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Unpacking Clean and Dirty Energy Market Linkages: Fresh Evidence from Quantile-on-Quantile Connectedness and Causality-in-Quantiles

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ABSTRACT

This research investigates the interrelationships between clean and dirty energy markets, focusing on both return and volatility dynamics over the period from March 03, 2005 to August 30, 2024. Employing the recently developed quantile-on-quantile connectedness (QQC) framework, alongside a causality-in-quantile (CiQ) analysis, the study explores directional spillovers across varying market conditions. The findings reveal several key insights. First, connectedness is highly heterogeneous across quantiles, with stronger spillovers observed in the tails of the distribution—indicating that extreme market conditions foster intensified transmission between energy sectors. Second, total connectedness among directly related quantiles is consistently higher than that of reversely related quantiles, for both return and volatility spillovers. Third, the connectedness between clean and dirty energy markets surpasses that between clean energy and WTI crude oil, reflecting tighter financial integration between equity-based energy indices. Notably, while the dirty energy market initially receives shocks from the clean market, it later emerges as a shock transmitter. Meanwhile, WTI plays a more symmetric role in return spillovers but predominantly transmits volatility shocks at moderate to higher quantiles. Additionally, quantile-based spillovers show marked time variation, spiking during systemic events such as the global financial crisis and the COVID-19 pandemic. CiQ analysis confirms the existence of bidirectional causality. These findings have important implications: for policymakers, they highlight the need to account for sectoral interdependence in energy transition planning; for investors, they underscore the limited hedging capacity between clean and dirty energy assets and the necessity of quantile-aware risk management strategies.

Keywords: Clean/Dirty Energy, WTI Oil, Return and Volatility Connectedness, Quantile-on-Quantile, Causality in Quantiles
JEL Classifications: C32, G11, G15, Q40, Q49

1. INTRODUCTION

Dirty energy sources, primarily derived from fossil fuels, have historically been the dominant force behind social and economic development worldwide (Farid et al., 2023). However, this development has had a substantial environmental impact and health cost due to the accelerated environmental degradation. Particularly, the increased reliance on fossil fuels has become a major driver of GHG emissions, which are known to be a key contributor to global warming (Dias and Galvão, 2023). In response to the environmental issues, there is an urgent global push to transition towards clean energy sources, like solar, wind, hydropower, and geothermal, alongside advancements in energy efficiency technologies, electric vehicles (EVs), and energy storage solutions (Dias et al., 2023). Renewable energy is now viewed not only as an environmental necessity but also as a catalyst for sustainable economic growth (Wesseh and Lin, 2016). As climate change mitigation becomes central to policy agendas, the development and deployment of clean energy technologies offer significant opportunities for innovation, investment, and resilience. International frameworks such as the 2015 Paris Agreement and subsequent COP summits have placed financial institutions, investors, and policymakers at the heart of this transition. Achieving global climate goals hinges on their ability to mobilize and allocate capital efficiently toward sustainable energy solutions.

The interplay between fossil fuel (dirty) and renewable (clean) energy markets has been the subject of a growing body of research, generally reflecting two dominant perspectives (Su et al., 2023). The first centers on the substitution effect, which posits an inverse relationship between the two markets. According to this view, increases in fossil fuel prices incentivize investment in renewables, thereby raising the returns of clean energy equities (Bondia et al., 2016; Ferrer et al., 2018; Foglia and Angelini 2020; Zhao, 2020). The second perspective, the decoupling hypothesis, suggests that clean and dirty energy markets operate independently, shaped by distinct economic drivers and market mechanisms (Ahmad, 2017; Yilanci et al., 2022). Understanding the linkages between these markets is crucial for investors, policymakers, and researchers alike. These interactions can influence investment strategies, asset pricing, risk management, and broader economic trends (Umar et al., 2022). As global energy systems evolve, the performance and risk profiles of both clean and dirty energy equities are becoming increasingly interdependent. This interconnectedness highlights the need for analytical frameworks that can capture the complexity and dynamics of these relationships.

This study aims to investigate the spillover effects between clean and dirty energy markets using the recently developed quantile-on-quantile connectedness (QQC) approach introduced by Gabauer and Stenfors (2024). To the best of our knowledge, this is the first application of the QQC method to analyze interconnectedness in the energy sector. While previous studies have largely focused on average or linear linkages, our approach enables a state-dependent, non-linear analysis of transmission mechanisms across the full conditional distribution of returns and volatility. This allows us to explore how shocks propagate differently across extreme, moderate, and neutral market conditions. The theoretical foundation of this research draws from the contagion theory and broader literature on market connectedness, which highlight that shocks in one market can spill over to others, especially under crisis conditions, leading to heterogeneous transmission across different parts of the return and volatility distributions (Bigerna, 2024; Ouyang et al., 2023; Wu et al., 2023).

Our study makes several contributions to the existing literature. First, we provide a dynamic analysis of energy market connectedness using the QQC approach, which distinguishes between directly and inversely related quantiles. This allows for a more nuanced understanding of how transmission mechanisms operate under varying market conditions, including times of stress and recovery. The QQC method also captures the evolving nature of clean–dirty relationships amid technological changes and shifting policy regimes. Second, we examine both return and volatility spillovers, providing deeper insight into the direction, magnitude, and persistence of cross-market transmission. This is crucial for evaluating hedging effectiveness, portfolio diversification, and systemic risk. Understanding how extreme returns or volatility in one market (e.g., oil price crashes) influence the other helps inform better risk mitigation strategies. Third, the paper explores the strategic implications of pairing clean energy stocks with either crude oil or dirty energy stocks. While pairing with crude oil may provide diversification and a potential hedge, combining clean and dirty energy stocks may appeal to investors seeking balanced exposure to the energy transition. These strategies are particularly relevant as investors navigate uncertainties associated with technological disruptions and regulatory shifts. Finally, our empirical analysis is based on a robust dataset from March 3, 2005, to August 30, 2024, covering a wide range of market conditions, including the 2008 global financial crisis, the oil price crash, the COVID-19 pandemic, and geopolitical conflicts such as the Russia–Ukraine and Israel–Palestine wars. These periods offer a rich backdrop to assess how spillovers evolve during systemic shocks and which markets act as net transmitters or receivers of shocks.

This study seeks to address key questions such as: Are there significant contagion effects between clean and dirty energy markets under extreme conditions? How do these effects vary across quantiles? What are the implications for portfolio construction when pairing clean energy stocks with dirty or crude oil equities? The answers provide valuable guidance for investors, portfolio managers, and policymakers striving to navigate an increasingly complex and volatile energy landscape.

The remainder of this paper is structured as follows: Section 2 reviews the relevant literature. Section 3 details the data and methodology. Section 4 presents the empirical findings. Section 5 discusses practical implications for portfolio and risk management. Finally, Section 6 concludes with a summary and key policy takeaways.

2. EXISTING LITERATURE

Energy transition has recently become more urgent, driven by the necessity to combat climate change and establish more sustainable economic systems. A carbon-resilient economy refers to an economy that can effectively decrease its GHG emissions and withstand the impacts of climate change, while promoting long-term economic growth and improving social well-being. This transition is essential for limiting global warming and minimizing the risks associated with a high-carbon economy. The Paris Agreement is central to global attempts to address climate change and lower atmospheric GHG emissions. It embodies milestones in the ongoing international collaboration aimed at preventing dangerous levels of global warming. The primary objective of the agreement is to mitigate the rise in global temperatures below 2°C above pre-industrial levels. COP28 held in Dubai is a crucial event following Paris Agreement and a platform for reviewing progress and enhancing action against climate change. The Paris Agreement set the framework and long-term goals, while COP28 assess and drive forward the actions needed to meet those goals, with particular attention to finance, equity, and adaptation.

As the world moves toward future COP conferences, such as COP28, the urgency to expedite the transition toward sustainable practices becomes more pronounced, particularly in the context of environmental degradation, climate change, and socio-economic inequality. Particularly, under the Paris agreement and COP28, corporations and investors are anticipated to take on an increasingly critical role in driving this transformation, channelling capital into sustainable ventures and influencing corporate behaviour (Luo et al., 2023; Lei et al., 2022; Fahmy, 2022) proved that investors are increasingly aware of climate-related risks and their focus on green investments has increased specifically following the adoption of Paris Agreement. In a similar vein, recent studies, including those by Bouri et al. (2022), have corroborated the substantial impact of climate policy on clean energy stock markets. In this context, renewable energy equities are considered as a remarkable investment category, garnering substantial interest from a range of actors within the financial sector. As a result, clean energy companies are drawing growing interest from investors and other stakeholders.

