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The nexus of blue economy, green finance, and energy commodities: A quantile VAR approach

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Abstract: The post-COVID era highlights the need for sustainable, resilient economies. This study investigates the interconnectedness between green finance, blue economy indices, clean energy assets, and energy commodities using a TVP-VAR and quantile VAR model from October 2021 to January 2024. Results show high connectedness (90–100%), with clean energy indices (OCEN, GNR) as key transmitters and oil/gas as net receivers, especially during stress periods. Spillover asymmetries across quantiles confirm non-linear risk transmission. Findings inform investors and policymakers on aligning green finance with energy policy, enhancing risk management tools, and promoting global cooperation for a just transition. This framework supports forward-looking, sustainable financial and energy strategies.

Keywords: Green finance, Blue economy, energy commodities, Q-VAR model, symmetrical spillover, non-linear dynamics

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1. Introduction

Increasing environmental degradation urges the world to address the surrounding sustainability and implement green energy projects. In this regard, the Paris Climate Agreement of 2015 pushes governments worldwide to transition from carbon-intensive energy sources toward renewable alternatives. The agreement aims to limit the global temperature rise to well below 2 degrees Celsius above pre-industrial levels, with a specific effort to limit the increase to 1.5 degrees Celsius. Hence, it pushes governments worldwide to prioritize the transition from dirty, fossil fuel-based energy systems to sustainable, renewable alternatives. Regarding the deficiencies in the financial market's arrangement, the United Nations Global Compact published a report in 2019 that urges the need to reorient the major global financial markets to achieve the Sustainable Development Goals (SDGs) by 2030.

In this framework, analyzing the relationship between the blue economy, green finance, and energy commodities is crucial to ensure a sustainable economic transition that is resilient to climate change and energy crises. Traditional energy commodities, such as oil, gas, and coal, continue to underpin the global economy but are vulnerable to price volatility and geopolitical risks. By investigating the potential of the blue economy (e.g., ocean energy), nations may diversify their energy sources and mitigate the risks associated with energy imports. Furthermore, the overexploitation of marine resources and increasing carbon emissions pose a threat to marine ecosystems. Green finance offers a solution to deal with these environmental issues through programs like green bonds for ocean protection. Examining the connections between the blue economy and green finance can therefore spur the creation of novel financial products, such as blue bonds, which encourage investments in marine renewable energy and lessen dependency on fossil fuels, stabilizing national economies and improving energy security. Furthermore, the majority of studies approach the blue economy, green finance, and energy commodities as separate fields rather than as interrelated domains, failing to look at the sector-specific linkages between them. For example, there is a lack of knowledge about how fluctuations in the prices of energy commodities impact the blue economy and green financing. This strategy runs the risk of overlooking important spillover channels that could impact sustainability, regulation, and investment. Policy and finance strategies may overlook interrelated dangers and opportunities if the interactions between these sectors are not nuancedly understood. This study aims to provide practical insights for enhancing energy resilience and fostering sustainable economic growth by thoroughly examining the connections between the blue economy, green finance, and energy commodities, and exposing cross-sectoral dynamics. Xu et al. (2023) highlight that introducing green finance markets can effectively mobilize environmentally friendly investment to respond to climate challenges. Specifically, green and blue financial instruments such as green bonds, blue bonds, and green Exchange-Traded Funds (ETFs) have been exploited to support clean energy projects by providing financial services, operating funds, and encouragement for green asset portfolios (Lee, 2020; Lin et al., 2022; Rasoulinezhad & Taghizadeh-Hesary, 2022; Madaleno et al., 2022), Puaschunder (2023), Maina et al. (2024). Alomari et al. (2024) demonstrated that ETFs present as interesting financial instruments that offer several benefits, including low costs, transparency, diversification, and flexibility in trading, thereby enabling more reliable diversification opportunities, effective asset allocation, potential hedging strategies, and efficient liquidity management.

During times of increased uncertainty, such as the Coronavirus pandemic, the Russia-Ukraine conflict, and the recent SVB collapse, there has been a notable uptick in the performance of ETFs and portfolios containing green assets. The disruptions in global markets resulting from COVID-19 have adversely affected both demand and supply, consequently slowing down the production of clean energy, as highlighted by Mzoughi et al. (2022) and Huang et al. (2023). However, the influx of investors into green finance markets has introduced a potential vulnerability, as increased interconnectedness among these markets may compromise their ability to achieve environmental goals. This crisis has sparked renewed interest in further research, particularly in exploring the necessity for safe-haven assets amid extreme market conditions and analyzing diversification strategies across asset classes (Jiang et al., 2023; Goa et al., 2024). Similarly, several studies highlighting the importance of the blue economy align with the United Nations' Sustainable Development Goals (SDGs). These goals aim to increase economic benefits to small island developing states (SIDS) by 2030 through the sustainable utilization of marine resources. In the post-COVID era, the blue economy presents significant opportunities to stimulate economic growth while concurrently safeguarding marine ecosystems and fortifying resilience against future challenges.

Sustainable practices promoted through green finance and the blue economy often focus on enhancing the management of natural resources, including water, fossil fuels, agricultural land, and others (Le et al., 2021; Dong et al., 2023). By reducing pressure on these limited resources, these approaches can mitigate the risks of shortages and price volatility, thereby stabilizing energy commodity markets. Nevertheless, these new markets may impact the availability of energy commodities, especially WTI and Gas. Hence, the study of dynamic spillovers among green finance, the blue economy, and commodities is crucial.

The research in the extant seam of the empirical literature has increasingly analyzed the impact of corporate financing instruments in the green finance market, Li et al. (2021), Jiang et al. (2023), Tiwari et al. (2022), and the economic impact of the blue economy, Bustamante et al. (2023), Pace et al. (2023), Fudge et al. (2023), and Stephenson and Hobday (2024). Existing studies have neglected how shock spillovers transmit across green and blue stock markets, alongside energy commodities indices, throughout a broad spectrum of market states. Hence, to our knowledge, this is the first study to integrate the risk transmission flows between green finance, the blue economy, and commodity indices. The analysis of risk transmission flows across these domains provides a more comprehensive understanding of the interconnected risks that may arise. For instance, disturbances in the commodity market can affect investments in renewable energy, while environmental crises in the blue economy can influence commodity prices. Having a holistic grasp of these risks enables decision-makers to anticipate potential impacts and implement suitable preventive measures. From the perspectives of environmental investors and policymakers, examining the interconnectedness and spillover effects among green, blue, and commodity markets holds significant importance. This information is crucial for adjusting asset portfolios and devising effective hedging strategies. Mensi et al.(2024) demonstrate a higher time-varying connectedness among West Texas Intermediate (WTI), crude oil, natural gas, heating oil, and petrol, particularly during major crisis episodes such as the China-US trade conflict, the COVID-19 Pandemic, and the Russia-Ukraine conflict. Through network analysis, they unveil that WTI, heating oil, and green bonds are net transmitters of spillovers, whereas other asset classes are predominantly receivers of risks. Our study focuses on this research by modifying green finance variables. Specifically, we introduce alterations to variables such as the Invesco Solar ETF (TAN) and the First Trust Global Wind Energy ETF, alongside the incorporation of additional blue economy variables. These blue economy variables include the Global Natural Resources ETF (CNRG), the share of the global clean energy ETF, and the IQ Clean Oceans ETF. It is important to note that ETFs, or exchange-traded funds, are utilized to represent both green finance and blue economy aspects within our study.

This study aims to gain insights into the resilience and transmission dynamics within green finance, the blue economy, and energy commodity markets during periods of extreme market conditions. Its significance lies in offering insights into the interconnectedness and asymmetries in spillover dynamics across green, blue, and conventional asset indices. This aims to foster a deeper understanding of the interdependence among different markets and the efficacy of various hedging strategies in risk management. Armed with this knowledge, investors can make more informed decisions and effectively manage their portfolios, particularly in times of market volatility and uncertainty. Understanding the asymmetrical nature of spillover dynamics and the effectiveness of diverse hedging strategies empowers investors to navigate market challenges and mitigate risks more effectively during periods of instability. Furthermore, policymakers can contribute to the promotion of green assets by enhancing transparency and standardization in the measurement of environmental, social, and governance factors. This initiative facilitates informed decision-making for investors, ensuring that their investments align with their values and sustainability objectives.

The motivation behind this article also stems from the growing need to understand how sustainable financial markets interact with traditional energy sectors in the context of global uncertainty, climate risks, and energy transitions. While prior research has primarily focused on individual markets in isolation, a critical gap remains in comprehensively assessing the dynamic interlinkages between green finance, the blue economy, and energy commodities under stress scenarios. By bridging this gap, our study provides a unified framework that not only captures the complex spillover patterns but also highlights the asymmetric transmission of shocks across markets. This is particularly useful for institutional investors, financial regulators, and policymakers seeking to enhance market resilience, design climate-resilient financial instruments, and support the transition toward a more sustainable and inclusive global economy. Our contribution is thus both theoretical and practical, offering empirical evidence that can inform long-term investment strategies and sustainable financial policymaking.

Our empirical findings are expected to provide valuable insights into both market portfolio diversification strategies and the development of policy frameworks aimed at achieving the Sustainable Development Goals (SDGs). Additionally, our research is poised to make a significant contribution to the expanding field of empirical studies in green finance and the blue economy, leveraging advanced econometric methodologies. We employ the novel estimation methodology proposed by Ando et al. (2018), which is an extension of the mean-based vector autoregression (VAR) method developed by Diebold and Yilmaz (2012). Several related studies have explored the return–spillover nexus using the mean-based method of connectedness (Diebold & Yilmaz, 2012). Previous studies have overlooked the mechanisms of return spillover at the extremes of the distribution. This paper fills this critical gap in the existing literature by examining the patterns of information flows across lower, middle, and upper quantile-based distributions. This approach effectively captures the dynamics of stress, stability, and bullish periods sequentially. We employ more advanced methods, including TVP-VAR extended by a quantile VAR connectedness (QVAR). Using the Quantile Vector Autoregression (QVAR) model enables the isolation of idiosyncratic shocks from each variable within the system. Furthermore, incorporating a factor structure simplifies the estimation process by ensuring cross-sectional independence among the equations comprising the VAR model. The QVAR model is particularly suited for analyzing idiosyncratic risk shocks and contagion, with the latter often characterized by differences in the spread of shocks between unusual occurrences and regular periods (Khalfaoui et al., 2022; Tang et al., 2022; Liao & Li, 2025).

