued to serve as a long-term transmitter of uncertainty, particularly after the COVID-19 outbreak, supporting Corbet et al. (2020) and Dutta et al. (2020b)'s reports of heightened spillovers from oil markets to renewable energy during crisis periods. We evidence heating oil (HOI) and gasoline (GAS)'s changing behavior and fluctuations in the net directional connectedness, yet natural gas (NGS) consistently remained in the volatility receiver position during the post-pandemic period.

The findings regarding green assets suggest a complex dynamic. Generally, wind, geothermal, and solar assets predominantly acted as net volatility receivers, in line with Banerjee et al. (2024). After the pandemic, SOL, BIO, and WAT took the role of net transmitters for a limited time, reflecting the findings of Tiwari et al. (2022) and Liu et al. (2021), who noted that renewable assets occasionally shift from passive to active volatility sources in high-uncertainty environments. WND and GEO were exceptions among green assets, receiving significant volatility shocks from the system. GBD received significant amounts of shocks from the system, becoming a leading net volatility receiver, even in the months before the COVID-19 outbreak. These results further support Bouri et al. (2021) and Dawar et al. (2021)'s arguments that the influence of fossil energy on green markets fluctuates according to market conditions.

Table 2 The Time and Frequency Connectedness Measures (average)

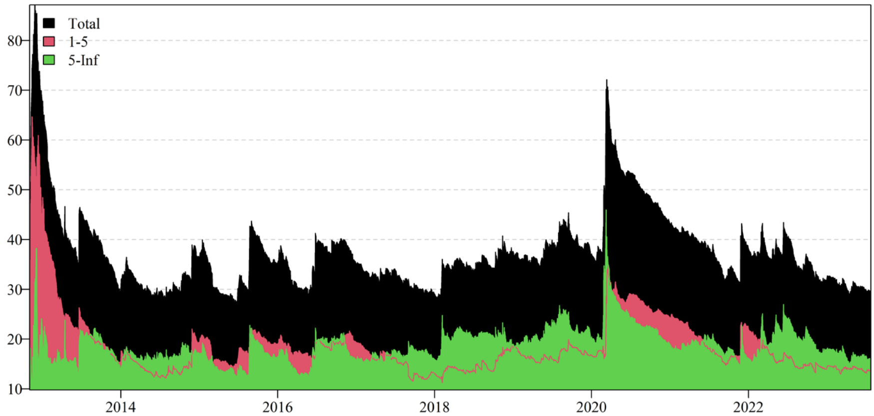
	WND	BIO	SOL	GEO	WAT	BND	OIL	NGS	GAS	HOI	VIX	OVX	GVZ	EVZ	FROM
Panel A.															
WND	70.62	1.68	3.76	2.60	6.59	3.67	0.77	0.91	0.94	0.97	3.14	1.06	1.77	1.52	29.38
BIO	1.76	69.97	3.90	1.77	6.11	1.81	2.07	0.71	1.33	1.51	3.24	2.98	1.62	1.22	30.03
SOL	3.50	4.31	66.93	2.44	8.40	1.72	1.03	0.82	1.22	1.34	4.50	1.46	1.46	0.88	33.07
GEO	2.59	2.20	2.98	73.18	4.78	1.45	0.96	0.66	1.65	0.87	4.22	1.67	1.84	0.95	26.82
WAT	5.31	4.87	6.94	3.51	56.31	2.98	1.68	0.79	2.01	1.55	7.69	2.53	2.17	1.65	43.69
BND	4.03	1.92	1.33	1.42	3.77	74.06	1.17	0.89	1.11	1.56	1.59	1.22	2.71	3.24	25.94
OIL	0.96	1.48	0.76	0.87	1.40	0.79	47.95	0.65	13.46	19.15	1.42	8.36	1.71	1.04	52.05
NGS	1.18	0.99	1.01	0.99	0.99	1.56	1.20	82.56	1.34	1.58	1.76	1.57	1.95	1.33	17.44
GAS	0.80	1.10	1.06	1.21	2.05	0.65	14.71	0.53	53.95	14.59	1.66	5.02	1.63	1.05	46.05
HOI	0.84	1.16	1.02	0.74	1.54	0.85	19.65	0.69	13.39	49.40	1.91	6.24	1.64	0.94	50.60
VIX	1.13	2.04	1.88	1.57	3.67	0.99	1.20	0.91	1.00	1.51	53.92	12.34	11.34	6.47	46.08
OVX	0.79	1.47	0.68	0.87	1.41	1.16	6.14	1.12	3.08	4.62	13.41	52.37	8.02	4.86	47.63
GVZ	0.75	0.96	0.90	1.04	1.52	1.38	1.44	0.89	1.15	1.33	13.54	6.72	58.04	10.35	41.96
EVZ	0.93	1.25	0.65	0.71	1.14	2.32	0.99	1.14	0.67	1.00	7.36	4.42	11.51	65.92	34.08
TO	24.58	25.42	26.86	19.75	43.37	21.32	53.01	10.71	42.35	51.57	65.43	55.58	49.37	35.51	524.83
Net	-4.80	-4.61	-6.21	-7.07	-0.32	-4.63	0.97	-6.74	-3.71	0.97	19.35	7.95	7.41	1.43	cTCI
NPDC	4	5	3	2	7	3	8	0	6	9	13	10	12	9	40.37