2.1. Research on the Relationship between Clean/Green and Dirty Energy Assets

The relationship between clean/green energy assets and dirty energy assets, particularly fossil fuels, has been a subject of increasing interest in academic literature. Henriques and Sadorsky (2008) were among the first to explore the impact of oil prices on the stock performance of alternative energy firms. Their findings indicated that fluctuations in oil prices significantly influence renewable energy stocks, suggesting that rising oil prices tend to increase investor interest in renewable energy as a hedge against the volatility of fossil fuel markets. Similarly, Kumar et al. (2012) examined the effects of oil prices on renewable energy stocks and proved a significant association between oil price movements and clean energy stocks, indicating that the increase in oil prices often boosts interest in clean energy investments. Moreover, the findings advocated that oil price volatility can strengthen the attraction of renewable energy stocks. Broadstock et al. (2012) also investigated the outcomes of oil prices on the stock price of alternative energy firms. Managi and Okimoto (2013) studied the influence of oil price shocks on the stock prices of renewable energy companies in Japan using the M-S VAR model. The findings suggest that increased oil prices may enhance the attractiveness of renewable energy investments, while also highlighting the significance of market volatility in determining the dynamics of the clean energy sector. Reboredo (2015) used copulas and conditional value at risk techniques, and concluded that oil price dynamics have a significant impact on both the downside and upside risks of renewable energy firms. Reboredo et al. (2017) built on the research of Reboredo (2015) by examining the influence of oil price shocks not just in the U.S. and Europe, but across multiple countries, including emerging markets, using wavelets. The findings reveal that dependence between oil and renewable energy returns was weak in the short run but progressively reinforced in the long run. Zhang and Du (2017) used a TVP-SV-VAR model and showed that the stock prices of new energy companies are more sharply correlated with high-tech stock prices than with those of coal and oil companies. Dutta (2017) examined whether the volatility of alternative energy stock returns could be linked to the information provided by the crude oil volatility index (OVX). He revealed that returns in the clean energy stock market are significantly influenced by fluctuations in the OVX. Using a quantile-founded framework, Dawar et al. (2021) investigated the connection between crude oil prices and renewable energy stock prices.

The findings indicate decreasing dependence among the prices of clean energy stock and crude oil. The delayed impact of oil price changes on the performance of clean energy stocks is often statistically substantial, implying that the performance of clean energy stocks reacts in varying ways to changes in oil prices, influenced by the prevailing market environment. Yahya et al. (2021) utilized an integrated approach, combining a two-regime threshold vector error correction model with the DCC-GARCH framework. Their findings revealed a nonlinear, regime-dependent long-term interconnectedness among the assets, observed in both the first and second moments. Moreover, results prove that the Clean Energy Index has emerged as the primary driver influencing crude oil prices during and after the ongoing COVID-19 pandemic. Using the quantile cross-spectral dependence approach, Maghyereh and Abdoh (2021) demonstrated that the effect of oil supply shocks on clean energy company returns is predominantly concentrated in the short term, whereas the influence of demand shocks is more pronounced over the medium and long term. Besides, supply shocks in the oil market exert a stronger influence on the returns of oil and gas stocks compared to those of clean energy stocks.

Farid et al. (2023) examined the interconnected dynamics between clean energy stocks and traditional fossil fuel markets, both prior to and throughout the COVID-19 pandemic, employing a wavelet-based methodology. The results demonstrate weak associations in the short-run, and few instances of elevated co- movements among the considered markets in the long-run. Moreover, the results also prove that clean energy market is fairly separated from dirty energies during the recent pandemic crisis.

Using the Granger causality test, Dias et al. (2023) explored the causal flows between various dirty and clean stock indexes whether clean energy indexes. The results indicate that neither energy index can act as a hedge or provide safe-haven protection for clean energy companies during periods of market volatility.

2.2. Research Focusing on Connectedness Measures

Certain studies have utilized the connectedness methods derived from the basic connectedness approach of Diebold and Yilmaz (2012) to examine the effects between crude oil or traditional energy stocks and clean energy stocks. For instance, Ahmad (2017) demonstrated that clean energy assets play a significant role in transmitting return and volatility shocks to crude oil prices. Similarly, Ferrer et al. (2018) adopted an approach based on Baruník and Křehlík (2018) to examined the relationship between oil price volatility, the stock performance of renewable energy firms. Their findings indicate that most return and volatility connectedness occur predominantly in the short term, with long-term connectedness contributing only marginally. Additionally, their results suggest that oil prices are not a key factor influencing the stock market performance of clean energy firms, indicating that other factors may be more influential in driving renewable energy stock movements. Naeem et al. (2020) found that the net pairwise directional connectedness between oil shocks and the clean energy index increased significantly during the shale oil revolution. Using a quantile-based connectedness approach, Saeed et al. (2021) underlined greater spillovers between clean and oil markets in upper and lower tails of distribution. Focusing on oil price and clean energy firms, Foglia and Angelini (2020) observed significant shifts in both static and dynamic volatility connectedness surrounding the onset of the COVID-19 pandemic.

Corbet et al. (2020) used the approach of Diebold and Yilmaz (2012) and a DCC-FIGARCH and showed positive and substantial spillovers from declining oil prices impacting both the renewable energy and coal sectors. Nevertheless, this outcome is merely retrieved for the limited portion of the sample encompassing the negative WTI event. Using a TV- VAR model with stochastic volatilities, Ghabri et al. (2021) showed a substantial strengthen in the returns of clean energy stocks following the steep decline in crude oil prices. Conversely, the inverse influence is observed on renewable energy stock returns after the OPEC+ accord. The findings also specify that the statement of COVID-19 outbreak a global pandemic triggered the prices of both renewables and Natural gas to upsurge after a decline. Similarly, Umar et al. (2022) applied both the time (Diebold and Yilmaz, 2012) and frequency (Baruník and Křehlík, 2018) domain connectedness approach and find feeble volatility relationships between clean-energy stocks and dirty energy markets. Further, the results also show that spillover influences between the energy markets augment in periods of crisis. Recently, using the TVP-VAR approach, Alharbey et al. (2023) assessed the volatility transmission between clean and fossil energy markets. Their findings revealed that the oil market and the Asian renewable energy stock market act as net receivers of volatility shocks, while the US and European renewable energy stock markets serve as net transmitters of such shocks.

This research aims to build upon the latest body of work by examining the dynamic relationship between clean and dirty energy markets. While previous studies have highlighted the time-varying nature and asymmetry in the connectedness between these markets, there is a notable gap in fully characterizing this relationship under varying market conditions. Although some recent studies have focused on the connectedness between the two series at means or under the assumption that all series are linked to the same quantile, none of them has assessed the spillover and transmission mechanisms between clean and dirty energy markets using a purely quantile-based spillovers approach. This study addresses this empirical gap by applying a quantile-based framework to explore how these markets interact across different quantiles, providing a more nuanced understanding of the dynamics and potential spillovers between clean and dirty energy markets under various market conditions.

3. DATA AND METHODOLOGY

3.1. Data and Preliminary Analysis

The sample of this study consists of Clean and Dirty assets over the period running from March 03, 2005 to August 30, 2024. This timeframe was chosen to ensure the availability of complete data for all series under consideration and to cover a significant period of market dynamics, including crises and transitions. Specifically, we use the Invesco WilderHill Clean Energy ETF (Fund) as a proxy for the clean energy index. This ETF is widely regarded as a representative measure of the clean energy sector, as it tracks companies involved in the development and commercialization of renewable energy technologies. The choice of this ETF is supported by its broad composition of clean energy firms, which makes it a reliable proxy. For the dirty energy index, we use the Energy Select Sector SPDR Fund (NYSEARCA: XLE), which primarily focuses on the oil and gas industries and is a commonly accepted benchmark for the traditional energy sector. This fund captures the performance of companies in the oil, gas, and energy equipment sectors, making it an appropriate proxy for dirty energy assets. Additionally, we include WTI crude oil prices as a direct measure of oil price dynamics, which are central to the functioning of dirty energy markets. These data sources were chosen based on their prominence and relevance to the energy sector and are widely utilized in both academic and industry research. The combination of these three proxies allows us to capture the performance of both clean and dirty energy markets comprehensively. The data is challenging to model since it contains several significant events such as the 2008 global financial crisis (GFC), an oil price crash, COVID-19 pandemic, Russia–Ukraine conflict, and the Israel-Palestine conflict. For empirical investigation, we transform all asset series into logarithmic returns to ensure consistency across the data. Both return and volatility[1] dynamics of the assets under examination are volatile and time-varying, with notable fluctuations observed during the GFC and the COVID-19 pandemic. Table 1 presents the descriptive statistics for the return and volatility series of the variables under consideration.