The remainder of this paper is divided as follows. Section 2 presents the literature review. Section 3 presents a set of empirical studies, along with their methodology and data description. Section 4 discusses the dynamic and static results of our model. Finally, Section 5 presents the conclusion and political implications.

2. Literature review

Due to growing global demands to combat climate change, the spillover effect of green finance and blue economy indices has become an increasingly intriguing subject for policymakers and investors. This dynamic highlights the possibilities for synergy and the potential challenges associated with transitioning towards sustainable development. In the climate change literature, studies on green finance and blue economy are closely aligned with two streams of literature: the measurement of volatility spillovers and the nexus among green finance markets, blue economy, and conventional financial assets, such as commodities.

In the green finance field, investors are greatly concerned about volatility. Fluctuations in asset prices associated with renewable energy and other green sectors can impact investment choices, portfolio makeup, and project profitability. Changes in renewable energy investments frequently influence commodity prices, government subsidies, and energy-related tax regulations. These factors contribute to volatility in investor income and returns, Fraundorfer and Rabitz (2020), Poponi et al. (2021), Lee (2021), Iskandarova et al. (2021), Zhang et al. (2022). Li et al. (2021) demonstrate that in extreme market conditions, green finance and renewable energy investment are more volatile than gross domestic product (GDP). They also demonstrate a bidirectional causality between renewable energy investment and renewable energy electricity output, both in the short term and the long term. Based on IV-GMM estimating methods and the OLS approach, Zhao et al. (2024) highlight a significant relationship between green finance and renewable energy investment, demonstrating the interconnectedness between green finance and the transition towards renewable energy sources, especially during periods of crisis. Employing a variety of methodologies, empirical studies on the spillover effects between green finance indices and commodities markets reinforce this relationship, suggesting that developments in green finance can have both positive and adverse impacts on commodity markets, further emphasizing the importance of understanding and managing the interactions between these domains for sustainable development, Dogan et al. (2022), Khalfaoui et al. (2022) Deep Sharma et al. (2022), Xion and Coa (2023), Trancoso and Gomes (2024), Goa et al. (2024), Ben Salem and El Aoun (2025).

Recent studies aim to analyze the interconnectedness and spillover effects within green finance and energy markets, especially during economic crises. Dogan et al. (2022) examine the relationship between green finance and renewable energy sources, using a Time-Varying Parameter Vector Autoregressive (TVP-VAR) model to reveal dynamic, event-sensitive connections, with green finance generally acting as a net shock receiver. Sharif et al. (2023) extend this inquiry into the realm of clean versus black cryptocurrencies, showing that clean cryptocurrencies maintain stronger linkages with green economy indices, particularly during the COVID-19 pandemic, underscoring the green economy's potential as a diversification tool. Dogan et al. (2023) similarly utilize the TVP-VAR framework to explore spillovers between renewable energy sources and carbon markets, identifying solar and biofuel as significant transmitters of shocks to global carbon. Economic crises, such as the COVID-19 pandemic, notably altered these interconnections, with unique patterns of shock transmission observed across various renewable energy sources. Together, these studies highlight the nuanced and evolving nature of interdependence within sustainable financial and energy markets, providing valuable insights for policymakers and investors focused on sustainability and resilience.

In the blue economy sector, volatility can impact industries related to marine resources. For example, the prevalence of seafood prices (PIO) can impact the income of fishermen and food processing companies. In the same way, blue economy industries, such as coastal tourism and marine renewable energy, can be sensitive to the preference of weather and ocean conditions, which could affect projects' profitability and businesses in these sectors, Ni et al. (2024), Stephenson and Hobday. (2024), Alsaleh et al. (2024). Le et al. (2021) demonstrate that during extreme market movements, the connectivity and the spillover effects between the blue economy and conventional commodities are stronger in the short term than in the long term. To draw generalized conclusions, Gao et al. (2024) investigate the connectedness effect among sustainable development, green technology innovation, oil indices, clean energy, and economic cycles. They found a typically short-lived connectivity and demonstrated that the economic cycle serves as a receiver of shock, while sustainable development is a transmitter of shock. The transmission channel between the blue economy and the commodity market is a multifaceted process that, to my knowledge, has not been extensively explored in current research. However, recognizing the potential spillover effects between these two sectors is crucial, as it holds implications for advancing sustainability and stability within the commodity market. Further research could provide valuable insights into the interplay between the green economy and commodity markets, contributing to a more comprehensive understanding of sustainable development pathways and economic resilience.

While studies across green finance, the blue economy, and commodity markets have advanced our understanding of financial risk transmission—such as how fluctuations in renewable energy and seafood prices affect investment decisions and project profitability (e.g., Debrah et al., 2023; Xiaohang et al., 2023)—significant gaps remain. Notably, the literature is fragmented, as most analyses treat green, blue, or commodity markets in isolation, without offering an integrated framework that captures simultaneous spillovers across all three domains, as highlighted by Eleston et al. (2024). Furthermore, empirical investigations generally focus on stable periods or a single crisis (e.g., COVID-19), with limited examination of how connectedness evolves during health, geopolitical, and endogenous financial shocks, and whether these effects persist in the medium and long term (Gökgöz et al. 2024; Maneejuk et al., 2025,). Lastly, commodity-volatility studies tend to concentrate on energy or agricultural markets and rarely model interactions with renewable energy, marine resources, and financial instruments within a unified framework (Melas et al., 2024). By developing a comprehensive, crisis-aware, multivariate framework that integrates green, blue, and commodity sectors across diverse shock regimes and time horizons, our study fills this critical gap. It offers investors, policymakers, and project developers actionable insights for improved risk management and enhanced sustainability outcomes in interconnected market systems.

In the spillover study, Diebold and Yilmaz (2009) developed measures of return and volatility spillovers through variance decompositions within the VAR framework. Expanding on this, Demirer et al. (2018a) utilized the Diebold and Yilmaz (2012, 2014) connectedness framework, employing the "Least Absolute Shrinkage and Selection Operator" (LASSO) approach to estimate an important dimensional network of the financial markets indices. Recently, enhancements have been made to the Diebold and Yilmaz model by incorporating the quantile approach (Chatziantoniou et al., 2021). This addition enables a more nuanced exploration of connectedness and contributes to a deeper comprehension of the transmission mechanism of monetary policy in a highly integrated global financial system.

We employ Quantile VAR (QVAR) to measure interconnectedness because it allows for a nuanced understanding of the dependency structure across different quantiles of the return distribution, capturing both average and extreme behaviors of blue economic, green finance, and energy commodities returns, especially under varying economic or environmental stress levels. Unlike standard VAR models, which typically focus on mean dependencies, QVAR can assess connectivity across varying market conditions—normal, stressed, or highly volatile—by examining different quantiles. In our study, the blue economy, green finance, and energy commodities are inherently volatile and sensitive to economic, environmental, and geopolitical factors. Hence, using the QVAR approach enables us to examine interconnectedness not just at the average level but also during crisis periods, where dependencies may be stronger or weaker. Furthermore, the connections between the blue economy, green finance, and energy commodities might not be linear; instead, they might change based on market conditions, environmental regulations, and technological developments (Khalfaoui et al., 2022; Abubakr, 2024; Kyriazis & Corbet, 2024). By examining several quantiles, QVAR can capture this nonlinearity and illustrate how the direction and intensity of linkages fluctuate between stable and volatile periods in the markets.

The empirical literature encompasses several models that model the connectivity among variables, including VAR models, vector error correction models (VECMs), and Granger causality tests. These models are often focused on mean or long-term relationships but may fail to capture dynamic and quantile-specific dependencies (Cepoi et al., 2021; Ahmed & Khan, 2024). In contrast, the Quantile VAR model is advantageous for research questions that require a closer examination of different states of financial markets, especially during periods of economic stress or exogenous shocks. For example, Standard VAR models capture the average interactions between time-series data but are limited in their ability to differentiate dynamics across varying market conditions. While useful for baseline analyses, VAR models may not capture extreme interdependencies between the green economy, blue finance, and energy commodities, especially under stress. Similarly, GARCH models, particularly multivariate GARCH, focus on volatility interactions and can capture spillovers in market risk. These methods help understand how volatility in one sector (e.g., energy commodities) might affect others (e.g., green finance). However, they typically analyze mean relationships rather than quantile-specific dependencies, potentially overlooking connectivity under extreme conditions. However, the QVAR approach stands out because it allows for a quantile-specific analysis of interconnectedness. This model captures dependencies not only during typical conditions but also under extreme market states (such as crises or regulatory shifts). For instance, QVAR can reveal whether green finance becomes more or less sensitive to energy commodity prices at different quantiles, a critical insight for assessing resilience in sustainable sectors (Hossain et al., 2024; Yousfi & Bouzgarrou, 2024). This does not prevent QVAR models from being computationally intensive and requiring a careful selection of quantiles to avoid overfitting. Additionally, interpreting QVAR results demands a more advanced understanding of quantile-based dependencies.

3. Methodology and data description

3.1. Methodologies

To examine the quantile spillover mechanism across various financial markets, we employ the novel quantile and frequency connectedness approach that enables the investigation of propagation mechanisms by quantile and frequency. The quantile connectedness approach was proposed by Ando et al. (2018), Bouri et al. (2021), and Chatziantoniou (2021). The Quantile VAR model is specifically chosen for its capacity to capture tail dependencies and asymmetries in asset relationships, which are often crucial during periods of economic stress or market instability. Traditional VAR models may not effectively capture these extreme co-movements, as they focus on average relationships. Quantile VAR, however, considers multiple conditional quantiles, allowing us to examine interconnectedness at both the median and tail levels, thereby providing a more comprehensive understanding of market linkages in both stable and turbulent times (White et al., 2015; Ando et al., 2018). This feature makes Quantile VAR highly suitable for addressing our research questions, which seek to understand the varying intensity of interconnectedness under different market conditions.

To further support the relevance of this methodology, we reference studies that have employed similar approaches to examine financial market dynamics. For instance, Ando et al. (2018) utilized Quantile VAR to capture asymmetric connectedness in financial markets, demonstrating the method's robustness in quantifying spillovers across different quantiles. Additionally, Diebold and Yilmaz (2009, 2012) introduced a spillover framework using traditional VAR, which inspired our quantile-based approach to extend spillover measurement across different market conditions. Similarly, Baruník and Křehlík (2018) adopted a time-frequency decomposition to examine spillovers over short-term and long-term horizons, validating the need for a time-frequency connectedness analysis in studies like ours that investigate dynamic, multi-horizon market relationships.