Table 2 The Average Time and Frequency Connectedness Measures (contd)

	WND	BIO	SOL	GEO	WAT	BND	OIL	NGS	GAS	HOI	VIX	OVX	GVZ	EVZ	FROM
Panel B.															
WND	62.92	1.27	3.04	2.07	5.43	3.10	0.59	0.72	0.71	0.75	0.82	0.39	0.43	0.52	19.84
BIO	1.47	62.56	3.27	1.36	5.11	1.49	1.58	0.57	1.13	1.13	1.33	0.73	0.72	0.74	20.64
SOL	3.03	3.60	59.30	1.89	6.95	1.50	0.78	0.72	0.99	1.03	1.21	0.73	0.57	0.44	23.44
GEO	2.15	1.64	2.21	63.71	3.75	1.21	0.70	0.56	1.28	0.62	1.03	0.64	0.44	0.53	16.77
WAT	4.68	3.90	5.74	2.80	49.20	2.50	1.26	0.65	1.62	1.17	1.94	0.76	0.60	0.54	28.14
BND	3.46	1.47	1.03	1.21	3.08	66.57	0.92	0.73	0.87	1.32	0.67	0.54	1.07	1.26	17.62
OIL	0.76	1.09	0.66	0.68	1.06	0.58	41.34	0.55	11.50	16.33	0.40	4.20	0.64	0.44	38.88
NGS	0.95	0.80	0.83	0.83	0.84	1.32	0.79	72.81	1.12	1.09	0.59	0.46	0.67	0.59	10.87
GAS	0.68	0.90	0.95	1.00	1.73	0.53	12.45	0.46	47.49	12.36	0.65	2.66	0.82	0.33	35.52
HOI	0.69	0.88	0.89	0.59	1.21	0.68	16.64	0.58	11.58	42.78	0.71	2.97	0.58	0.37	38.37
VIX	0.15	0.25	0.20	0.18	0.37	0.14	0.16	0.17	0.19	0.26	4.75	0.53	0.80	0.66	4.07
OVX	0.08	0.07	0.07	0.08	0.15	0.12	0.35	0.09	0.21	0.25	0.21	1.24	0.14	0.18	1.99
GVZ	0.11	0.14	0.10	0.12	0.18	0.20	0.15	0.13	0.13	0.15	0.53	0.33	2.80	0.41	2.68
EVZ	0.12	0.17	0.09	0.10	0.15	0.17	0.18	0.08	0.08	0.17	0.79	0.56	0.45	3.30	3.11
TO	18.33	16.19	19.06	12.90	30.01	13.55	36.56	6.01	31.41	36.63	10.88	15.49	7.92	6.99	261.93
Net	-1.51	-4.45	-4.38	-3.87	1.87	-4.07	-2.32	-4.86	-4.11	-1.74	6.81	13.50	5.24	3.88	cTCI
NPDC	5	3	3	1	8	4	8	0	6	7	11	13	12	10	20.15
Panel C.															
WND	7.70	0.40	0.72	0.52	1.16	0.57	0.18	0.19	0.23	0.22	2.32	0.68	1.34	1.00	9.54
BIO	0.29	7.41	0.64	0.42	1.00	0.32	0.50	0.13	0.20	0.38	1.91	2.25	0.89	0.47	9.39