Figure 1 illustrates the time series trajectories of the return (Ret) and volatility (Vol) series for the selected assets, providing a visual representation of their dynamic behaviour over time. Table 1 reports the key statistical properties of these series, including measures of central tendency, dispersion, and distributional characteristics. In Panel A, the return series display high kurtosis and significant negative skewness—especially pronounced for WTI, indicating the presence of heavy tails and asymmetry. These features are further confirmed by the highly significant Jarque-Bera test results, rejecting normality across all series. The ERS unit root test confirms stationarity, and the Ljung-Box Q and Q^2 statistics highlight the presence of both autocorrelation and strong conditional heteroskedasticity. The correlation matrix suggests moderate return co-movement between clean and dirty assets (0.61), with a weaker relationship between clean and oil (0.24). Panel B shows that volatility series are strongly skewed and leptokurtic, particularly for WTI, with maximum volatility peaking during turbulent market episodes. Significant ERS and Q-statistics confirm volatility clustering and serial dependence. Notably, clean and dirty volatilities are highly correlated (0.804), while WTI exhibits a more moderate relationship with both. These stylized facts highlight the dynamic and nonlinear behaviour of the

1 The volatility series were derived from an optimal GARCH model, which was selected based on model fit criteria.

Table 1: Descriptive statistics and preliminary tests for return and volatility series

Statistics	Clean	Dirty	WTI
Panel A: Return series			
Mean	−0.028	0.015	0.007
Median	0	0.015	0.092
Maximum	15.82	15.25	42.583
Minimum	−15.637	−22.491	−72.027
Standard deviation	2.261	1.897	2.894
Skewness	−0.289***	−0.704***	−2.342***
Ex. Kurtosis	4.583***	13.278***	100.751***
Jarque-Bera	4498.726 (0.00)	37597.25 (0.00)	2145176 (0.00)
ERS	−32.325*** (0.00)	−13.337*** (0.00)	−22.696*** (0.00)
Q (10)	17.575*** (0.00)	25.329*** (0.00)	77.084*** (0.00)
Q^2 (10)	2304.057***	2100.707***	752.563***
Correlation matrix			
Clean	1		
Dirty	0.61***	1	
WTI	0.24***	0.48***	1
Panel B: Volatility series			
Mean	2.066	1.65	2.261
Median	1.849	1.461	2.001
Maximum	7.811	8.561	20.566
Minimum	0.893	0.527	0.868
Standard deviation	0.921	0.84	1.305
Skewness	2.03	3.141	5.772
Ex. Kurtosis	6.788***	15.369***	52.889***
Jarque-Bera	13192.188*** (0.00)	58135.356*** (0.00)	617974.867*** (0.00)
ERS	−5.575*** (0.00)	−5.320*** (0.00)	−6.395*** (0.00)
Q (10)	25325.131*** (0.00)	25570.928*** (0.00)	24009.631*** (0.00)
Correlation matrix			
Clean	1		
Dirty	0.804***	1	
WTI	0.561***	0.740***	1

***denotes statistically significant at 1% confidence level. Values in parentheses are the *P* values on the corresponding tests

series, motivating the application of quantile-based connectedness techniques in subsequent analysis.

To provide a more thorough evaluation of the stationary stationarity status of the data series, we also perform the Quantile Unit Root Test (QURT), introduced by Galvao (2009) and Koenker and Xiao (2004). The primary advantage of this test is that it allows evaluating the stationary properties of a series under different distributional levels, a capability that traditional unit root tests lack. The findings, as shown in Table 2, confirm the stationarity of all examined series across all considered quantiles of the conditional distribution. The above analysis confirms that all series have non-null skewness and Excess kurtosis is omnipresent, and Statistics from the Jarque-Bera (JB) test show that all returns are not normally distributed and justifies the adoption of quantile-based analysis to comprehend the transmission spillover between the considered series.

Table 2: Unit root test in quantile results for return series

Quantile order	Clean		Dirty		WTI	
	t-stat	CV	t-stat	CV	t-stat	CV
0.05	−13.04	−3.26	−20.21	−3.16	−22.44	−2.76
0.1	−31.22	−3.29	−32.05	−3.01	−38.04	−2.73
0.15	−35.84	−3.31	−43.05	−3.1	−52.54	−2.73
0.2	−43.75	−3.3	−51.58	−3.11	−60.39	−2.67
0.25	−51.03	−3.29	−60.14	−3.03	−67	−2.68
0.3	−56.32	−3.25	−67.9	−3.03	−71.1	−2.7
0.35	−62.44	−3.21	−76.24	−2.99	−77.75	−2.68
0.4	−73.9	−3.16	−89.56	−2.95	−85.22	−2.65
0.45	−76.16	−3.1	−93.95	−2.93	−88.62	−2.6
0.5	−80.35	−3.05	−97.11	−2.92	−92.74	−2.59
0.55	−79.03	−2.97	−96.89	−2.88	−94.22	−2.59
0.6	−73.76	−2.86	−84.59	−2.79	−94.59	−2.58
0.65	−68.65	−2.77	−80.71	−2.67	−90.94	−2.54
0.7	−65.27	−2.67	−73.58	−2.6	−87.8	−2.51
0.75	−61.98	−2.61	−67.76	−2.54	−78.35	−2.46
0.8	−56.24	−2.59	−63.15	−2.45	−71.46	−2.34
0.85	−50.71	−2.47	−53.62	−2.4	−64.7	−2.27
0.9	−43.18	−2.36	−40.68	−2.31	−53.07	−2.17
0.95	−20.6	−2.31	−25.59	−2.31	−25.49	−2.12

The null hypothesis is rejected at the α quantile level (α=0.05, …, 0.95) if the t-statistic falls below the 5% critical value (CV). It is worth noting that the volatility results are not included here for brevity but are available upon request

3.2. Methodology

3.2.1. QQC approach

The current study employs the QQC method, introduced by Gabauer and Stenfors (2024), to examine the transmission mechanisms in both returns and volatility between Clean and Dirty assets. The QQC is an extension of the quantile vector autoregressive model, QVAR(q), given by:

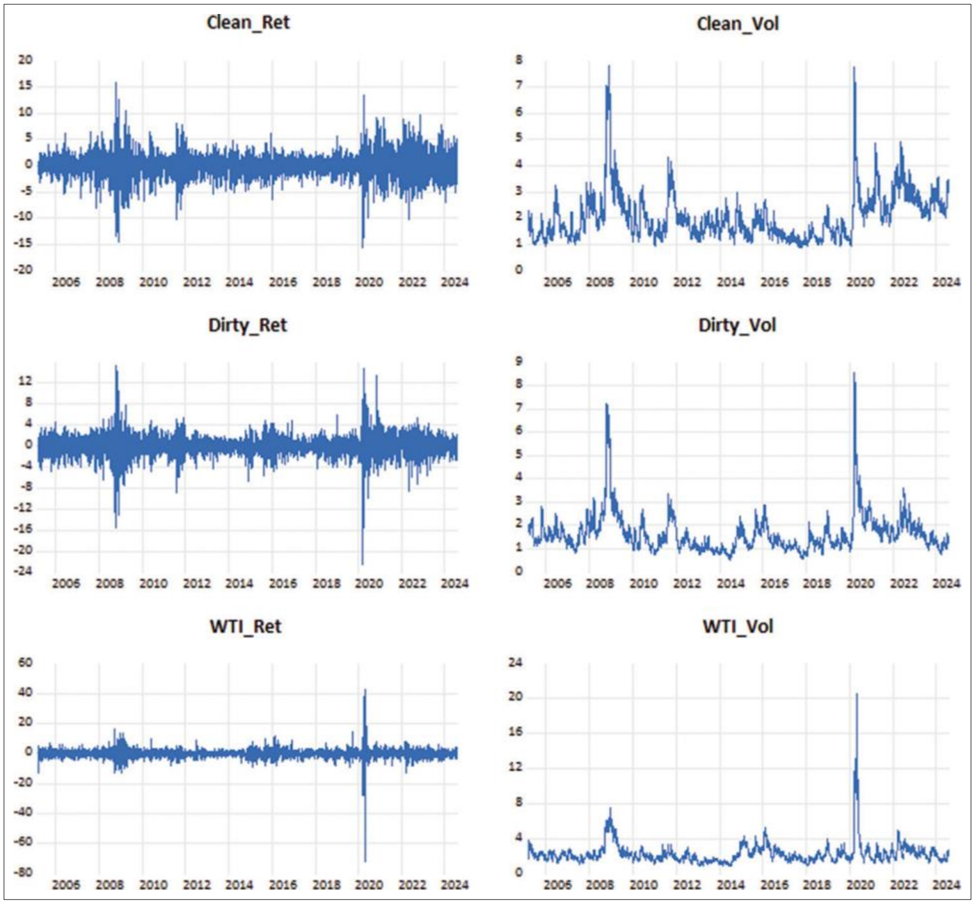
$$Z_t = v(\tau) + \sum_{j=0}^{q} \Pi_{jt}(\tau) Z_{t-j} + w(\tau) \tag{1}$$

where Z_t and Z_{t-1} are the L×1 dimensional endogenous variable vectors, α represents a vector of quantiles ranging between 0 and 1, q represents the lag order of the QVAR, while v(τ) is an L×1 dimensional conditional mean vector, Π_{jt} is L×L dimensional QVAR coefficient matrix, and w(τ) is a L ×1 dimensional error vector with a L×L dimensional variance–covariance matrix, H(τ). Converting QVAR to Quantile Vector Moving Average (QVMA) is essential for variance decomposition, and we use the Wald representation theorem: $Z_t = v(\tau) + \sum_{j=1}^{q} \Pi_j(\tau) Z_{t-j} + w(\tau) = v(\tau) + \sum_{i=0}^{\infty} {}_i(\tau) u_{t-i} + w(\tau)$. This step is necessary to derive the quantile-based impulse response functions and to construct the generalized forecast error variance decomposition (GFEVD), which forms the basis of our connectedness analysis.