Our model integrated, apart from the index on six blue economy and two green finance indices, the Invesco Solar ETF and the First Trust Global Wind Energy ETF. Commodity performance indices, such as the Gas and WTI indices, were used to analyze the transmission channel of risks and to address issues related to institutional responsibility for climate change, ensuring sustainability.

To capture the overall connectedness measure, we estimate a quantile vector autoregressive (QVAR(p)) model. The model can be summarized as follows:

$$\mathbf{x}_t = \boldsymbol{\mu}_t(\tau) + \Phi_1(\tau)\mathbf{x}_{t-1} + \Phi_2(\tau)\mathbf{x}_{t-2} + \cdots + \Phi_p(\tau)\mathbf{x}_{t-p} + \boldsymbol{u}_t(\tau) \quad (1)$$

Where $\boldsymbol{xt}$ and $\boldsymbol{xt}$–j are vectors representing endogenous variables with dimensions N × 1, the parameter τ is a closed interval within the range [0, 1], while p represents the lag length of the QVAR model. (τ) is a N×1 dimensional vector that represents the conditional mean, $\boldsymbol{\Phi j}$ (τ) is a N × N dimensional matrix of QVAR coefficients, and (τ) is a N ×1 dimensional error vector with an N×N dimensional error variance-covariance matrix, (τ).

Secondly, to compute the forward M-step Generalized Forecast Error Variance Decomposition (GFEVD), Eq. (1) needs to be transformed into the QVMA (∞) form by applying Wold's theorem. The QVMA (∞) is presented in the following equation:

$$\mathrm{x}_t = \boldsymbol{\mu}(\tau) + \sum_{j=1}^{p} \Phi_j(\tau)\mathbf{x}_{t-j} + \boldsymbol{u}_t(\tau) = \boldsymbol{\mu}(\tau) + \sum_{i=0}^{\infty} \Psi_i(\tau)\boldsymbol{u}_{t-i}. \quad (2)$$

The next step involves calculating the generalized forecast error variance decomposition (GFEVD) with a forecast horizon of H, a crucial component of the connectedness approach (Koop et al., 1996; Pesaran & Shin, 1998). It could be interpreted as the impact that series j has on variable i in terms of its forecast error variances:

$$\theta_{ij}(\mathrm{H}) = \frac{(\Sigma(\tau))_{jj}^{-1} \sum_{\mathrm{h}=0}^{\mathrm{H}-1}\left((\Psi_h(\tau)\Sigma(\tau))_{ij}\right)^2}{\sum_{\mathrm{h}=0}^{\mathrm{H}}\left(\Psi_h(\tau)\Sigma(\tau)\Psi'_h(\tau)\right)_{ii}} \quad \tilde{\tilde{\theta}}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{k=1}^{N}\theta_{ij}(H)} \quad (3)$$

The rows of $\tilde{\theta}_{ij}(H)$ Do not sum up to one; we need to normalize them by the row sum, which results in $\tilde{\theta}_{ij}$ in (3). Through the normalization. The row sum is equal to unity, representing how a shock in series i has influenced the series itself and all other series. Next, we get the following identities $\Sigma^{N}_{i=1}\tilde{\theta}_{ij}$ (H)=1 and $\Sigma^{N}_{j=1}\Sigma^{N}_{i=1}\tilde{\theta}_{ij}$ (H)= N.

In the next phase, all connection measures may be computed. First, we start with the net pairwise connectivity as follows:

$$NPDC_{ij}(\mathrm{H}) = \tilde{\theta}_{ij}(\mathrm{H}) - \tilde{\theta}_{ji}(\mathrm{H}) \tag{4}$$

If $NPDC_{ij}(H) > 0$ $NPDC_{ij}(H) < 0$, it signifies that series j has a greater (lesser) influence on series I than the other way around.

The total directional connectedness for others assesses how much an impact in series i influences all other series j.

$$TO_i(H) = \sum_{i=1, i\neq j}^{N} \tilde{\tilde{\theta}}_{ji}(\mathrm{H}) \tag{5}$$

The total directional connectedness originating from others quantifies the level of impact on series i caused by shocks in all other series j.

$$FROM_i(\mathrm{H}) = \sum_{i=1, i\neq j}^{N} \tilde{\theta}_{ij}(\mathrm{H}) \tag{6}$$

The overall net total directional connectedness captures the difference between the total directional connectedness towards others and the total directional connectedness from others. This disparity can be interpreted as the net impact of series i on the predefined network.

$$NET_i(H) = TO_i(\mathrm{H}) - FROM_i(\mathrm{H}) \tag{7}$$

When NETi> 0 (NETi< 0), it means that series i has a greater (lesser) influence on all other series j compared to the amount of influence it receives from them. Therefore, it is categorized as a net transmitter (net receiver) of shocks.

The computation of the overall total connectedness index (TCI) evaluates the degree of interconnectedness within the network. A higher value of TCI signifies increased market risk, while a lower value indicates the opposite.

$$TCI(H) = N^{-1} \sum_{i=1}^{N} TO_i(H) = N^{-1} \sum_{i=1}^{N} FROM_i(H) \tag{8}$$

To investigate the connectedness within the temporal domain, we assess the connectivity within the frequency domain. We utilize Stiassny's (1996) spectral decomposition method. Initially, we examine the frequency response function, represented as $\boldsymbol{\Psi}(e^{-i\omega}) = \Sigma^{\infty}_{h=0}\, e^{-i\omega h}\boldsymbol{\Psi}_h$, where $i = \sqrt{(-1)}$ and ω is the frequency. Next, we proceed to analyze the spectral density of x_t at a specific frequency ω. This can be obtained by applying a Fourier transformation to the QVMA(∞):

$$\boldsymbol{S}_x(\omega) = \sum_{h=-\infty}^{\infty} E(x_t x'_{t-h})\, e^{-iwh} = \boldsymbol{\Psi}(e^{-i\omega h}) \sum_t \boldsymbol{\Psi}'(e^{+i\omega h}) \tag{9}$$

Likewise, the frequency-based Generalized Forecast Error Variance Decomposition (GFEVD) is a fusion of the spectral density and the GFEVD. GFEVD should be normalized in the frequency domain, similar to the requirement for normalization in the time domain. Its representation is as follows:

$$\theta_{ij}(\omega) = \frac{(\Sigma(\tau))^{-1}_{jj} \left| \sum_{h=0}^{\infty} \left(\boldsymbol{\Psi}(\tau)(e^{-iwh})\Sigma(\tau) \right)_{ij} \right|^2}{\sum_{h=0}^{\infty} \left(\boldsymbol{\Psi}(e^{-iwh})\Sigma(\tau)\boldsymbol{\Psi}(\tau)(e^{iwh}) \right)_{ii}} \tag{10}$$

$$\tilde{\theta}_{ij}(\omega) = \frac{\theta_{ij}(\omega)}{\sum_{k=1}^{N} \theta_{ij}(\omega)} \tag{11}$$

The expression $\tilde{\theta}_{ij}(\omega)$ refers to the fraction of the spectrum of the ith series at a given frequency ω that can be attributed to an impact on the jth series. This measurement is commonly referred to as an intra-frequency indicator. To evaluate connectedness across both short-term and long-term time frames, instead of focusing on a single frequency, we aggregate all frequencies within a specified range, denoted as: $d = (a, b)$: $a, b \in (-\pi, \pi)$, $a<b$:

$$\tilde{\theta}_{ij}(d) = \int_a^b \tilde{\theta}_{ij}(w)dw \tag{12}$$

From this stage, we can compute similar connectedness measures as mentioned before; it can be evaluated using the same method. However, in this scenario, these measures are known as frequency connectedness measures. They offer insights into the transmission of effects within specific frequency ranges (represented by d), which can be interpreted in a similar manner:

$$NPDC_{ij}(d) = \tilde{\tilde{\theta}}_{ij}(d) - \tilde{\tilde{\theta}}_{ji}(d) \tag{13}$$

$$TO_i(d) = \sum_{i=1, i \neq j}^{N} \tilde{\tilde{\theta}}_{ji}(d) \tag{14}$$

$$FROM_i(d) = \sum_{i=1, i \neq j}^{N} \tilde{\tilde{\theta}}_{ij}(d) \tag{15}$$

$$NET_i(d) = TO_i(d) - FROM_i(d) \tag{16}$$

$$TCI(d) = N^{-1} \sum_{i=1}^{N} TO_i(d) = N^{-1} \sum_{i=1}^{N} FROM_i(d) \tag{17}$$

In our analysis, we define two frequency bands that capture short-term and long-term dynamics. The first band, $d1 = (\pi/5, \pi)$, covers a range of 1 to 5 days, while the second band, $d2 = (0, \pi/5]$, encompasses timeframes from 6 days to an infinite horizon. Consequently, $NPDC_{ij}(d1)$, $TO_i(d1)$, $FROM_i(d1)$, $NET_i(d1)$, and $TCI(d1)$ represent short-term total directional connectedness towards others, short-term total directional connectedness from others, short-term net total directional connectedness, and short-term total connectedness index, respectively. On the other hand, $NPDC_{ij}(d2)$, $TO_i(d2)$, $FROM_i(d2)$, $NET_i(d2)$, and $TCI(d2)$ depict long-term total directional connectedness towards others, long-term total directional connectedness from others, long-term net total directional connectedness, and long-term total connectedness index, respectively. Furthermore, we establish a relationship between the frequency-domain measures proposed by Baruník and Křehlík (2018) and the time-domain measures introduced by Diebold and Yılmaz (2009, 2012, 2014).

$$NPDC_{ij}(H) = \cdot \sum_d NPDC_{ij}(d) \tag{18}$$

$$TO_i(H) = \sum_d (\mathrm{d}) \cdot TO_i(d) \tag{19}$$

$$FROM_i(d) = \sum_d (\mathrm{d}) \cdot FROM_i(d) \tag{20}$$

$$NET_i(H) = \sum_d (\mathrm{d}) \cdot NET_i(d) \tag{21}$$

$$TCI(H) = \sum_d (\mathrm{d}) \cdot TCI(d) \tag{22}$$

Simply put, the total connectedness measures can be derived by aggregating the frequency connectedness measures. It is crucial to highlight that all these measures are calculated using a specific quantile, denoted as τ.2.