SOL	0.47	0.71	7.62	0.55	1.45	0.21	0.25	0.09	0.23	0.31	3.29	0.73	0.89	0.44	9.63
GEO	0.44	0.55	0.77	9.47	1.03	0.23	0.26	0.10	0.37	0.25	3.19	1.03	1.40	0.42	10.05
WAT	0.63	0.97	1.20	0.71	7.11	0.48	0.42	0.14	0.39	0.39	5.75	1.77	1.57	1.12	15.55
BND	0.57	0.44	0.30	0.21	0.70	7.49	0.25	0.15	0.24	0.25	0.92	0.67	1.64	1.98	8.33
OIL	0.21	0.39	0.11	0.19	0.34	0.21	6.61	0.10	1.96	2.82	1.02	4.16	1.07	0.60	13.17
NGS	0.23	0.19	0.18	0.15	0.15	0.24	0.40	9.74	0.22	0.49	1.17	1.12	1.28	0.75	6.57
GAS	0.12	0.20	0.11	0.21	0.32	0.12	2.25	0.07	6.46	2.22	1.01	2.36	0.81	0.72	10.53
HOI	0.15	0.28	0.13	0.15	0.33	0.17	3.01	0.11	1.81	6.62	1.20	3.26	1.06	0.57	12.23
VIX	0.98	1.80	1.68	1.39	3.30	0.85	1.04	0.74	0.81	1.25	49.17	11.81	10.54	5.82	42.01
OVX	0.71	1.40	0.61	0.79	1.26	1.04	5.79	1.03	2.87	4.37	13.21	51.13	7.88	4.69	45.64
GVZ	0.65	0.81	0.80	0.93	1.34	1.18	1.29	0.76	1.02	1.18	13.00	6.39	55.24	9.94	39.28
EVZ	0.81	1.08	0.56	0.61	0.99	2.15	0.82	1.05	0.58	0.83	6.57	3.86	11.06	62.62	30.97
TO	6.25	9.24	7.80	6.85	13.36	7.77	16.46	4.69	10.94	14.94	54.55	40.09	41.44	28.51	262.90
Net	-3.29	-0.16	-1.83	-3.20	-2.19	-0.56	3.28	-1.88	0.41	2.72	12.54	-5.55	2.17	-2.45	cTCI
NPDC	4	7	5	3	6	4	12	1	8	12	11	5	9	4	20.22

Notes: The outcomes are derived from a TVP-VAR model with one lag. TO denotes the transmission from a variable to others, excluding its shares. The degree of spillover received by one variable from others is indicated by the term FROM, with its shares excluded. Net shows the difference between TO and FROM, which means net transmission. TCI denotes the total connectedness index. cTCI denotes the corrected Total Connectedness Index. NPDC stands for net pairwise directional connectedness, which measures the frequency with which a variable dominates other variables.