Accordingly, the F-step ahead generalized forecast error variance decomposition (GFEVD), of Koop et al. (1996), matches to the influence a shock in series *i* has on series *j*, and is specified by:

$$\Psi^{g}_{i\leftarrow j,\tau}(F) = \frac{\sum_{f=0}^{F-1}\left(e_i'\Omega_f(\tau)\, H(\tau) e_j\right)^2}{H_{ii}(\tau)\sum_{f=0}^{F-1}\left(e_i'\Omega_f(\tau)\, H(\tau)\Omega_f'(\tau) e_j\right)} \tag{2}$$

Figure 1: Time series trajectories of the return (Ret) and volatility (Vol) series



Where e_t is K×1-dimensional zero vector with a value of 1 in its i-th position and 0 elsewhere. Diebold and Yılmaz (2012) suggest the scaled GFEVD, $gSOT_{i\leftarrow j,\tau}$ (F) obtained by normalizing $\psi^{gen}_{i\leftarrow j,\tau}(H)$.

$$gSOT_{i\leftarrow j,\tau}(\mathrm{F}) = \frac{\psi^{g}_{i\leftarrow j,\tau}(\mathrm{F})}{\sum_{j=1}^{k}\psi^{g}_{i\leftarrow j,\tau}(\mathrm{F})} \tag{3}$$

The scaled formula is fundamental for the connectedness method. It serves in the determination of the total directional connectedness TO (FROM) others. These measures are formulated by:

$$S^{gen,TO}_{i\rightarrow .}(\tau) = \sum_{k=1,i\neq j}^{K} gSOT_{k\leftarrow i,\tau} \tag{4}$$

$$S^{gen,FROM}_{i\rightarrow .}(\tau) = \sum_{k=1,i\neq j}^{K} gSOT_{i\leftarrow k,\tau} \tag{5}$$

The net effect of variable *i* is calculated by taking the difference between the TO and FROM total directional connectedness as shown in equation (6):

$$S^{gen,net}_{i,\tau} = S^{gen,TO}_{i\rightarrow .} - S^{gen,FROM}_{i\leftarrow .} \tag{6}$$

This measure permits to check whether a given asset acts as either a net transmitter or a net receiver of spillover effects, depending on the sign of $S^{gen,\,net}_{i,\tau}$. Positive (negative) values signify that variable *i* is a net recipient (receiver) of shocks from other variables in the network.

Lastly, the adjusted Total Connectedness Index (TCI) measures the intensity of network interconnectedness and falls within the unit interval [0,1]. It is given by:

$$TCI_{\tau}(F) = \frac{L}{L-1}\sum_{l=1,i\neq j}^{L} S^{gen,FROM}_{k\leftarrow .,\tau} = \frac{L}{L-1}\sum_{l=1,i\neq j}^{L} S^{gen,TO}_{k\leftarrow .,\tau} \tag{7}$$

3.2.2. Granger causality in quantiles

We complete our investigation by performing the Granger causality in quantiles test between Clean and Dirty indices, employing the methodology introduced by Troster (2018). This approach evaluates the direction of causality across several quantiles of the conditional distribution, offering a deeper insight into the causal relationships between the variables.

Consider the explanatory vector $J_t \in \mathrm{R}^d$, d = *s* + q is the total dimension of the explanatory vector, with *s* and *q* representing the number of lags for Y_t and Z_t respectively,, is constructed as: $J_t \equiv (J_t^Y, J_t^Z)$, where $J_t^Y := \{Y_{t-1},\ldots,Y_{t-s}\}' \in \mathrm{R}^s$ denotes the lagged values of the dependent variable Y_t and $J_t^Z := \{Z_{t-1},\ldots,Z_{t-q}\}' \in \mathrm{R}^q$ defines the lagged values of the explanatory variable Z_t.

The Granger causality test's null hypothesis states that Z_t does not Granger-cause Y_t and is expressed as follows:

$$H_0^{Z \square Y} : F_Y\left(y \setminus J_t^Y, J_t^Z\right) = F_Y\left(y \setminus J_t^Y\right) \textit{ for all } y \in \mathrm{R} \quad (8)$$

Where $F_Y\left(. \setminus J_t^Y, J_t^Z\right)$ and $F_Y\left(. \setminus J_t^Y\right)$ describe the conditional distribution function of Y_t given (J_t^Y, J_t^Z) and J_t^Y, respectively. The Granger (non)-causation test from Z_t to Y_t, across τ-quantiles, derived from Equation (7):

$$H_0^{QC,Z\text{¿}Y} : Q_\tau^{Y,Z}\left(y \setminus J_t^Y, J_t^Z\right) = Q_\tau^Y\left(y \setminus J_t^Y\right), a.s. \textit{ for all } \tau \in \Gamma \quad (9)$$

where Γ is a compact set satisfying $\Gamma \subset [0,1]$, and represents the conditional τ-quantiles of Y_t. Readers interested in a more detailed background on the test may refer to the original paper of Troster (2018).

5. EMPIRICAL OUTCOMES

5.1. QQC Results

To investigate the quantile-on-quantile spillover effects between green and dirty indices, we rely on the QVAR model to the return and volatility series. In this study, we utilized a 200-day rolling window[2] in estimating the QVAR model. This choice reflects a careful trade-off between two competing considerations: statistical precision and responsiveness to structural changes. A shorter window may lead to noisy and unstable parameter estimates due to insufficient observations, while a much longer window could obscure important short-term dynamics and structural changes in the connectedness between the series. This choice aligns with previous studies (e.g., Balli et al., 2023; Gabauer and Stenfors, 2024) that examine high-frequency spillover effects, and has been empirically shown to capture medium-term fluctuations effectively without sacrificing estimation precision. We also selected a first-order QVAR model since it minimizes the Bayesian Information Criterion (BIC) and a 20-step-ahead forecast as in Gabauer and Stenfors, (2024).

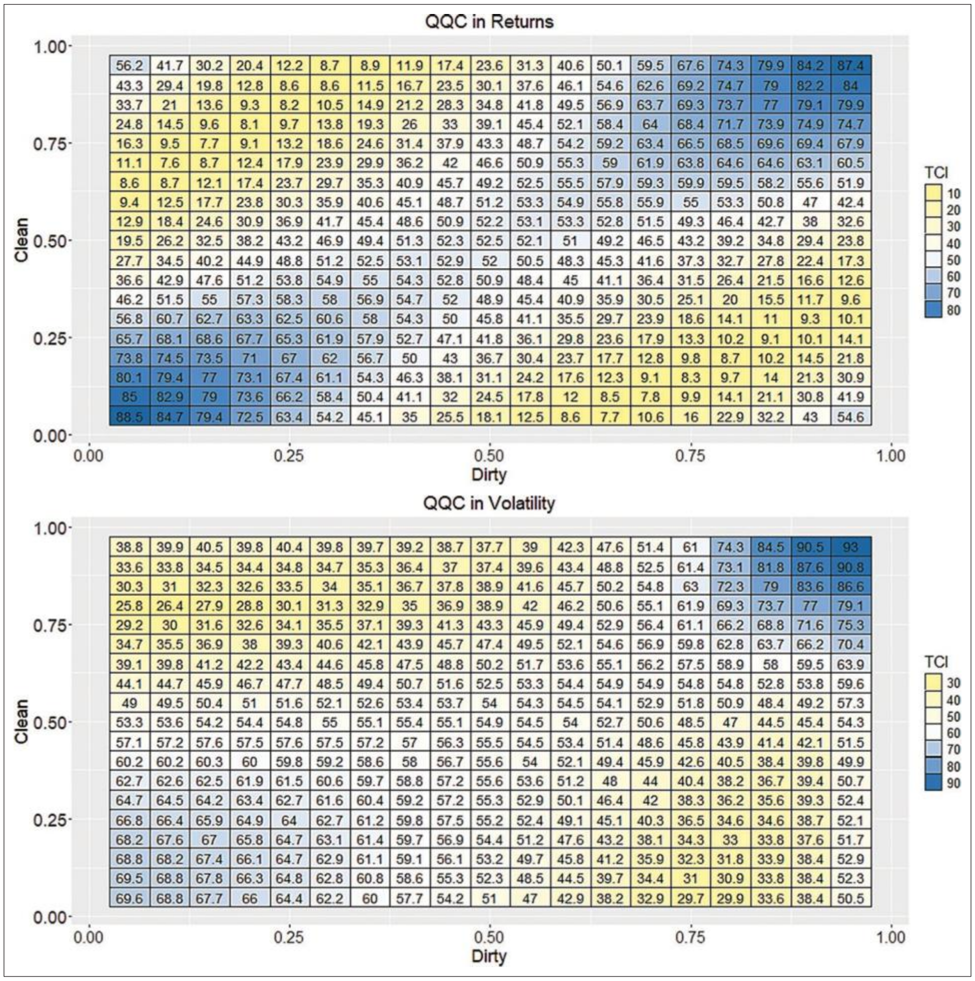
We discuss both the dynamic return and volatility[3] connectedness results. Figures 2 and 3 display the averaged dynamic total connectedness indices across the bivariate quantile spectrum, for both returns and volatility series, relative to each pair under consideration. It is worth noting that the results are presented in a heatmap that illustrates the average connectedness across different quantile combinations of the considered series. For clarity, a darker colour in the heatmap indicates a higher level of connectedness between the variables considered, whereas a lighter colour represents a lower level of connectedness. Specially, in Figure 2, we present the results for the Clean-Dirty pair. The figure shows that the highest levels of return pairwise connectedness are found along the diagonal of the heatmap matrix, with the extremes (upper and lower) of the quantile spectrum exhibiting more pronounced connections. This result proves that the directly related quantiles ([α_1 = 5%, α_2 = 5%],…, [α_1 = 95%, α_2 = 95%]) are more significantly higher total connectedness than the reversely related quantiles ([α_1 = 5%), α_2 = 95%,…, [α_1 = 95%, α_2 = 5%]), indicating that these markets offer limited diversification and hedging opportunities for investors and portfolio managers seeking to mitigate the potential downside of their portfolios, when the series evolute in the same direction (rise or fall together). This result highlights a crucial insight: clean and dirty energy markets tend to move together, especially during periods of market stress or euphoria, reducing their effectiveness as diversification or hedging tools during those critical times. From a portfolio management perspective, this pattern challenges the assumption that investing in both markets inherently provides downside protection. During downturns-precisely when diversification benefits are most needed-clean and dirty assets exhibit elevated return and volatility spillovers, exposing portfolios to compounded risks rather than offsetting effects. Therefore, the lack of strong inverse relationships across quantiles underscores the limited potential of clean and dirty energy assets to serve as effective hedges against one another. This result aligns with the findings of Wang et al. (2024), who reported similar conclusions of the connectedness between the US dollar and gold prices, however, it opposes the finding of (Gabauer and Stenfors, 2024) regarding the spillovers across the 2-year US Treasury yield and the yield curve spread between the 10-year and 2-year US Treasury yield. By contrast, when shifting our attention to volatility pairwise connectedness, displayed in the bottom of Figure 3, note that the highest levels of pairwise connectedness are mainly clustered in the upper quantile spectrum of the heatmap ([α_1 = 70%, α_2 = 75%] to [α_1 = 95%,…, α_2 = 95%]). This indicates a greater connectedness in upper tail volatility between the Clean and Dirty markets. This outcome is consistent with the studies by Billah et al. (2022); Tiwari et al. (2022) and Anyikwa and Phiri (2023), who observed similar behaviour between commodity and equity markets as well as among BRICS equity markets. Furthermore, we also noted that the directly related quantiles ([α_1= 5%, α_2= 5%],…, [α_1 = 95%,…, α_2 = 95%]) are more higher than reversely related quantiles ([α_1 = 5%, α_2 = 95%],…, [α_1 = 95%, α_2 = 5%]).