3.2. Data and model descrition

We analyzed the interconnectedness between green and blue stock indices, including BJLE, OCEN, GNR, PIO, ICLN, CNRG, FAN, TAN, as well as oil and gas indices (WTI, Gas). This analysis covered various endogenous and exogenous crises, utilizing closing prices of stock indices from October 26, 2021, to January 05, 2024, sourced from www.datastream.com. This sample period coincides with several critical global events that have had a significant impact on financial and energy markets. These events include the post-COVID-19 economic recovery, the Russia-Ukraine war, the global energy supply crisis, and financial instability episodes such as the 2023 Silicon Valley Bank collapse. These events provide a rich context to assess the evolving and stress-sensitive interconnectedness across markets, especially under conditions of heightened uncertainty and policy shifts toward decarbonization. Hence, the selected period is ideal for capturing both normal and extreme market conditions, which is crucial for understanding the robustness and variability of spillover effects.

Table 1. Variable measurement and focus[1]

Abbreviation	Full Name	Role / Focus
BJLE	BNP Paribas Easy ECPI Global ESG Blue Economy UCITS ETF	Targets companies contributing to the sustainable use of ocean and water resources (Blue Economy).
OCEN	IQ Clean Oceans ETF	Focuses on firms involved in ocean health, pollution control, and sustainable marine technologies.
GNR	SPDR S&P Global Natural Resources ETF	Provides exposure to global companies involved in energy, metals, and agricultural resources.
PIO	Invesco Global Water ETF	Invests in companies engaged in water treatment, infrastructure, and conservation.
CNRG	SPDR S&P Kensho Clean Power ETF	Tracks firms advancing clean energy technologies, including solar, wind, and geothermal energy.
ICLN	iShares Global Clean Energy ETF	Offers exposure to global companies producing renewable energy from solar, wind, and similar sources.
TAN	Invesco Solar ETF	Targets companies involved in the development and production of solar energy and related technologies.
FAN	First Trust Global Wind Energy ETF	Targets companies involved in the development and production of wind energy and related components.
WTI	West Texas Intermediate Crude Oil	A benchmark for U.S. crude oil prices, representing traditional fossil fuel energy markets.
Gas	Natural Gas Index or Futures (e.g., Henry Hub)	Represents prices or returns in the natural gas market, reflecting fossil-based energy sources.

The returns are calculated by using the equation Rt=ln (Pt/Pt-1), where Pt represents the price on a given day. The green and blue stock indices were chosen based on their relevance to the research questions concerning the interconnectedness of clean and traditional energy sectors, which is central to understanding energy transition dynamics. These indices reflect key assets in the green finance and energy markets, capturing the interplay between clean and conventional energy assets amid global economic, geopolitical, and environmental crises. Prior studies, such as those by Bouri et al. (2020) and Nguyen et al. (2021), have demonstrated that the interconnectedness between clean and traditional energy markets is crucial for understanding market spillovers and risk management during periods of crisis. Additionally, the literature suggests that indices like WTI and Gas serve as key indicators for traditional energy, while ICLN, CNRG, and TAN are prominent in clean energy investment. By incorporating these indices, our study extends previous work by examining dynamic spillovers and connectedness at different quantiles, thereby contributing to a deeper understanding of market behavior across diverse economic conditions. Our study begins with TVP-VAR-based connectedness at the quantile level of 0.5 and then extends to different quantiles (QVAR). This approach highlights how structural shocks of varying intensities influence the interconnection and responses of variables, particularly during extreme events.

The selection comprises a variety of ETFs focused on specific environmental and energy themes, including the blue economy, ocean cleanliness, global natural resources,

1. ETFs represent diversified exposure to clean energy sectors, reflecting investor sentiment and sectoral trends, while futures contracts (e.g., WTI, Gas) capture real-time price dynamics in traditional energy markets. Including both allows for a comprehensive analysis of connectedness between clean and dirty energy assets.

water, and clean and renewable energy, such as solar and wind energy. These ETFs include BJLE, OCEN, GNR, PIO, CNRG, ICLN, TAN, and FAN. Additionally, the data incorporates futures indices for WTI and Gas.

The descriptive statistics in Table 2 offer initial insights into the characteristics and behavior of each variable over the observed period. The mean values reflect the average daily returns. Variables such as BJLE and GNR exhibit positive mean values, indicating that they tend to deliver positive average returns. Conversely, OCEN, PIO, ICLN, CNRG, FAN, TAN, WTI, and Gas have negative mean returns, indicating generally declining values over the sample period.

The variance values reveal the degree of return dispersion or volatility. Higher variance values observed for TAN, WTI, and Gas suggest greater variability in these assets, highlighting their relatively higher risk. In contrast, lower variance values, such as those for BJLE, indicate more stable return behavior.

Understanding the mean and variance of each variable is crucial for assessing their behavior, identifying trends, and evaluating the level of risk or uncertainty associated with them. These statistics serve as essential measures for making informed decisions in various analytical contexts.

Table 2. Descriptive statistics of the main variables

	BJLE	OCEN	GNR	PIO	ICLN	CNRG	FAN	TAN	WTI	Gas
Mean	.0000503	-.0002888	.0000292	-.0001642	-.0008753	-.0007932	-.0005557	-.0011563	-.0002308	-.0012999
Variance	.0095444	.0133759	.0147714	.0126705	.0193319	.0216109	.0145472	.0263751	.0266597	.0495942
Skewness	-0.123	0.316***	-0.268**	0.157	0.524***	0.366***	0.419***	0.446***	-0.644***	-0.325***
Ex. Kurtosis	0.807***	1.471***	0.979***	1.072***	1.363***	0.537**	1.596***	0.939***	2.303***	0.426*
JB	16.257***	58.532***	28.420***	28.499***	67.476***	18.799***	74.185***	38.287***	158.996***	13.779***
ERS	-7.086***	-6.111***	-11.478***	-9.734***	-9.792***	-7.960***	-11.202***	-7.604***	-8.144***	-10.692***
Q(20)	11.870	10.421	10.681	10.031	17.048*	9.018	17.172*	12.470	18.698**	14.040
Q2(20)	37.301***	37.081***	61.383***	41.181***	28.890***	12.084	34.340***	26.164***	48.604***	27.194***

Note: This table reports descriptive statistics for the main variables including mean, variance, skewness, excess kurtosis (Ex.Kurtosis), Jarque-Bera test (JB) for normality, Elliott-Rothenberg-Stock unit root test (ERS), and Ljung-Box Q-tests for serial correlation at lag 20 (Q(20)) and squared returns (Q2(20)). Significance levels: *p<0.1, **p<0.05, ***p<0.01.

Table 3 presents Kendall's τ rank correlations among ten return series, spanning green finance, blue economy, clean energy ETFs, and traditional commodities. The table reveals strong, highly significant positive correlations within the green/clean-energy cluster—e.g., ICLN–TAN and ICLN–CNRG, as well as OCEN–PIO, indicating tightly linked performance dynamics. By contrast, correlations between traditional commodities (WTI, Gas) and sustainable indices are weak, albeit statistically significant in some cases, reflecting minimal co-movement. These results underscore a bifurcation in market behavior: sustainable-sector returns move cohesively, suggesting risk contagion within green and blue markets, whereas traditional fossil-fuel commodities show limited integration. This delineation emphasizes the importance of sector-specific volatility analysis and targeted risk management strategies for stakeholders operating across these asset classes.

Table 3. Correlation across the various return series

kendall	BJLE	OCEN	GNR	PIO	ICLN	CNRG	FAN	TAN	WTI	Gas
BJLE	1.000***	0.439***	0.297***	0.394***	0.364***	0.332***	0.387***	0.323***	0.100***	0.072**
OCEN	0.439***	1.000***	0.455***	0.709***	0.578***	0.553***	0.602***	0.514***	0.071**	0.076***
GNR	0.297***	0.455***	1.000***	0.396***	0.375***	0.386***	0.403***	0.340***	0.346***	0.108***
PIO	0.394***	0.709***	0.396***	1.000***	0.483***	0.487***	0.531***	0.419***	0.039	0.072**

ICLN	0.364***	0.578***	0.375***	0.483***	1.000***	0.781***	0.626***	0.816***	0.100***	0.059**
CNRG	0.332***	0.553***	0.386***	0.487***	0.781***	1.000***	0.521***	0.783***	0.108***	0.067**
FAN	0.387***	0.602***	0.403***	0.531***	0.626***	0.521***	1.000***	0.517***	0.107***	0.047
TAN	0.323***	0.514***	0.340***	0.419***	0.816***	0.783***	0.517***	1.000***	0.097***	0.052
WTI	0.100***	0.071**	0.346***	0.039	0.100***	0.108***	0.107***	0.097***	1.000***	0.063**
Gas	0.072**	0.076***	0.108***	0.072**	0.059**	0.067**	0.047	0.052	0.063**	1.000***

Note: The table presents Kendall rank correlations among return series. Significance levels are indicated as: *p<0.1, **p<0.05, *** p<0.01.

4. Empirical results

Table 4 presents the dynamic total connectedness among a selection of green and blue economy indices, alongside gas and oil indices, indicating how each index influences and is influenced by others. The diagonal values (in bold) represent each index's connectedness, while the off-diagonal elements show the degree of connectedness with other indices. Notably, total connectedness (TO) values provide insights into the overall interconnections, with OCEN, GNR, and Gas demonstrating particularly high levels of connectedness, indicating their significant roles in influencing the system's dynamics.