Figure 3 Dynamic Connectedness Measures

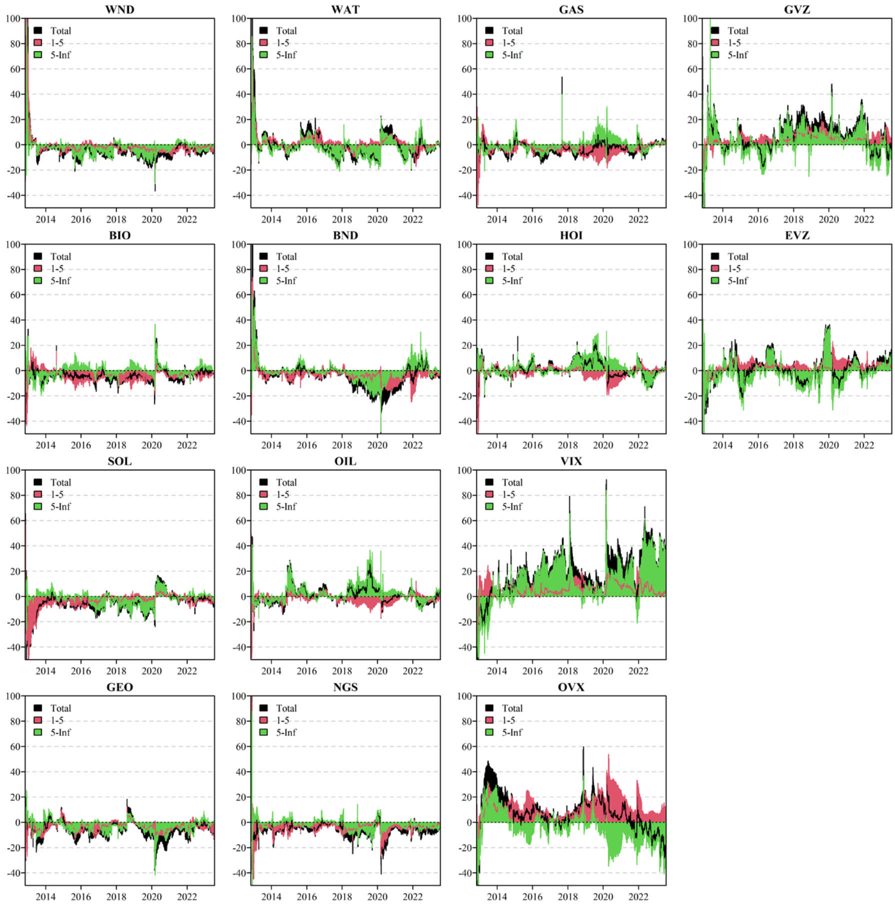


Notes: The outcomes are derived from a TVP-VAR model with one lag, which is determined by the SIC. The field shaded in black indicates the time TCI (Diebold and Yilmaz, 2012). The fields shaded in red and green indicate frequency connectedness indices (Baruník and Křehlík, 2018)- short (1-5) and long-term (5-Inf), respectively.

Table 3 presents the portfolio weights, the standard deviation of the weights, and the corresponding hedging effectiveness statistics. In line with Antonakakis et al. (2020b), we evaluate the significance of the hedging effectiveness statistics using the Brown and Forsythe (1974) test. For the minimum connectedness portfolio, referring to total measures, the three substantial average weights are as follows: natural gas with 14.3%, geothermal with 12.5%, and green bond with 12.2%. The total weight of renewable energy constitutes 51.8%. As an essential part of the green market, if investors also invest in green bonds, the weight of greens increases to approximately 64%, with the remaining 36% from fossil energy commodities. The portfolio weights are visualized in Figure 5. The long-term portfolio weights are subject to a higher standard deviation, which indicates more variation in terms of weight.

All scores are significant at the 1% level, except for bio/clean fuels. If investors invest on average 11% in wind, 10.2% in Solar, 12.5% in Geothermal, 7.3% in Oil, 14.3% in Natural Gas, 8.2% in Gasoline, and 6.4% in Heating Oil, each asset's volatility will reduce by 53.8%, 70.5%, 62.3%, 89%, 90.1%, 86.5%, and 79.5%, respectively. Volatility will increase if investors invest 6.7% in Water and 12.2% in green bonds, respectively. In the short term, the investment percentage is almost identical, while in the long term, the investment proportion and effectiveness vary.

