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From Carbon Signals to Crypto Waves: Tail Spillovers in the Energy Transition

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Abstract: As the global energy transition unfolds, carbon markets and energy cryptocurrency markets collectively mirror the evolving economic and regulatory forces that are reshaping the future of energy systems. This paper employs a novel Quantile-on-Quantile connectedness approach explore the dynamic connectedness of European Union Allowance and renewable energy token with dirty energy. The results reveal a markedly state-dependent spillover structure in which cross-market influence intensifies in the tails of the return distribution, while linkages remain muted in ordinary market states. We also find that dirty energy tends to absorb rather than transmit shocks, particularly when carbon prices or clean-token valuations reach elevated levels, which suggests a growing disciplinary role of decarbonization assets in fossil-fuel pricing. A comparison of direct and reverse quantile configurations shows persistent dominance of carbon price movements over dirty energy, while leadership alternates over time between renewable-token markets and fossil-fuel markets. These findings refine the understanding of transition-risk propagation and offer guidance for portfolio design and market-stability assessment.

Keywords: renewable energy tokens; cryptocurrency; carbon market; dirty energy; tail risk spillover; quantile-on-quantile connectedness

1. Introduction

The escalating global climate crisis has fundamentally reshaped economic priorities and long-term policy orientations, placing decarbonization at the center of national development strategies [1,2]. Despite this shift, the transition is unfolding within a global energy structure that continues to rely heavily on fossil fuels [3–5]. Dirty energy (DE), which includes crude oil, natural gas, and coal, still accounts for the majority of global energy consumption and remains deeply embedded in the functioning of the world economy. Its price fluctuations affect inflation dynamics and geopolitical stability, meaning that decarbonization efforts unfold within economic structures still organized around carbon-intensive production.

In response, governments have increasingly sought to internalize the externalities associated with greenhouse gas emissions (GHG) through market-based policy instruments. Among these instruments, the European Union Emissions Trading System (EU ETS) has become the most comprehensive and institutionally mature cap-and-trade program in operation [6,7]. The EU ETS imposes binding emission caps on regulated sectors and generates a forward-looking carbon price that influences firms' marginal abatement costs and investment decisions [8,9]. The price of emission allowances reflects expectations about regulatory stringency and broader energy market conditions [10]. As a result, carbon allowances have emerged as a distinct financial asset class whose behavior captures both climate-related policy signals and evolving market fundamentals [11]. Through this mechanism, the EU ETS translates climate policy ambition into tangible economic incentives and risk assessments.

Concurrently, the rapid evolution of distributed-ledger technologies, most notably blockchain, has introduced a new class of digital instruments capable of reshaping the incentive structure inherent in traditional clean-energy policy design [12,13]. These technologies are no longer confined to the passive recording of transactions [14]. They now support the creation of programmable claims on renewable-energy attributes, which allows environmental value to be expressed and traded in new ways [15,16]. This development expands the institutional boundaries within which market participants can internalize environmental benefits. Renewable energy tokens (RETs) constitute a salient manifestation of this shift. These tokens function as digitally verifiable claims linked to clean-energy production and environmental attributes. In contrast to carbon allowances, whose valuation is anchored in regulatory scarcity, RETs operate at the intersection of technological adoption and the highly speculative dynamics of crypto-asset markets. Their decentralized architecture promises lower transaction frictions and greater transparency for mobilizing capital toward green technologies [17], thereby expanding the frontier of market-based climate solutions [18].

The coexistence of persistent fossil-fuel dependence and accelerating decarbonization generates a set of structural interlinkages between dirty energy, the EU carbon market, and renewable energy tokens. Within the EU ETS, fossil-fuel prices shape firms' marginal abatement incentives by altering the relative carbon cost [19,20]. An increase in fossil-fuel prices raises the opportunity cost of emission-intensive activities, thereby elevating the shadow value of carbon allowances and strengthening the informational connection between DE and EU ETS. Likewise, expectations about future regulatory tightening reinforce these dynamics by embedding carbon-policy risk premia into the valuation of both fossil-fuel assets and emission allowances. The price of RETs incorporate expectations regarding the long-run diffusion of clean technologies, the credibility of decarbonization commitments, and investors' willingness to reallocate capital toward environmentally aligned assets. RETs are also influenced by liquidity conditions and speculative forces in the broader crypto-asset ecosystem, which may amplify the transmission of fossil-fuel shocks relative to the patterns observed in carbon markets.