Table 4. Dynamic total connectedness

	BJLE	OCEN	GNR	PIO	ICLN	CNRG	FAN	TAN	WTI	Gas	FROM
BJLE	27.28	13.16	6.24	11.87	10.69	9.08	10.44	9.36	0.58	1.30	72.72
OCEN	8.42	19.66	8.75	15.66	12.02	11.07	13.26	10.18	0.42	0.57	80.34
GNR	5.75	12.43	28.12	10.40	8.63	8.94	10.08	7.62	6.85	1.18	71.88
PIO	8.23	18.02	8.31	22.61	10.20	10.13	13.25	8.07	0.41	0.76	77.39
ICLN	6.50	11.57	5.59	8.42	19.54	16.59	13.17	17.67	0.52	0.43	80.46
CNRG	5.82	11.37	6.01	9.22	17.39	20.48	10.79	17.46	0.66	0.80	79.52
FAN	7.57	14.00	7.60	11.89	14.56	11.10	21.06	11.26	0.69	0.28	78.94
TAN	6.19	10.62	5.27	7.39	19.13	18.07	11.09	21.22	0.55	0.47	78.78
WTI	2.16	1.44	17.02	1.50	2.42	3.24	2.17	3.32	65.10	1.63	34.90
Gas	2.54	2.62	3.70	2.41	2.27	3.46	1.28	2.58	1.81	77.32	22.68
TO	53.18	95.23	68.50	78.76	97.32	91.69	85.53	87.51	12.49	7.41	677.62
Inc.Own	80.46	114.89	96.62	101.37	116.86	112.17	106.59	108.73	77.58	84.74	cTCI/TCI
NET	-19.54	14.89	-3.38	1.37	16.86	12.17	6.59	8.73	-22.42	-15.26	75.29/67.76
NPT	2.00	8.00	3.00	4.00	9.00	7.00	5.00	6.00	1.00	0.00	

Note: ETFs represent clean energy sectors, while WTI and Gas refer to fossil fuel markets. Values indicate return spillovers; diagonal elements show own shocks. "FROM" and "TO" represent received and transmitted spillovers. "NET" is the difference (TO − FROM).

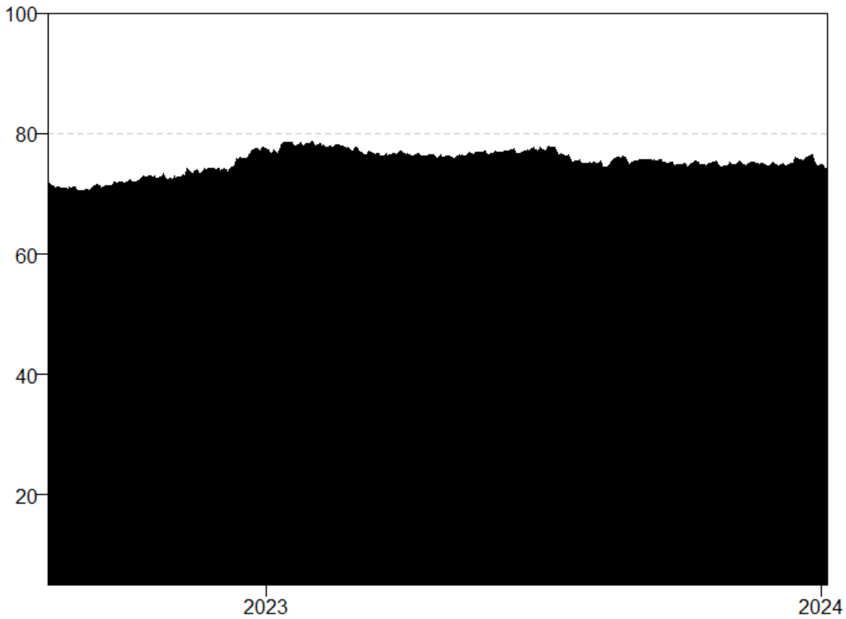
Furthermore, increased own connectedness (Inc.Own) metrics shed light on the extent to which each variable contributes to its own connectedness within the system. Variables such as OCEN, GNR, and Gas exhibit elevated levels of increased own connectedness, suggesting their importance in driving their dynamics.

Net position total (NET) values indicate the net impact of each variable on the overall connectedness. Positive values imply a positive contribution, while negative values suggest a negative influence. Notably, OCEN, GNR, and Gas show positive net positions, indicating their positive contributions to the overall connectedness of the system.

Moreover, the ratio of net position total to total connectedness increase (cTCI/TCI) provides insights into the relative impact of each variable on the total connectedness increase. Ratios greater than 1 indicate that the variable contributes more than the average to the increase in total connectedness, highlighting its significance in shaping the system's dynamics. BJLE, OCEN, GNR, and PIO exhibit moderate self-connectedness levels (22-28%), indicating significant but not dominant internal dependencies. Green indices, such as ICLN, CNRG, FAN, and TAN, demonstrate high levels of connectedness with one another, reflecting strong interdependence among sustainable energy indices. WTI and Gas display unique characteristics: Gas has a high internal connectedness (77.32%), indicating substantial self-containment, while WTI exhibits relatively lower internal dependence (65.10%) and higher external connectedness, particularly with GNR (17.02%), pointing to a broader influence within the network. The net connectedness (NET row) shows that ICLN and OCEN are net transmitters, indicating they exert more influence than they receive, while BJLE, WTI, and Gas are net receivers, being more influenced by others. The Total Connectedness Index (TCI) of 75.29% indicates a high degree of interconnectedness across all indices, with notable distinctions between green energy indices and traditional fossil fuel sources.

The dynamic total connectedness depicted in Figure 1 provides a comprehensive overview of the evolving Total Connectedness Index (TCI) over time. Notably, the TCI exhibits pronounced fluctuations, ranging between 90% and 100%, indicative of the consistently high levels of connectivity among the assets under investigation. Subsequently, in examining the dynamic net total connectedness illustrated in the subsequent figure, we observe a considerable degree of fluctuation between net receiver and net transmitter statuses across the variables. However, these fluctuations alone do not yield conclusive insights. Therefore, we turn our attention to analyzing the net pairwise total connectedness, as depicted in the following plot.

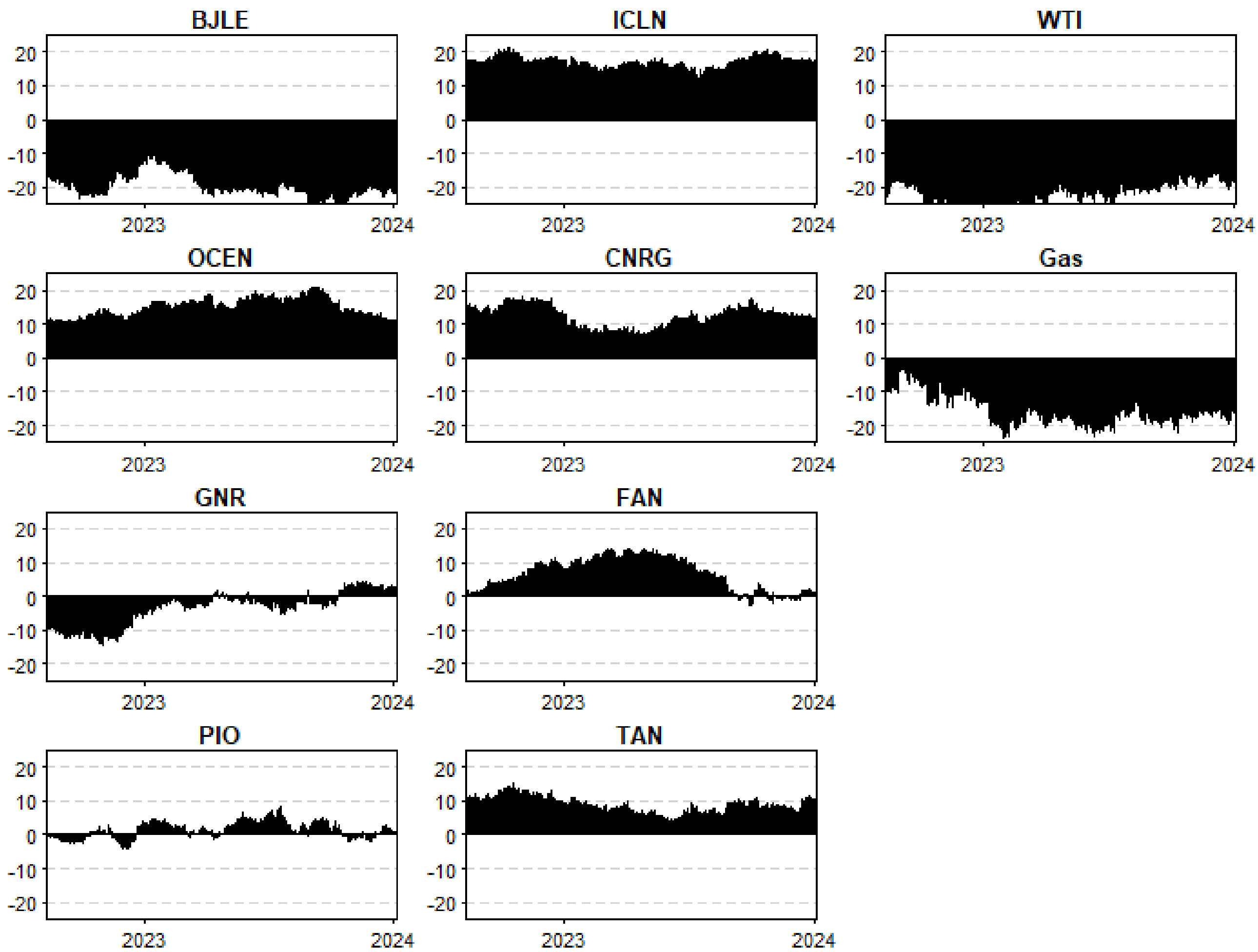
Figure 1. Total Dynamic Connectedness



The analysis of net pairwise total connectedness offers a more granular understanding of the relationships between individual pairs of variables. By assessing the strength and directionality of connections between specific pairs, we can glean insights into the underlying dynamics of the system. This allows us to identify key relationships, potential areas of influence, and patterns of interaction among the studied assets. Ultimately, this analysis facilitates more informed decision-making processes in various domains, including risk management, portfolio optimization, and policy formulation.