Figures 4 Net Directional Connectedness



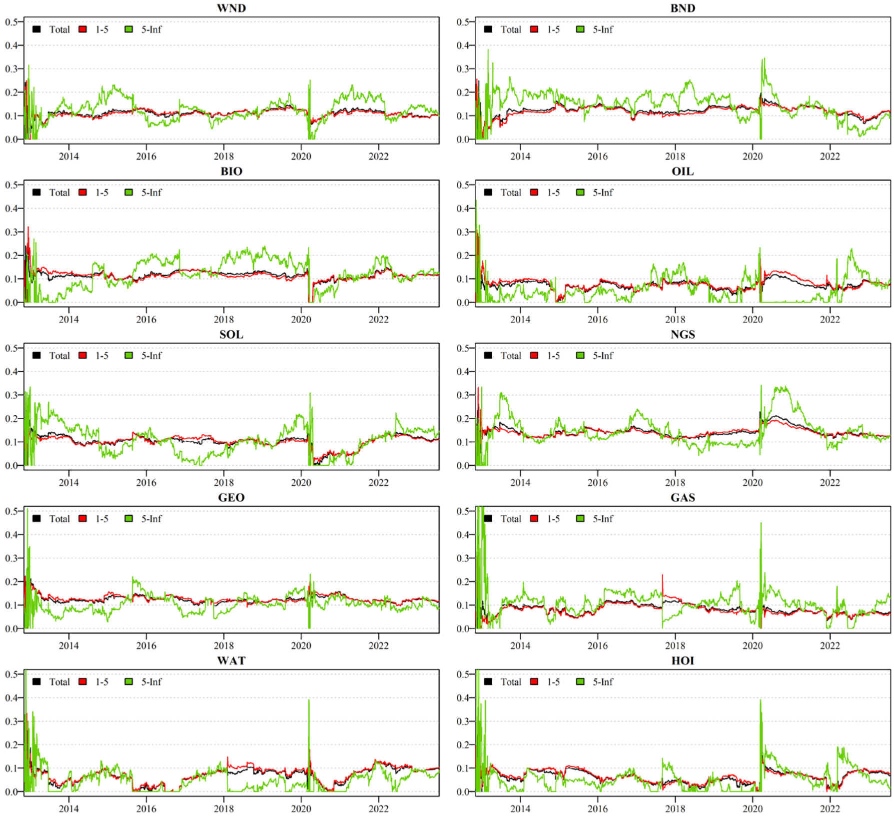
Notes: The outcomes are derived from a TVP-VAR model with one lag determined by the SIC. The field shaded in black indicates the total net directional connectedness. The area shaded in red represents short-term (1-5) frequency net directional connectedness, while the area shaded in green represents long-term (5-Inf) frequency net directional connectedness.

Table 2 Minimum Connectedness Portfolio

	Mean	Std. Dev.	0.05	0.95	HE	p-value
Panel A. Total connectedness						
WND	0.110	0.019	0.081	0.131	0.538	0.000
BIO	0.114	0.020	0.087	0.137	0.673	0.528
SOL	0.102	0.028	0.043	0.136	0.705	0.001
GEO	0.125	0.017	0.106	0.149	0.623	0.000
WAT	0.067	0.034	0.000	0.112	-0.210	0.000
BND	0.122	0.023	0.081	0.152	-8.765	0.000
OIL	0.073	0.021	0.043	0.104	0.890	0.000
NGS	0.143	0.023	0.118	0.194	0.901	0.000
GAS	0.082	0.025	0.047	0.116	0.865	0.000
HOI	0.064	0.027	0.021	0.099	0.795	0.000
Panel B. Short-term connectedness						
WND	0.107	0.018	0.082	0.129	0.528	0.000
BIO	0.113	0.022	0.090	0.138	0.666	0.543
SOL	0.101	0.026	0.045	0.129	0.699	0.001
GEO	0.126	0.016	0.107	0.153	0.615	0.000
WAT	0.072	0.035	0.006	0.120	-0.237	0.000
BND	0.118	0.023	0.075	0.144	-8.983	0.000
OIL	0.079	0.025	0.048	0.126	0.887	0.000
NGS	0.140	0.020	0.118	0.179	0.899	0.000
GAS	0.078	0.026	0.045	0.119	0.862	0.000
HOI	0.066	0.026	0.023	0.103	0.791	0.000
Panel C. Long-term connectedness						
WND	0.123	0.046	0.055	0.198	0.443	0.000
BIO	0.123	0.059	0.010	0.204	0.606	0.205
SOL	0.105	0.061	0.000	0.209	0.645	0.009
GEO	0.104	0.036	0.052	0.164	0.546	0.000
WAT	0.046	0.047	0.000	0.119	-0.459	0.000
BND	0.145	0.056	0.040	0.225	-10.781	0.000
OIL	0.050	0.051	0.000	0.144	0.867	0.000
NGS	0.145	0.063	0.074	0.290	0.881	0.000
GAS	0.105	0.057	0.025	0.167	0.837	0.000
HOI	0.053	0.052	0.000	0.147	0.753	0.000