In Figure 3, we observe the averaged dynamic total connectedness in returns and volatility for Clean and WTI. The figure indicates that the highest pairwise connectedness levels are focalized in the four corners of the quantile spectrum of the heatmap ([α_1 = 5%, α_2 = 5%] to [α_1 = 20%,…, α_2 = 20%], [α_1 = 5%, α_2 = 90%] to [α_1 = 10%,…,α_2 = 95%], [α_1 = 90%, α_2 = 5%] to [α_1 = 95%,…, α_2 = 10%], and [α_1 = 80%, α_2 = 80%] to [α_1 = 95%,…, α_2 = 95%). However, the strongest ones are also linked to the directly related quantiles, indicating that selecting these assets is not benefits mainly when the markets co-move as they exhibit a limited hedging and diversification occasions. In turns, regarding the volatility pairwise connectedness for WTI-Clean, it appears that the higher averaged dynamic total connectedness indicators

2 To enhance the robustness of the findings, we also used two window lengths of 180 and 220 days. The results of the are generally consistent with our findings. The results are available upon request from the authors.

3 Volatility series are obtained from the adequate GARCH specification that best suit the characteristics of the data. Starting with a battery of GARCH models (linear and nonlinear), we found, for different series, that the EGARCH (1, 1) model, with Student's t-distribution, outperforms other models according to the Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC).

Figure 2: Averaged dynamic quantile-on-quantile total connectedness in returns and volatility for clean and dirty



are concentrated in the upper quantile spectrum of the heatmap ([α_1 = 80%, α_2 = 80%] to [α_1 = 95%,…, α_2 = 95%]), with the strongest ones are also related to directly related quantiles.

The comparison between the results of the averaged dynamic total connectedness for the pair Clean-Dirty (Figure 2) to that of Clean-WTI (Figure 3) reveals that the intensity of the connectedness of the Clean index to Dirty index is stronger than of the Clean index to WTI crude oil prices. For instance, at the directly related quantiles, the connectedness in returns with Clean oscillates between 52.5% (16.9%) and 88.5% (78.5%) for Dirty (WTI), while the connectedness in volatility varies between 54.3% (26.5%) and 93% (91.6%) for Clean (Dirty). For the reversely related quantiles, the connectedness in returns with Clean oscillates between 7.6% (5.1%) and 85% (72.5%) for Dirty (WTI), while the connectedness in volatility varies between 25.8% (15.3%) and 90.8% (87.7%) for Clean (Dirty). The strong connectedness (up to 93%) between Clean and Dirty energy indices reflects the deep financial and structural interdependencies between these two segments of the energy market. Although they represent opposing sides of the sustainability spectrum, both markets are significantly influenced by shared macroeconomic conditions, global energy demand, investor sentiment, and major geopolitical or economic events (e.g., COVID-19, oil shocks, policy shifts). These common external shocks can simultaneously affect the risk profiles of both clean and dirty energy firms, causing their volatilities to co-move strongly. Moreover, the high connectedness between Clean and Dirty energy markets is partly driven by growing investor focus on ESG principles, which leads to capital shifting between the two sectors in response to regulatory, technological, or environmental developments. This creates a feedback loop where volatility in one market quickly affects the other. Additionally, the evolving composition of energy firms—many of which now engage in both traditional and renewable energy—further strengthens this interconnection at the volatility level.

On the other hand, as noted above, for both for return and volatility connectedness, that the directly related quantiles are higher than reversely related quantiles. However, departures from this pattern are also watched in several cases, where quantiles that are inversely related exhibit stronger connectedness compared to those that are directly related. By looking at Figure 4 shaping the percentage of cases where the reversely related quantiles surpass the directly ones, it appears that this percentage is roughly equal to 10% for both return and volatility connectedness for the case of Dirty-Clean pair. By contrast, for the case of WTI-Clean, the same figure shows that this percentage is 19% (28%) for return (volatility) connectedness. Furthermore, we also note from Figures 2 and 3, that the sturdier transmission of shocks is observed at the tails of the conditional distributions than at the middle of the distribution

Figure 3: Averaged dynamic quantile-on-quantile total connectedness in returns and volatility for clean and WTI

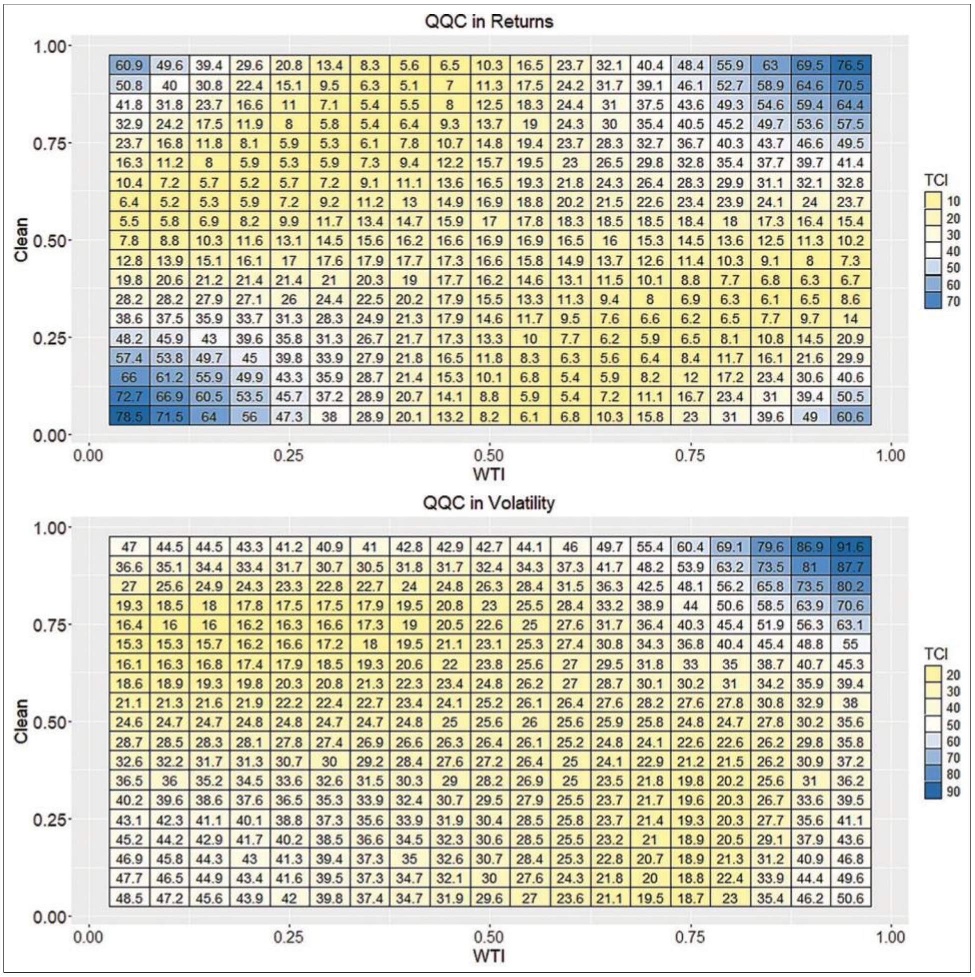
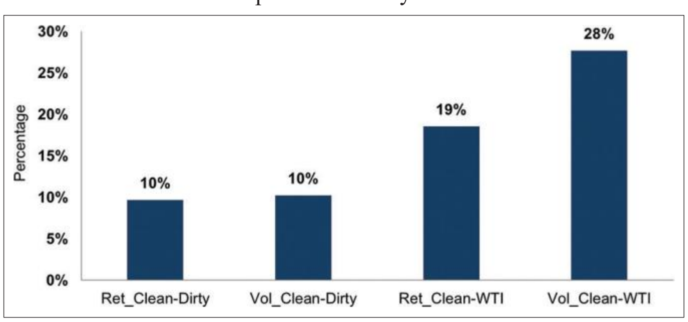