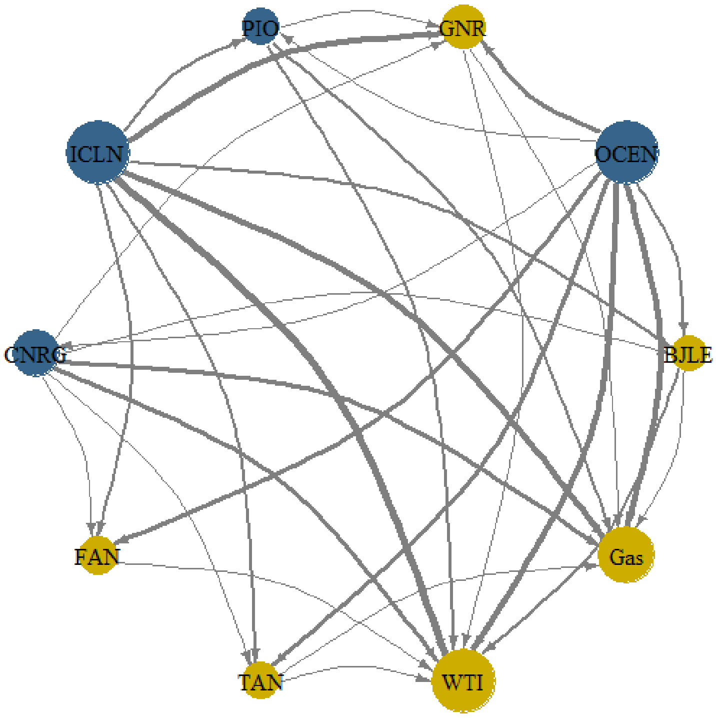
Figure 2 illustrates the dynamic net status of each index, providing insights into their roles as either net transmitters or receivers of shocks over time. The analysis reveals that oil, gas, GNR, and BJLE maintain a consistent status as net receivers, meaning they predominantly absorb shocks from other indices rather than transmit them. In contrast, indices related to green energy, including CNRG, OCEN, ICLN, TAN, and FAN, function as net transmitters, indicating that they are primary sources of influence within the network. Notably, PIO demonstrates a variable pattern, alternating between being a net transmitter and a net receiver. This shifting behavior for PIO suggests a dynamic role in the network, potentially responding to market fluctuations or external shocks differently than other indices.

Figure 2. Net total directional connectedness



The net pairwise connectedness in Figure 3 analysis provides a detailed glimpse into the intricate web of relationships among the variables under examination. Results should be more fully explained and need further in-depth discussion. The discussion should include further discussion on the previous findings about the existing ones. It would be better to explain the results according to clear economic intuition or theoretical foundation, not just focus on discovering some empirical patterns. Notably, certain variables such as ICLN emerge as pivotal nodes, displaying robust connectivity with key entities like oil, gas, and GNR. This strong linkage could stem from the reliance on renewable energy technologies in traditional energy markets, as oil and gas prices influence the relative cost-competitiveness of renewables. Rising oil prices, for example, often make renewables more attractive, thereby increasing investment in clean energy sectors, such as ICLN. Moreover, ICLN's robust connections to GNR highlight the interdependence within renewable energy markets, where shifts in green finance can drive spillovers across various clean energy-focused entities. Similarly, OCEN stands out for its significant ties with the oil and gas sectors. This connection may signal a transitional phase for the ocean economy as it transitions toward greener practices, where shifts in traditional energy markets create ripple effects across the sector.

Figure 3. Net-Pairwise Directional Connectedness



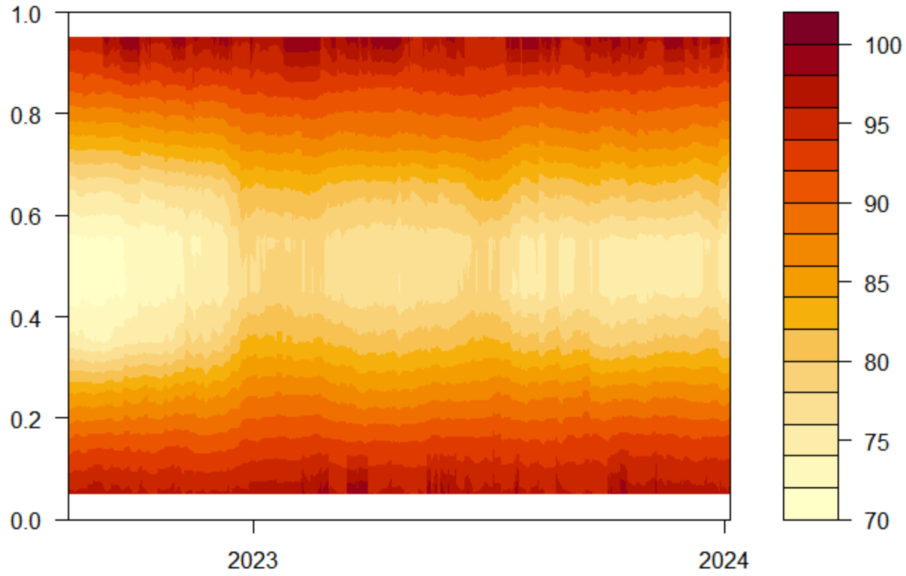
Conversely, the analysis reveals weaker connections between GNR and PIO, as well as CNRG and OCEN, TAN, and FAN, which explain the results by clear economic intuition or theoretical foundations. Each index may represent unique technologies with distinct market drivers and regulatory policies, leading to limited direct interdependencies. For example, solar and wind sectors (represented by TAN and FAN) are influenced by unique factors such as technology-specific subsidies and weather conditions, resulting in weaker spillover effects with other renewable sectors. Similarly, the limited connection between water resource indices and green energy highlights the sectoral independence, as water resource management operates primarily outside the direct influence of the energy market. These findings align with economic intuition, suggesting that while certain green finance and renewable sectors are interdependent, others operate under sector-specific dynamics that moderate their interconnectedness. This understanding offers a nuanced perspective on how sectoral characteristics and energy dependencies influence the transmission of shocks and correlations across sustainable finance and energy markets.

Furthermore, these findings demonstrate that understanding these strong connections in the realm of risk management enables more precise identification and mitigation of risks, particularly within energy-related portfolios. Portfolio optimization strategies can leverage the strong connectivity between OCEN, oil, and gas to potentially enhance overall portfolio performance through strategic allocation. Meanwhile, insights gleaned from the weaker connections shed light on sectors or assets that exhibit relatively independent movements, guiding diversification efforts and providing valuable market analysis insights.

Furthermore, the implications extend beyond investment strategies. Policymakers and industry stakeholders can leverage the insights gained from this analysis to develop more informed energy policies and strategies. By understanding the interdependencies among energy-related variables, policymakers can better allocate resources, plan infrastructure development, and design sustainable initiatives. In essence, the net pairwise connectedness analysis serves as a powerful tool for decision-makers in financial and energy sectors, offering invaluable insights that drive effective risk management, portfolio optimization, market analysis, and policy formulation endeavors.

To draw deep conclusions, we examine the total and net connectedness through quantiles, as shown in Figure 4. Precisely, the heatmap depicted in Figure 4 was generated using a 200-day rolling window and a 20-day ahead forecast based on the QVAR (1) model. The timeline is represented on the x-axis, and the quantiles, which range from 0.05 to 0.95 and are iterated at 1% intervals, are plotted on the y-axis. Warmer segments show higher levels of connectedness, whereas lighter regions present lower levels. Dynamic shocks emanate from both significantly positive (above the 75th percentile) and negatively shifted assets (below the 25th percentile). Our results demonstrate robust interconnections across almost the entire sample period, with particularly high levels of connectedness observed from the second half of 2022 through early 2023. This period of heightened connectedness is followed by alternating phases of high and lower connectedness, persisting intermittently until the end of the period.

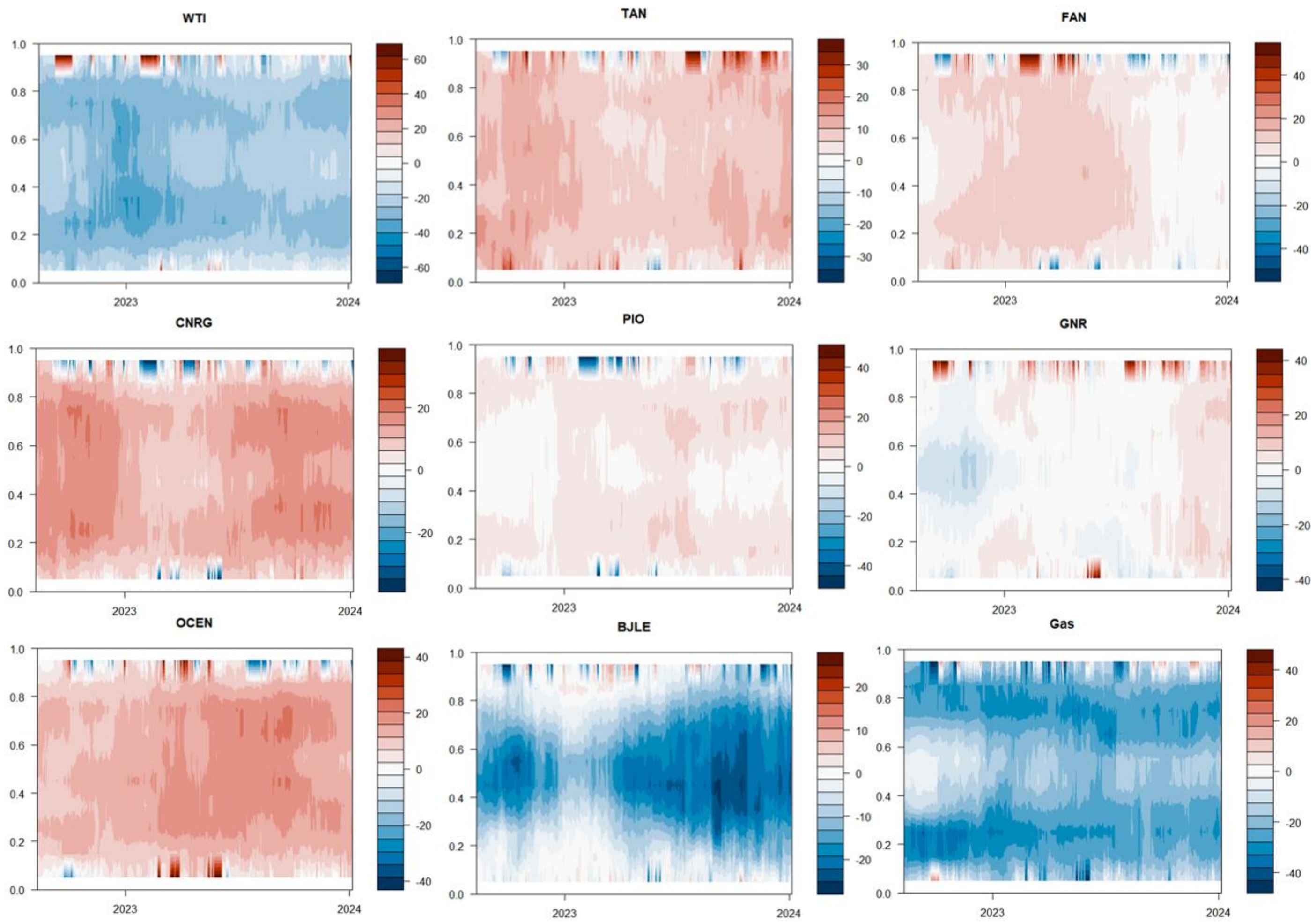
Figure 4. Dynamic total connectedness



Note: The heatmap was generated using a 100-day rolling window and a 20-day ahead forecast based on the QVAR(1) model. The x-axis represents the timeline, and the y-axis reports the quantiles. The quantiles are from 0.05 to 0.95 with a 1% iteration. The color gradient in the heatmap ranges from light yellow (low level of connectedness) to dark red (high level of connectedness)