These considerations motivate a systematic investigation of how the interactions between DE, the EU ETS, and RETs vary across market states. In markets that exhibit heavy tails, average dependence measures obscure the asymmetric and nonlinear channels through which shocks propagate. The most consequential forms of spillover dynamics frequently emerge in the tails of the return distribution, where shifts in liquidity conditions and investor behavior depart most sharply from normal market patterns. In this regard, this study offers a more complete characterization of cross-market spillovers and identifies the conditions under which linkages between dirty energy, carbon allowances, and renewable energy tokens become more pronounced.

Our contribution is reflected in several key aspects. First, we develop an integrated analytical framework that links markets operating under fundamentally different institutional architectures, namely DE markets, EU ETS, and decentralized digital RETs. This framework reveals that institutional heterogeneity plays a central role in shaping information transmission within the energy–financial system, extending conventional views of cross-market linkages by showing that institutional design itself governs patterns of inter-asset dependence. Second, the paper sheds new light on the price dynamics of emerging clean-energy digital assets by examining RETs within the broader context of the energy transition. This contribution clarifies the mechanism through which digital-market volatility is incorporated into the valuation of green digital instruments, providing a new perspective on asset pricing during the low-carbon shift. Third, this paper links the transmission of risks from dirty-energy markets to the stability of decarbonization instruments. Although EUA and RETs differ fundamentally in governance structure, both are designed to support emissions reduction. By identifying how the sensitivity of EUA and RET to fossil-fuel shocks varies across market states, the paper provides new evidence on how DE volatility compromises the stability of instruments intended to facilitate decarbonization.

The remainder of this paper is structured as follows. Section 2 reviews relevant literature. Section 3 discusses the theoretical mechanisms and research hypotheses. Section 4 introduces empirical methods. Section 5 describes the data. Section 6 details the empirical analysis. Section 7 concludes with findings and policy implications.

2. Literature Review

The interaction between fossil-fuel markets and carbon pricing mechanisms has been a central theme in climate finance research, with emphasis gradually shifting from linear correlations to nonlinear, state-dependent relationships. Reboredo (2014) examines the oil–EUA nexus using a multivariate log-normal interval volatility model, focusing on volatility dynamics during Phase II of the EU ETS rather than directional spillovers [21]. Ren et al. (2022) introduce a quantile-based dependence framework, shifting attention to tail-specific co-movements and showing that oil shocks modify EUA market efficiency differently depending on shock origin [22]. Work then expanded toward broader green-finance instruments. In this regard, Sohag et al. (2023) study oil-linked equity returns against green bonds and stocks using quantile cross-spectral tools [23], while Al-Fayoumi et al. (2025) decompose oil shocks into demand, supply and risk channels to trace upper-tail risk transfer into carbon, clean energy, ESG, and green-bond markets [24]. Later research adopted multi-market systems to map energy–carbon interaction beyond bivariate settings. Wang and Guo (2018) benefit from the connectedness network analysis, and they find that WTI and natural gas spill over into carbon markets with clear asymmetry and stronger transmission under extreme conditions [25]. Chen et al. (2022) apply quantile connectedness across carbon, metal, and energy assets [26]. Qi et al. (2025) use time–frequency spillovers to trace carbon–energy–green finance link structures [7]. Naeem et al. (2024) incorporate uncertainty indicators to examine how energy cryptocurrencies and conventional dirty-energy assets respond across horizons [27].