Notes: The outcomes are derived from a TVP-VAR model with one lag, and 5% and 95% show lower and upper quantiles.

Figure 5 Minimum Connectedness Portfolio Weights



Notes: The outcomes are derived from a TVP-VAR model with one lag.

5. Conclusions

Energy consumption is vital for sustaining economic activities. Energy is extremely important in key sectors such as manufacturing, transportation, agriculture, housing, and information and communication technologies. It is expected that developments in artificial intelligence will further increase the consumption of energy as well as water. Thus, energy efficiency and green energy sources are becoming increasingly important due to the limited availability of fossil energy sources and their environmental impacts. Therefore, the emergence of ESG principles and SDGs has accelerated the transition from fossils to green energy, increasing investments in green energy projects in recent years. Investors sensitive to the environment and realizing the growth potential in green markets are increasing their investments in green stocks and bonds. However, the situation in energy markets has been greatly complicated by recent global economic, financial, and political uncertainties (such as the COVID-19 pandemic, wars, changes in monetary policies, etc.

The study aims to take a dynamic approach to empirically analyzing the roles of global risk factors, namely S&P 500 volatility (VIX), crude oil (OVX), gold (GVZ), and Eurocurrency (EVZ) in energy markets in the long run and short run. We contribute to the academic literature by including comprehensive data on energy markets. Fossil energy commodities are determined as crude oil, natural gas, gasoline, and heating oil, while green markets are made up of the subsectors of green stock markets, such as wind, bio/clean fuels, solar, geothermal, and water, as well as green bonds. The study employs the time-varying vector autoregression (TVP-VAR) frequency connectedness of Chatziantoniou et al. (2023) and the Minimum Connectedness Portfolio (MCoP) technique of Broadstock et al. (2022) over the period from Nov 2, 2012, to July 25, 2023. Our findings have crucial implications for investors, corporate managers, and policymakers.

Our analysis reveals a moderate level of connectedness between fossil energy markets, green markets, and volatility indices, implying potential diversification opportunities for investors and portfolio managers. Interestingly, short-term and long-term factors contribute equally to this connectedness, indicating that both short-term and long-term investors can benefit from this moderate relationship between different markets. The dynamic nature of the network's interconnectedness appears to have significantly increased with the beginning of the pandemic in early 2020. Although the impact was not as great as the pandemic, the effects of global risks increased with the outbreak of the Russia-Ukraine crisis. These findings indicate that, during uncertainty periods, investors should take care to manage their portfolio risk by replacing assets that are more integrated into this connectedness system with less sensitive ones.

All volatility indices act as dominant transmitters of risk within the network; however, the recipients of this volatility vary. All fossil energy markets, except oil and heating oil, act as net receivers of volatility, indicating their vulnerability to external market fluctuations. Natural gas is a volatility receiver due to its higher susceptibility to market risks. This pattern is reversed for oil, which operates as a transmitter due to its market dominance. According to Sánchez García and Rambaud (2023), oil markets are net transmitters of volatility to stock markets when the source of the shock is economic. In contrast to oil, all green stocks and green bonds are net receivers. Our results indicate a greater impact of conventional energy markets compared to that of green energy substitutes on overall market volatility.