Overall, these findings highlight that, despite fluctuations, the overall interconnectedness within the indices remains stable, with notable peaks during periods of heightened market volatility, which reinforces the robustness and resilience of the observed relationships. It is also important to highlight that this dynamic connectedness shows a symmetrical pattern. Additionally, the fluctuations in the 50% quantile, which represents the network's average Total Connectedness Index (TCI), show a cyclical pattern. Spillovers were particularly intensified during 2022 and the fourth quarter of 2023.The timeline is represented on the x-axis, and the quantiles, which range from 0.05 to 0.95 and are iterated at 1% intervals, are plotted on the y-axis. Warmer segments show higher levels of connectedness, whereas lighter regions present lower levels. Dynamic shocks emanating from both significantly positive (above the 75th percentile) and negatively shifted assets (below the 25th percentile) demonstrate robust interconnections across the entire sample period. It is also important to highlight that this dynamic connectedness shows a symmetrical pattern. Additionally, the fluctuations in the 50% quantile, which represents the network's average Total Connectedness Index (TCI), show a cyclical pattern. Spillovers were particularly intensified during 2022 and the fourth quarter of 2023

Figure 5. Net Directional Connectedness



The analysis of net total connectedness in Figure 5 across quantiles unveils a dynamic landscape where variables exhibit shifting roles as net transmitters or receivers over time and quantiles. Notably, oil and gas consistently assume a net receiver status throughout most of the study period, while PIO and BJLE display such status during specific years (especially during 2023). Conversely, OCEN, GNR, ICLN, CNRG, FAN, TAN, and Gas consistently act as weak net transmitters across the entire study period, as indicated by median quantiles. Moreover, the asymmetrical net connectedness between lower and upper quantiles underscores non-linear dynamics within the system. These insights hold significant implications for risk management, portfolio optimization, market analysis, and policy formulation, enabling stakeholders to navigate market complexities and make informed decisions in various domains.

The interpretation of the time-frequency connectedness plot suggests a dynamic interplay between short-term and long-term connectedness among the variables. While the overall trend indicates that total connectedness leans towards the short term, this can be attributed to the higher frequency of fluctuations and interactions occurring within shorter time intervals. Therefore, the dominance of short-term connectedness may reflect the rapid transmission of information and the heightened sensitivity of asset prices to short-term events. Additionally, this dominance can be attributed to events such as economic announcements, geopolitical crises, policy shifts, or fluctuations in market sentiment, which often generate immediate price reactions. For instance, sudden changes in oil prices, regulatory updates affecting renewable energy, or news related to environmental policies can cause quick adjustments in green finance and energy markets.

These fast-moving events lead to short-term interconnectedness, as the markets react rapidly to new information. The dominance of short-term connectedness reflects the immediate responsiveness of markets to information, shocks, and speculative behavior,Baruník et al. (2018), Cui et al. (2021), Umar et al. (2022). Economic events, whether related to changes in energy prices, policy shifts, or broader market fluctuations, tend to have rapid and widespread effects on the interconnectedness between green finance, energy commodities, and the blue economy. Theoretical frameworks, such as the Efficient Market Hypothesis, time-varying parameter models, and behavioral finance, all provide insights into why short-term interactions are more pronounced in this context. This understanding is crucial for market participants looking to navigate the volatility and short-term dependencies within these interconnected sectors. While the overall trend indicates that total connectedness leans towards the short term, there are specific periods where this relationship shifts. During certain intervals (specifically, 2022 and once at the beginning of 2023), the short-term connectedness exceeds the total connectedness, indicating heightened interactions and dependencies among the variables over shorter time horizons. Conversely, in other periods (mid-2023 and at the beginning of the fourth quarter of 2023), the long-term connectedness exceeds the total connectedness, suggesting that the relationships between variables are more enduring and pronounced over longer durations. These fluctuations in the dominance of short-term and long-term connectedness underscore the evolving nature of interactions within the system, reflecting varying degrees of influence and correlation over different time scales. Understanding these dynamics is crucial for formulating effective risk management strategies, optimizing portfolio allocations, and making informed decisions in dynamic financial environments.

Figure 6. Dynamic Total Connectedness by frequencies

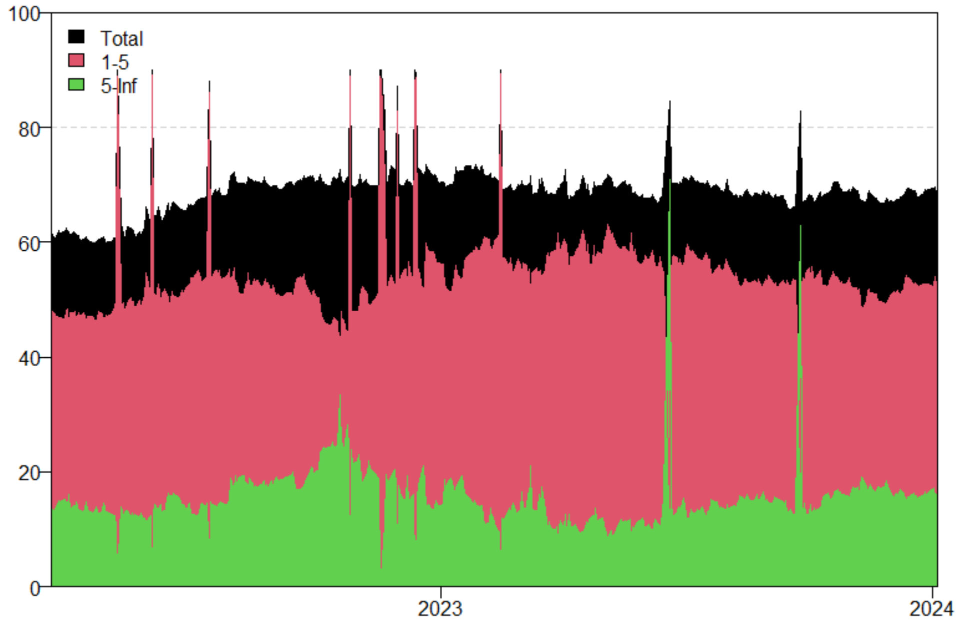


Figure 7. Dynamic Total Net Connectedness by frequencies

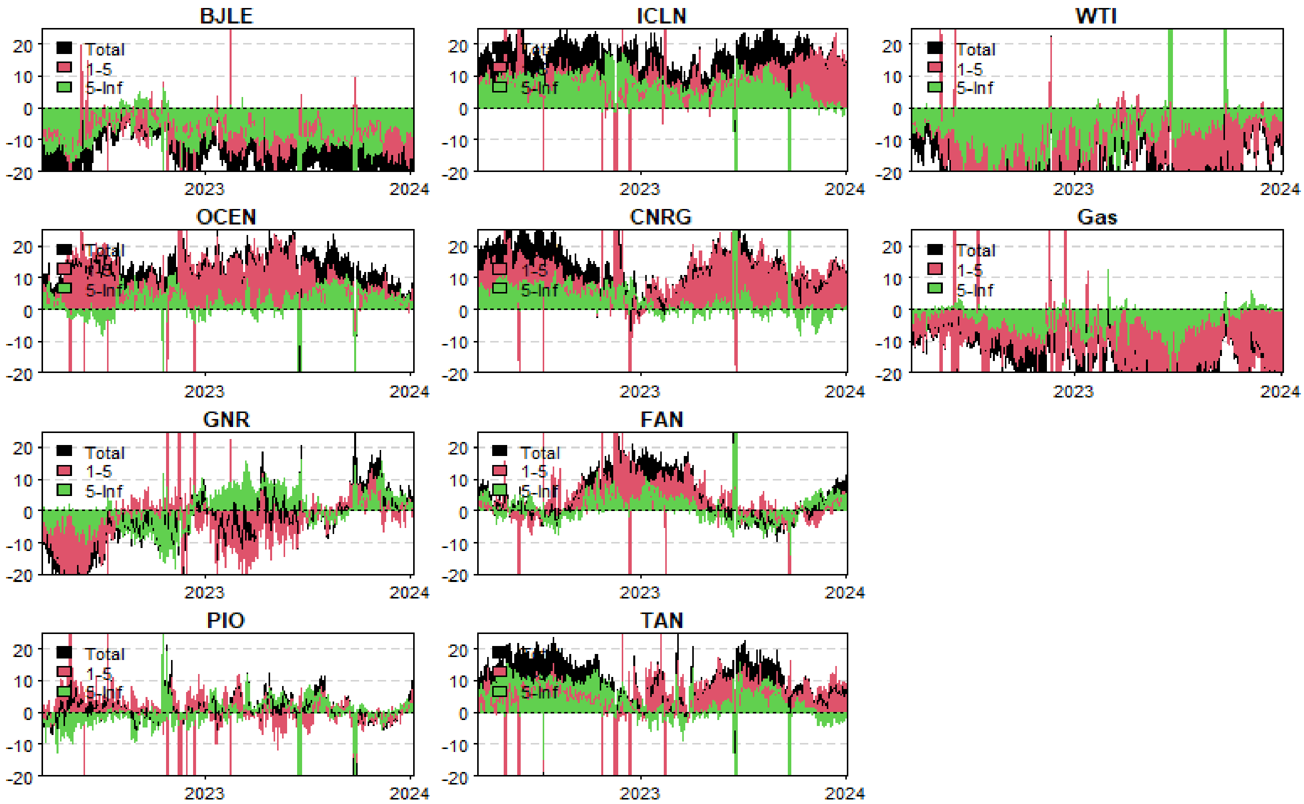
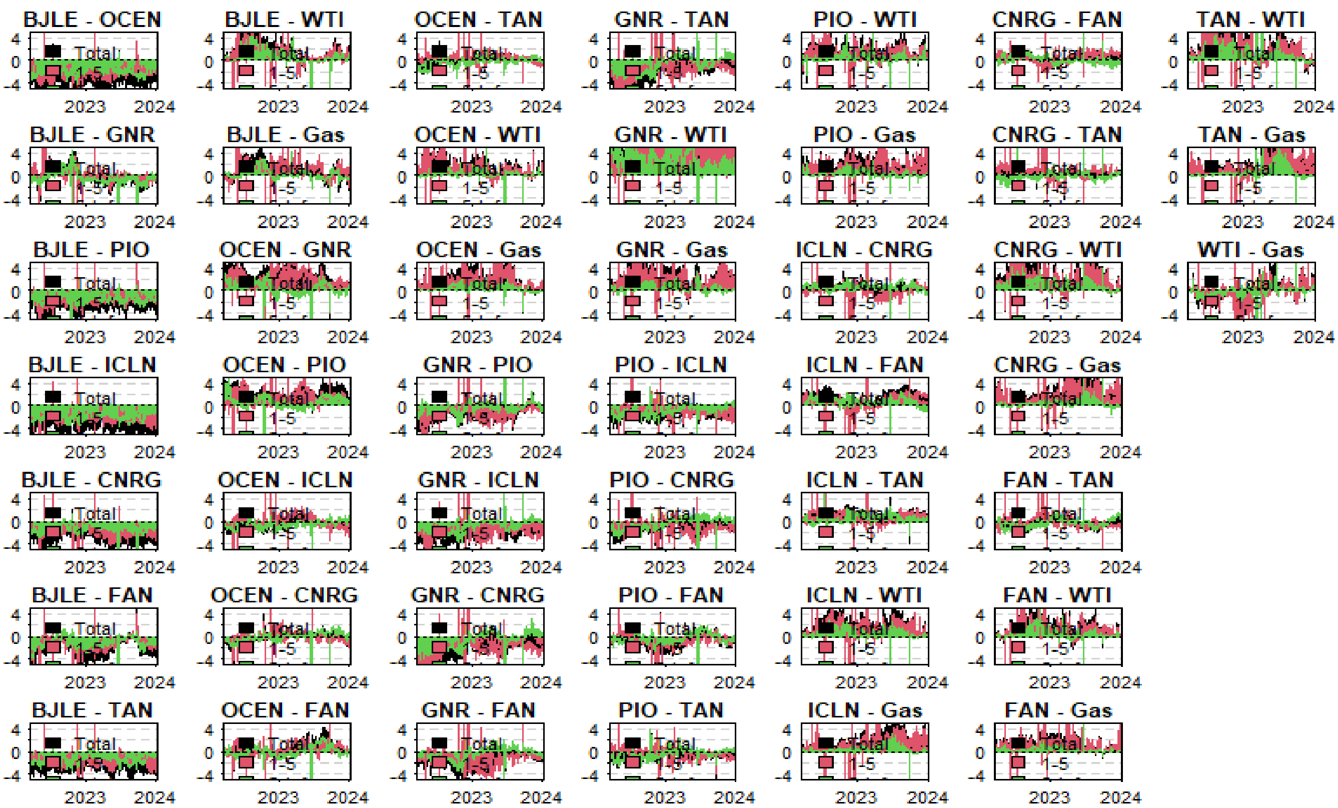