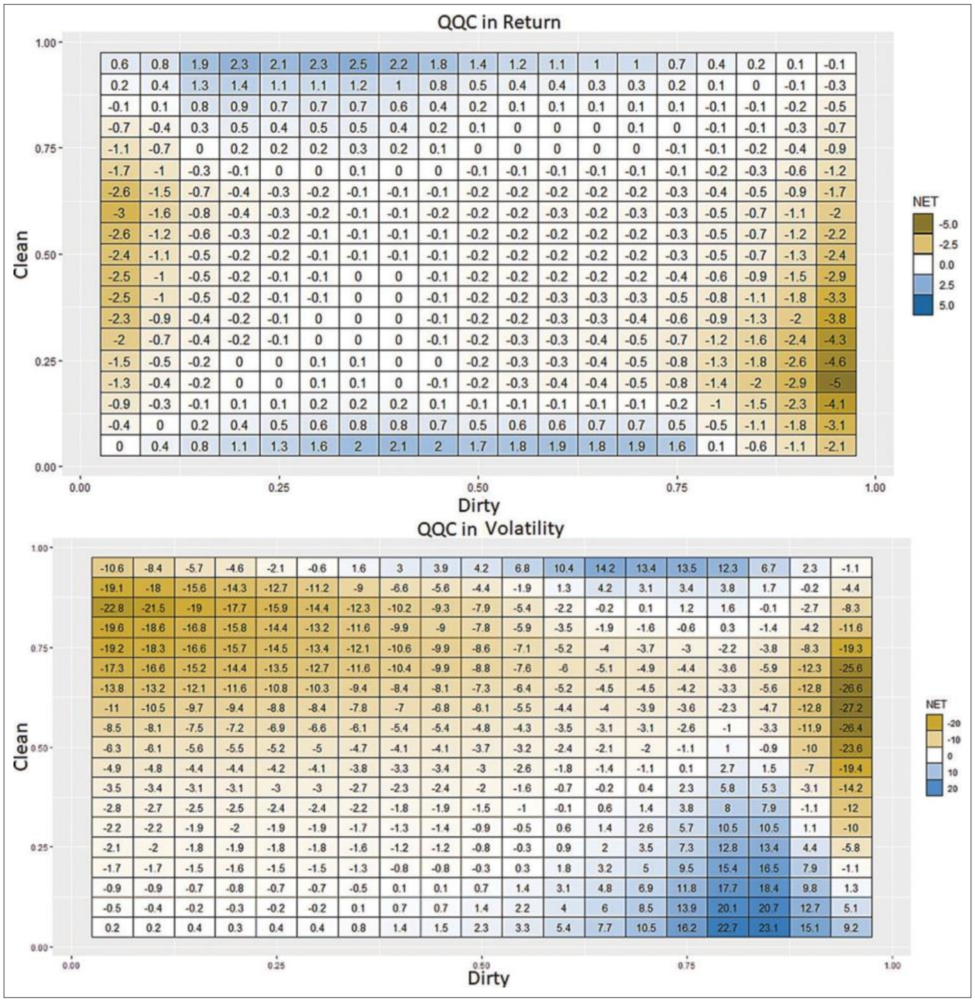
Figure 4: Percentages of cases where the reversely related quantiles surpass the directly ones



for both returns and volatility shocks. The previous analysis is of crucial interest and underlines the need of treating directly and reversely related quantiles for a comprehensive investigation of mechanism transmissions, across various conditions, between clean and dirty markets, and therefore justify the adopted approach. The comparison between the Clean–Dirty and Clean–WTI pairs reveals key differences in their connectivity dynamics. The first difference is linked to asset class characteristics: Clean and Dirty indices represent opposite sectors—sustainable/green technologies versus fossil fuel industries-leading to a more direct, inverse relationship. The WTI crude oil price, being a commodity, is influenced by broader supply-demand factors and geopolitical conditions rather than stock market performance. The second is related to connectivity differences: The Clean–Dirty pair exhibits stronger and more consistent connectivity due to the shared influence of policy and market transitions toward renewable energy, whereas the Clean–WTI relationship is weaker because oil prices are more affected by global market conditions than by stock performance of clean energy firms. Clean–Dirty indices offer stronger diversification and risk management opportunities compared to Clean–WTI due to their direct sectoral linkages. Investors seeking to mitigate risk or hedge should consider the stronger connectivity between clean and dirty sectors, while the Clean–WTI relationship may offer less predictable dynamics due to the differing drivers of oil prices versus clean energy stocks. In summary, Clean–Dirty connectedness is stronger and more relevant for investors focused on energy transition, while Clean–WTI relationships offer less reliable diversification, given the differences in their underlying drivers.

In the next step, we move to the analysis of the net quantile-on-quantile total directional connectedness between each considered pairs (Clean-Dirty, and Clean-WTI) across the bivariate quantile spectrum, given in Figures 5 and 6. Before the analysis of these figures, we plot in Figure 7, the histogram of frequencies where Dirty (WTI) act as a transmitter/receiver in its interactions with the clean stock market. This figure shows that Dirty is the primary

Figure 5: Net total quantile-on-quantile connectedness for dirty and clean stocks



recipients, of both return and volatility, connectedness in their exchanges with Clean, whereas for the WTI-Clean, the results seem different. WTI share equal roles in its interactions with the clean stock market for the return connectedness, however, it is predominantly a transmitter of volatility connectedness. This preliminary investigation highlights the unstable relations between Dirty and Clean and the Clean, indicating that the direction and intensity of linkages substantially swing under different quantile pairs. This result is partially consistent with Ahmad (2017), who found that clean energy indices act as primary transmitters of return and volatility spillovers to crude oil prices.

A closer look to Figure 5 reveals the dominance negative values across a wide surface of the spectrum quantile, which confirms the primary receiver role of Dirty its interactions with the clean stock market. However, Dirty shifts its role and becomes a transmitter, particularly in the quantile pairs [α_1 = 10~80%, α_2 = 5~10%], and [α_1 = 10~80%, α_2 = 85~95%], indicating that this role is mainly seen when Dirty lies at most quantiles and Clean is at extreme quantiles (lower/upper). For volatility spillovers, the results mainly prove that Dirty is the primary receivers of connectedness in its interactions with Clean for most quantile pairings. Nevertheless, exemptions appear mainly in the ranges of ([α_1 = 40%~80, α_2 = 5~15%]), where the role of Dirty changes to being a net transmitter of connectedness. When focusing on the Net Quantile on Quantile Total Connectedness for WTI and Clean, reported Figure 6, the results of return and volatility seem different from that observed in Figure 4. For return, WTI can play roughly equally double roles in its interactions with Clean. Particularly, the WTI is a net receiver of shocks mainly across some quantiles ([α_1 = 5%~20%, α_2 =25~70%], and [α_1 = 55%~95%, α_2 = 20~70%]). However, it changes to a net emitter role outside these ranges.

For volatility, the same figure reveals that WTI predominantly a transmitter of volatility chocs to Clean over a wide quantile pairing, specially associated with moderate to higher quantiles of WTI, whereas its role shifts to become a receiver in the remaining quantiles. This indicates that risk transfer between the oil market and clean market is dominated by the transmissions from the oil market. This finding aligns with the results of Maghyereh et al. (2016), who observed a similar pattern when examining volatility transmission between crude oil and equity markets.

In Figures 8 and 9, we observe the dynamic directly related and reversely related quantiles total connectedness, along with the differences that arise from the selection the choice of (α_1, α_2)-quantiles for the considered pairs (Dirty-Clean and WTI-Clean). Results depicted in the graphical representations figures show