As expected, the VIX index emerges as the most significant transmitter, followed by oil, gold, and the eurocurrency index. In many papers (e.g., Copeland and Copeland, 1999; Black, 2006; and Banerjee et al., 2007), the VIX index is a significant predictor of stock market returns. In addition, it has a strong influence on stock markets, acting as a leading transmitter of volatility spillovers across global markets (Shu and Chang, 2019). This study reveals significant interactions among all indices except the Eurocurrency volatility index. High interaction among the VIX, oil, and gold volatility indices limits the positive impacts of asset allocation on the returns of global portfolios. On the other hand, the limited effects of these volatility indices on fossil and green energy markets provide diversification opportunities. The VIX index has only a limited impact on fossil commodity prices, green bond and stock markets. Compared to other green stocks, water stocks have a higher volatility transmission to and from the system. Rapid population growth, pollution, and climate change problems hinder access to sufficient and clean water. Water's key importance for human life means that stocks have become more sensitive to the changes in global risks. In contrast, supporting the findings of Saeed et al. (2021), green bonds are much more isolated from the system of volatility spillovers, thus highlighting their diversification potential in portfolios that include fossil fuels.

In addition, our analysis reveals that the oil and euro currency volatility indices drive only short-term connectedness. Interestingly, it also shows a more extensive volatility transmission to green energy markets compared to fossil markets. Therefore, investors in energy assets during high uncertainty may benefit from prioritizing fossil markets over green energy stocks and bonds. Furthermore, observing minimal spillovers from fossil to green markets highlights further diversification opportunities in holding both types of assets.

Our analysis of hedging effectiveness reveals promising strategies for risk reduction. Investors can mitigate risk by optimally allocating fossil and green energy assets in their portfolios. For instance, studies show potential reductions of up to 90% in portfolio risk when primarily invested in fossil assets, particularly oil and natural gas. However, it is crucial to note that water and green bonds may have the opposite effect, potentially increasing volatility. These findings can guide investment decisions on risk management and short- and long-term volatility forecasts during turbulent and stable periods.

Our findings offer valuable insights for corporate managers, policymakers, and investors. Managers of the companies issuing green stocks and bonds are becoming increasingly aware of the sensitivity of these financial assets to predicted stock market fluctuations. The global risk indicators in the system impact the stocks of all companies, although water companies are relatively insulated. Thus, companies should closely monitor the negative impacts of uncertainties and take steps to alleviate them. Fossil fuels are still crucial inputs for production; therefore, managers of companies heavily relying on fossil fuels, such as natural gas, should consider the negative impacts of global risk factors, such as the volatility indices of crude oil and Eurocurrency. For policymakers, evidence of a high level of connectedness among global risk indicators, particularly among stock, oil, and gold volatility indices, indicates that a shock in any of these markets significantly affects the others. Thus, by promoting policies that reduce volatility in stock markets, policymakers may provide greater stability in the volatility of oil and gold markets. Therefore, policymakers need to consider that the decisions made in one market may also affect others. Our results can guide policymakers in establishing more effective policies in dealing with global risks and reducing fluctuations in stocks, crude oil, and the gold market. Additionally, policymakers can gain a more nuanced understanding of factors driving energy price volatility, enabling them to develop proactive measures to mitigate risks and promote stability in energy markets. In particular, the relative independence of water stocks from the system would appear to make them more appealing green investments. Therefore, governments can promote green investments by developing policies encouraging and supporting the water industry. Supporting green energy is essential for countries to achieve their environmental goals and economic and social development.

Future research may examine the impacts of various uncertainty measures, such as economic policy, geopolitical risks, climate policy uncertainties, or macroeconomic indicators on green and fossil energy markets. The global economic outlook is increasingly unstable and is vulnerable to uncertainties, which may be responsible for the shrinkage in overall economic activity (Işık et al., 2020). Economic policy uncertainty is related to renewable energy consumption- CO2 emissions, and influences investments in renewable energy. Increases in economic uncertainty may negatively impact renewable energy investments, which will, in turn, adversely impact the achievement of climate objectives (Işık et al., 2023). Therefore, researchers may need to incorporate policy uncertainties into their analysis. Other approaches may include involving green cryptocurrencies and applying different techniques, such as the quantile-based connectedness approach, to understand how these factors affect the connectedness level during extreme positive and adverse shocks.

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