Figure 8. Dynamic Pairwise Connectedness by frequencies



5. Conclusion and discussion

This study provides a comprehensive analysis of the interconnectedness between green finance and blue economy stock indices, and oil and gas indices, from October 26, 2021, to January 5, 2024. By employing TVP-VAR-based connectedness analysis across various quantiles, and extending it to the QVAR model, we uncover nuanced responses of these variables to structural shocks, particularly during extreme market conditions. The results reveal consistently high levels of total connectedness, with fluctuations between 90% and 100%, reflecting the significant and persistent connectivity among the assets under investigation. This supports the findings of Lorente et al. (2023), who also highlighted the substantial influence of green financial assets and clean energy on financial markets. A key finding of our study is the dynamic net total connectedness, which demonstrates considerable fluctuations between net receiver and net transmitter roles across different variables. Specifically, oil and gas indices are consistently net receivers of shocks throughout the study period, while PIO and BJLE assume this role only during specific years (2022 and 2023). This aligns with the work of Umar et al. (2021) and Rehman et al. (2023), who noted that oil indices act as net receivers of volatility during extreme market conditions. On the other hand, clean energy indices such as OCEN, GNR, ICLN, CNRG, FAN, and TAN maintain weak net transmitter characteristics, particularly in the median quantiles.

Our study also highlights non-linear dynamics, with asymmetrical net connectedness observed between the lower and upper quartiles. These non-linear patterns suggest that the strength and direction of spillovers differ under varying market conditions. The presence of such asymmetry underscores the need for a deeper understanding of how different economic factors interact over time, particularly during periods of heightened market stress, as seen in 2022 and the fourth quarter of 2023. This finding extends the work of Dogan et al. (2022) and Gao et al. (2024) by demonstrating that this asymmetry not only emerges during stable periods but also intensifies under crisis conditions—a nuance previously unexplored.

In terms of practical implications, our findings offer valuable insights for risk management, portfolio optimization, and market analysis. The identification of consistent net receivers and transmitters of shocks provides crucial information for energy-related portfolios, helping investors manage risk exposure and enhance portfolio performance. The study also provides actionable insights for policymakers and industry stakeholders, who can leverage these findings to design more effective energy policies and strategies, contributing to sustainable and resilient economic development.

By advancing the understanding of the interconnectedness between green finance, the blue economy, and energy commodities, this study enriches the current understanding of market dynamics. It provides a framework for navigating the complexities of financial and energy markets. The findings underscore the need for continuous monitoring of these interconnected markets, particularly in light of their increasing importance for both economic stability and achieving sustainability goals.

6. Policy and practical implications

In light of the study's findings, it is crucial to identify specific areas where current policies fall short and propose actionable recommendations for addressing these deficiencies. Given the increasing interconnectedness between green finance, the blue economy, and energy commodities, it is evident that existing policy frameworks often lack the flexibility and foresight to effectively manage these dynamic relationships.

Firstly, current energy policies often treat green finance and clean energy as separate entities, with limited consideration of their synergies and the potential risks associated with their interconnectedness. As our study reveals, green finance and clean energy indices demonstrate substantial spillover effects on each other, especially during periods of market turbulence. Therefore, policymakers should establish a more integrated framework that encourages alignment between green finance initiatives and energy policies. This can be achieved either by incentivizing investments in green energy sectors through targeted subsidies or tax incentives, or by encouraging financial products and portfolios that combine clean energy investments with green finance instruments. In this framework, policymakers should establish inter-ministerial committees that focus on integrating financial and energy policies, alongside creating a regulatory sandbox to test novel green finance and energy solutions. This integration would not only strengthen the financial resilience of the green economy but also enhance the long-term sustainability of energy transition goals.

Secondly, policymakers should improve risk management and diversification for green energy portfolios. Indeed, financial markets, especially those focused on energy commodities, often lack sufficient mechanisms for managing risk, particularly in the context of extreme market fluctuations and environmental shocks. Hence, policymakers should encourage the development of more sophisticated risk management tools that account for the complex, non-linear relationships between green finance, blue economy indices, and energy commodities. This can be achieved either by promoting the development of financial instruments, such as green bonds, ESG-focused derivatives, and climate risk-adjusted portfolios, or by mandating disclosure requirements for climate-related financial risks and their impact on energy markets. In this context , policymakers should introduce legislation requiring financial institutions to integrate climate risk assessments into their investment strategies and portfolio management processes. This collaboration among financial regulators, financial institutions, and climate experts aims to develop suitable risk models and enhance financial stability within the green energy sector, ultimately fostering greater investor confidence.

Thirdly, this circumstance necessitates promoting global cooperation on green finance and energy policy: Green finance and energy policies are often fragmented at the national level, with limited global coordination. This can lead to inconsistent outcomes and hinder the achievement of global sustainability goals. Hence, policymakers should strengthen international cooperation to ensure that green finance and energy transition efforts are globally coordinated and aligned. This could be achieved by supporting global frameworks for green finance and carbon markets, such as the Paris Agreement, to align national policies with global climate goals, or by encouraging multilateral agreements on clean energy investments and financing, particularly for developing economies. in this context, policymakers should engage in international dialogues and forums, such as the UN Climate Change Conference (COP), to push for stronger commitments to integrated green finance and energy policies. This strategy will enhance global alignment on energy transition and green finance goals, thereby amplifying the effectiveness of national policies and helping to meet international climate targets.

In addition to policy changes, the findings of this study offer practical guidance to market participants and stakeholders in the energy and financial sectors: For example, the identification of consistent net transmitters and receivers of shocks (e.g., gas and oil as net receivers; certain clean energy indices as transmitters) provides actionable insights for portfolio diversification, risk hedging, and tail-risk management—especially in volatile or crisis-prone periods.

For financial institutions, our study highlighted dynamic and asymmetric spillovers across quantiles, emphasizing the importance of incorporating climate scenario analysis and stress testing into portfolio strategies. Financial institutions should refine their modeling tools to better capture non-linear dependencies across green and traditional energy assets. Furthermore, clean energy and blue economy enterprises can utilize our findings to gain a deeper understanding of how financial market volatility affects their access to finance. Aligning business strategies with green finance trends may improve funding prospects and investor appeal.

7. Limitations and future recommendations

While this study provides valuable insights into the interconnectedness between green finance, the blue economy, and energy commodities, some limitations must be acknowledged to contextualize the findings, especially in the methodology and exogenous shock integration: The use of TVP-VAR and QVAR models provides robust results but may not fully capture nonlinearities or higher-order dependencies that other advanced models like machine learning techniques could uncover. In addition, while the study identifies periods of heightened connectedness due to events like the COVID-19 pandemic and geopolitical events, the analysis does not explicitly model the impact of other exogenous shocks such as financial crises or policy changes. To build on these findings and address existing limitations, future research could explore several areas. Firstly, we can employ advanced nonlinear econometric or machine learning models, such as Deep Neural Networks, to uncover hidden patterns and improve the predictive accuracy of interconnectedness measures. Secondly, we can Conduct scenario-based analyses to isolate the effects of distinct exogenous shocks, such as geopolitical crises or major policy shifts (e.g., carbon taxes), which would enhance understanding of how these events reshape market interconnectedness. Finally, we can improve our study by integrating investor sentiment and behavioral biases, and exploring how these variables influence connectedness among green finance, energy commodities, and blue economy indices. This could provide new perspectives on market dynamics.

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