Figure 6: Total net quantile on quantile connectedness for WTI and clean stocks

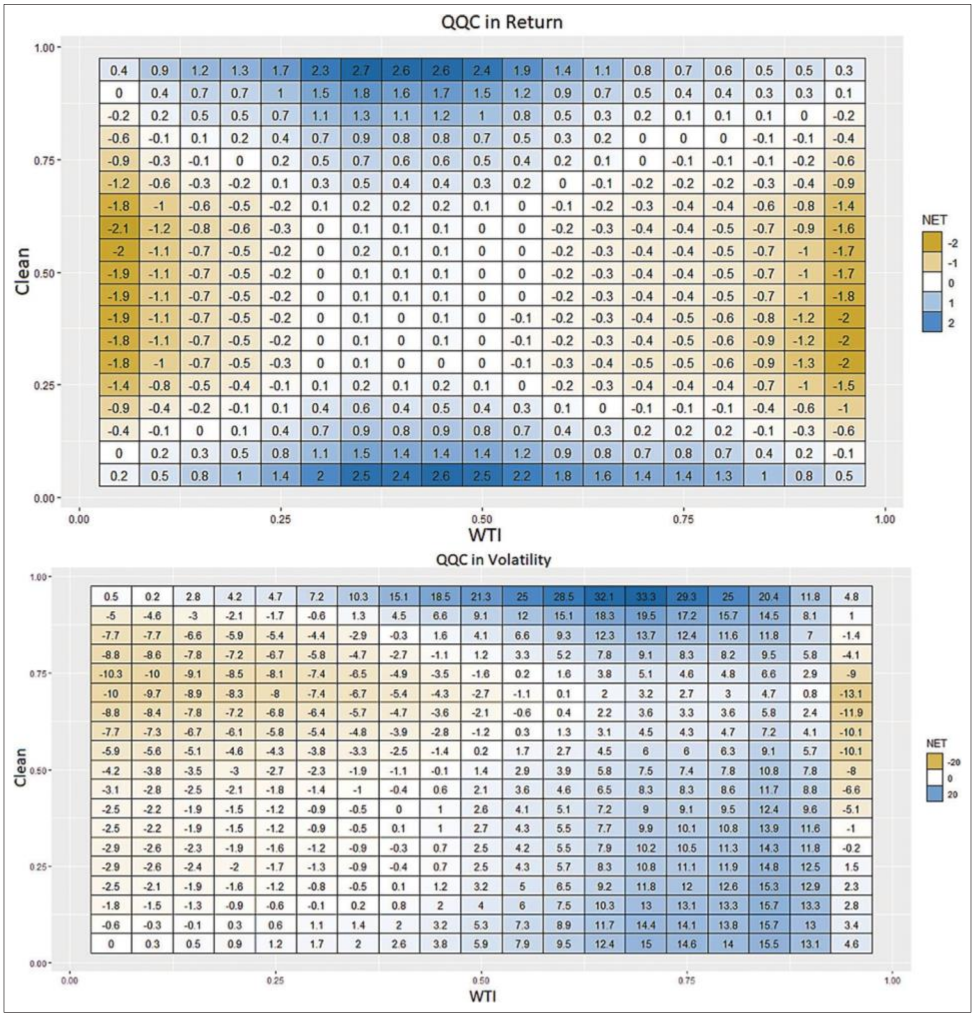
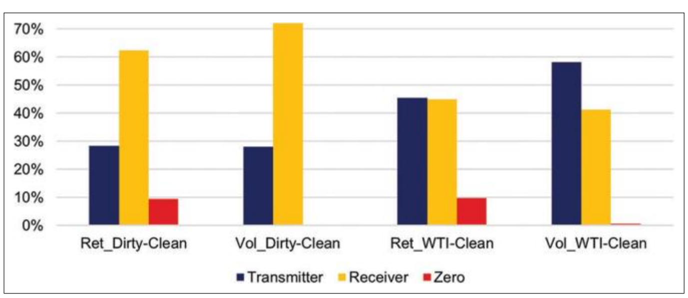


Figure 7: Frequencies where dirty (WTI) act as a transmitter/receiver in its interactions with the clean stock market



that the Direct TCI overreaches the direct TCI by a substantial reverse TCI, demonstrating a more complicated intermarket relationships when Dirty/WTI move in the same directions as Clean. Furthermore, we note the dynamic directly related and reversely related quantiles total connectedness are much closer to each other for the case of volatility connectedness. What stands out from the dynamic analysis is the elevated total connectedness during periods of systemic stress, notably during the 2009-2010 global financial crisis and the 2020 COVID-19 pandemic. These episodes saw pronounced spikes in both return and volatility connectedness, particularly at extreme quantiles, reflecting intense market co-movements, heightened uncertainty, and contagion effects. The connectedness remained elevated for sustained periods, signalling not only immediate transmission of shocks but also persistent interdependencies during and after the crises. This crisis-specific behavior highlights the nonlinear and state-dependent nature of energy market linkages—insights that cannot be captured by traditional average-based models. During these turbulent times, investor behavior becomes more synchronized, liquidity shocks propagate more quickly, and policy uncertainty amplifies cross-asset interactions.

These findings are consistent with the empirical evidence reported by Foglia and Angelini (2020), who found elevated oil-clean energy volatility connectedness during COVID-19; Dias et al. (2023), who documented stronger co-movements amid global financial stress; and broader literature (e.g., Ashraf, 2020; Liu et al., 2022; Karamti and Belhassine, 2022) that links crisis episodes with heightened financial interconnectedness. Overall, the dynamic connectedness analysis during crisis periods reinforces the value of a quantile-based, time-varying approach in uncovering hidden vulnerabilities and transmission channels within the energy markets—insights that are critical for both investors and policymakers in designing adaptive risk management strategies and resilient energy policies. Figures 8 and 9 reveal a lower total connectedness between WTI and Clean markets, compared to

Figure 8: Dynamic directly- and reversely-related quantiles total connectedness for dirty-clean stocks

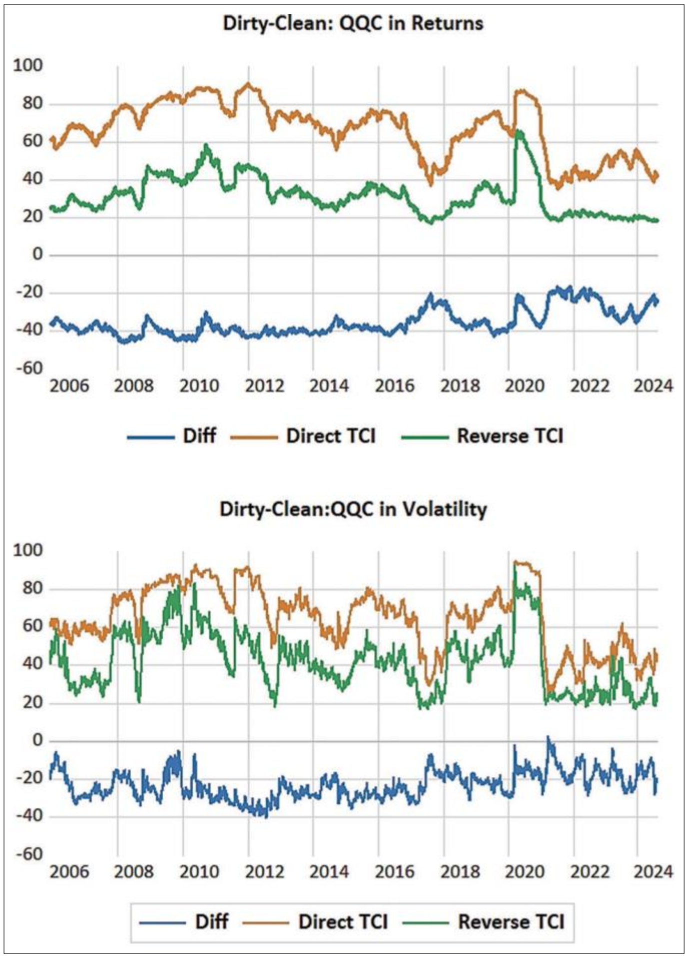
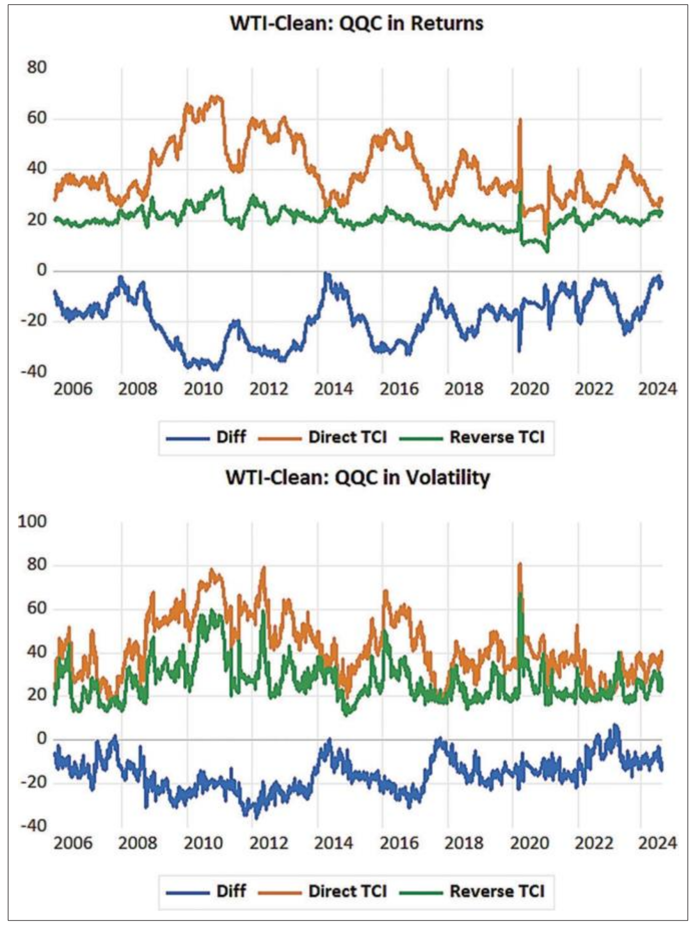


Figure 9: Dynamic directly- and reversely-related quantiles total connectedness for WTI-clean stocks



Dirty and Clean markets, stems from structural differences. Clean and Dirty indices both represent energy-related stocks influenced by similar market forces, including investor sentiment, regulatory changes, and environmental factors-resulting in stronger co-movements. In contrast, WTI crude oil is a commodity influenced by broader macroeconomic variables and lacks the financial asset characteristics and ESG sensitivities of the indices, leading to a more limited and indirect connection with clean energy stocks.

5.2. Granger Causality in Quantiles Results

While the Quantile-on-Quantile Connectedness (QQC) approach effectively uncovers the degree of connectedness or dependence between clean and dirty energy markets across different quantiles, inherently distinguish causal relationships. That is, QQC provides valuable insights into interdependence, but it does not establish whether one variable Granger-causes another, especially in a nonlinear or tail-dependent context. To complement the connectedness analysis and explore directional predictability, we employ the causality-in-quantiles test proposed by Troster (2018). This method extends the classical Granger causality framework (Granger, 1969) by allowing for the detection of quantile-specific causality across the entire conditional distribution of the dependent variable, thus capturing nonlinear and asymmetric causal effects that are not visible using traditional linear tests.

Table 3 presents the P-values from the Granger causality-in-quantiles tests across the 0.05-0.95 quantile range for both returns and volatility of clean and dirty energy markets. These results offer deep insights into how causal dynamics vary across different market regimes, from extreme downturns to exuberant booms. First, for the returns panel, the p-values indicate statistically significant bidirectional causality between clean and dirty energy returns across almost the entire distribution. Specifically: (i) Strong bi-directional causality is observed from the 0.05 to 0.35 quantiles, indicating robust interactions during market downturns. This suggests that extreme negative returns in one market (e.g., WTI) can significantly predict the behavior of the other (e.g., clean energy), and vice versa. Such relationships likely reflect systemic stress or contagion during crises. (ii) At the 0.40 quantile, the P-value for “Clean to WTI” increases to 0.0167, indicating that although the causality remains statistically significant at the 5% level, it weakens relative to adjacent quantiles. This may reflect a transition zone between market regimes, where predictive power becomes less stable. (iii) At 0.50 and 0.55 quantiles, we observe a notable change: Dirty to Clean at 0.55 has a P-value of 0.0079 (still significant, but notably higher than others), WTI to Clean at 0.55 rises to 0.0273, and Clean to WTI at 0.50 and 0.55 shows P-values of 0.0047 and 0.0029, respectively. These mid-quantile results suggest that causality weakens during neutral or moderately expanding markets, likely due to reduced volatility clustering or balanced investor behavior across energy types. In the upper

Table 3: Granger causality in quantiles: subsample P values

Quantiles	Return (%)				Volatility (%)			
	Clean to Dirty	Dirty to Clean	Clean to WTI	WTI to Clean	Clean to Dirty	Dirty to Clean	Clean to WTI	WTI to Clean
0.05	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
0.1	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
0.15	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
0.2	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
0.25	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
0.3	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
0.35	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.06
0.4	0.02	0.02	0.02	0.02	0.02	0.02	0.45	0.02
0.45	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
0.5	0.36	0.10	0.57	0.10	0.02	0.02	0.02	0.02
0.55	0.02	0.77	0.10	2.25	0.02	0.02	0.02	0.02
0.6	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
0.65	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
0.7	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
0.75	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
0.8	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
0.85	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
0.9	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
0.95	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02

Values in the table are the P values (%)

quantiles (0.6-0.95), all relationships again become strongly significant (P = 0.0002), implying renewed causal strength in bullish market conditions. This reaffirms that investor sentiment and capital flows are tightly interlinked when optimism is high, potentially driven by speculative or policy-driven demand for both energy sectors. Second, For Volatility Panel, the volatility results are uniformly significant (P = 0.0002) across all quantiles and directions, with only one exception: At the 0.40 quantile, the P-value for Clean to WTI volatility rises to 0.0167, still below the 5% threshold but indicating slightly weaker causality. This pervasive significance suggests that volatility spillovers are consistent and symmetric, regardless of market conditions. It implies that volatility in one sector almost always influences the other, pointing to structural interdependencies likely arising from shared macroeconomic risks, geopolitical shocks, or joint exposure to investor sentiment.

6. CONCLUDING REMARKS

6.1. Summary of the Findings

This paper investigates the quantile-on-quantile transmission mechanism between clean and dirty markets from March 02, 2005, to August 30, 2024, utilizing the new QQC approach suggested by Gabauer and Stenfors (2024) and the causality-in-quantile test proposed by Troster (2018). The key empirical results can be summarized as follows: First, the transmission mechanism between clean and dirty assets exhibits heterogeneous behavior across quantiles. The average total connectedness between directly related quantiles is stronger than that between inversely related quantiles, whether considering returns or volatility. However, some cases deviate from this pattern. For the Dirty-Clean pair, the connectedness for inversely related quantiles surpasses that for directly related quantiles in 10% of cases for both return and volatility connectedness. In the case of WTI-Clean, this percentage rises to 19% (29%) for return (volatility) connectedness. Moreover, stronger transmission of shocks is observed at the tails of the conditional distributions than at the middle, for both returns and volatility shocks. Second, the intensity of connectedness between Clean and Dirty assets is stronger than between Clean and WTI for both returns and volatility, at both directly related and inversely related quantiles. Third, Dirty is the primary recipient of return and volatility connectedness in its interactions with Clean. However, Dirty shifts its role to become a transmitter of return (volatility) shocks, particularly when Clean is at extreme quantiles (when Dirty is at intermediate to lower upper quantiles, and Clean is at lower quantiles). In contrast, WTI plays an equal role in return connectedness with Clean, but is predominantly a transmitter of volatility connectedness, especially associated with moderate to higher quantiles of WTI. Fourth, the results reveal that the Direct TCI substantially exceeds the reverse TCI, suggesting more complex intermarket relationships when Dirty/WTI move in the same direction as Clean. Furthermore, dynamic total connectedness between directly and inversely related quantiles is much closer for volatility connectedness. Of particular interest is the variability in total connectedness across quantiles, peaking during the 2009-2010 period and during the COVID-19 pandemic crisis of 2020. These high points highlight the dynamic nature of financial markets and the impact of large-scale political or economic disruption on market interconnections.

6.2. Policy and Investment Implications

The observed stronger connectedness at directly related quantiles-along with notable cases where inversely related quantiles dominate-reinforces the value of our quantile-based modeling approach. This finding challenges the adequacy of traditional mean-based connectedness models or models restricted to same-quantile comparisons, which may obscure important asymmetries and dynamic dependencies between clean and dirty energy markets. Hence, such models risk providing an incomplete or even misleading view of the underlying transmission mechanisms. Our results carry significant implications for energy policy, particularly in the context of a global transition toward sustainable energy systems. Policymakers must take into account the complex, quantile-dependent interlinkages between clean and dirty energy markets-especially under periods of stress and crisis. Key policy recommendations include: (i) The adoption of a balanced and gradual transition strategy: Given the strong bidirectional linkages, especially during market extremes, a phased and well-managed transition from fossil fuels to renewables is essential. Policymakers should support fossil fuel-dependent sectors during the transition period while accelerating investments and incentives for clean energy. Examples include carbon offset initiatives, transitional subsidies for fossil fuel firms adopting green technologies, and innovation grants for renewable startups. (ii) The design of resilient and adaptive energy policies: The spikes in connectedness observed during the 2009-2010 financial crisis and the COVID-19 pandemic illustrate the vulnerability of energy markets to global shocks. Policymakers should embed flexibility and resilience into energy regulations-such as through dynamic carbon pricing, strategic energy reserves, and contingency planning mechanisms-to better withstand future disruptions. (iii) The promotion of scalable green finance and infrastructure: The deep integration between clean and dirty markets highlights the urgency of scaling up investments in renewable infrastructure, energy storage technologies, and decarbonization pathways. Policymakers should foster green finance ecosystems by incentivizing green bonds, easing regulatory hurdles for clean energy investments, and collaborating with financial institutions to maintain sustainable investment products.

The results also provide actionable insights for investors managing exposure to energy assets in an increasingly complex and volatile market environment. It includes: (i) The Diversification across quantiles and energy types: The heterogeneous shock transmission across quantiles suggests that clean and dirty assets behave differently under varying market conditions. Investors should diversify their portfolios with sensitivity to these dynamics, ensuring that asset allocations can absorb and adapt to both moderate and extreme market events. (ii) Implementation of quantile-aware risk management strategies: Traditional risk models may fall short in capturing the nuanced transmission of shocks at different quantiles. Investors are encouraged to adopt quantile-based models that dynamically adjust exposure based on market states. For instance, during periods of heightened tail volatility, increasing exposure to clean energy or hedging against dirty energy assets may improve portfolio resilience.

6.3. Future Research Directions

Several important avenues for future research have emerged from this study: (i) Future studies could explore the co-movement patterns between clean and dirty energy markets across different regions, such as Europe, Asia, and the U.S., where energy policies and market conditions differ. Examining sector-specific co-movements (e.g., transportation, manufacturing) and how these transitions vary could provide deeper insights into market dynamics. (ii) The application of advanced econometric techniques, including AI and machine learning, could further enhance the understanding of complex relationships between clean and dirty energy markets. These tools enable more accurate forecasting, enhance risk management strategies for investors, and support real-time policy decision-making through early warning systems and trend detection. Their ability to process large and diverse datasets makes them valuable for navigating the dynamic energy landscape and facilitating a more informed and resilient energy transition.

7. FUNDING

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