A parallel research stream examines fossil-fuel pricing against cryptocurrencies and renewable-energy digital assets. Huynh et al. (2022) explore causal information transfer between crude oil and major cryptocurrencies using transfer entropy, positioning crypto assets as potential hedge components within energy portfolios. Subsequent work introduced environmental differentiation within crypto markets [28]: Ren and Lucey (2022) evaluate whether clean-energy indices can hedge dirty/clean cryptocurrencies under stress conditions [29]; Będowska-Sójka and Kliber (2024) connect crypto volatility to environmental attention shocks using NARDL models, showing stronger sensitivity among dirty tokens [30]. Network-based approaches further expanded the analytical scope. This analytical scope broadens as researchers shift from price linkage to network connectedness. Chen et al. (2024) construct co-bubble networks for 37 cryptocurrencies and showed shifts in contagion centers across COVID-19 and the Russo-Ukrainian conflict [31]. Zhou et al. (2025) use R-vine copulas to structure risk linkages between clean-crypto, dirty-crypto, and energy benchmarks, identifying asymmetric spillover routing through solar and ETH [32]. Yousaf et al. (2022) apply quantile regression to returns between WTI/Brent/gas and Powerledger, showing opposite spillover direction under positive and negative extremes [33]. Wei et al. (2024) and Deng et al. (2025) link carbon-market performance to cryptocurrency market efficiency and tail-risk co-movement [34,35]. In addition, Gök (2025) further extends methodology to jointly observe state-dependent spillovers and their time-horizon decomposition. The study reveals that spillover strength is greater at matched-tail quantiles and weakens at longer horizons [36].

Although existing literature has generated valuable evidence on fossil-fuel transmission across financial systems, the two relevant research streams have largely evolved in isolation. One examines carbon-allowance pricing within compliance-based markets where regulation defines scarcity and price discovery. The other studies clean-energy crypto markets where valuation reflects technological expectations and speculative dynamics. As a result, the literature still lacks a coherent understanding of whether the strength of propagation is conditioned by the joint distribution of market states rather than by average tendencies. Most empirical work centers on means, variances, or aggregate spillover indicators. These methods perform well in tranquil environments yet remain agnostic to the tail-driven reallocation that dominate during transition volatility. The absence of a framework capable of mapping spillovers along the full quantile space has therefore limited the ability of prior studies to characterize the transition process as one that is nonlinear, state contingent, and institutionally segmented. This paper addresses this blind spot by applying a quantile-on-quantile connectedness approach that evaluates dirty-energy transmission into carbon market and green cryptocurrency within a single empirical structure. This framework separates amplification in the tails from muted dependence in median states, reveals when fossil-fuel shocks dominate and measures transmission under regulatory scarcity on one side and decentralized token valuation on the other.

3. Theoretical Mechanisms and Hypotheses

This section develops the institutional logic through which tail risk spillovers may arise among DE, EUA and RET. The three markets are connected by the energy transition, but their prices are formed under markedly different institutional conditions. Dirty-energy prices are anchored in commodity-market fundamentals, including physical supply and demand, inventories, geopolitical disruptions and macroeconomic conditions. EUA prices are shaped by a compliance-market regime in which allowance scarcity, allocation rules, emissions caps and the Market Stability Reserve (MSR) jointly determine expectations about future abatement costs. RET prices, by contrast, are formed in a decentralized digital-asset environment where expectations about clean-energy applications coexist with crypto-market liquidity, investor attention and speculative trading. These differences suggest that spillovers are unlikely to be constant across market states. They should become more visible when shocks change the relative valuation of carbon-intensive production, regulated decarbonization instruments and green digital assets.

The transmission mechanism can be understood from three related perspectives. First, EUA prices enter the cost structure of regulated firms by changing the marginal cost of emissions. A sharp rise in allowance prices therefore affects fossil-fuel-related assets through expected demand adjustment, compliance-cost pass-through and the revaluation of carbon-intensive cash flows. Second, extreme movements in energy or carbon prices alter investors' assessment of transition risk and may lead to portfolio reallocation between fossil-fuel exposure, carbon-linked assets and clean-energy tokens. Third, the RET market adds a digital-finance component to the spillover system. RET valuation may incorporate expectations about clean-energy diffusion, but it is also exposed to liquidity cycles, attention-driven trading and speculative sentiment in crypto markets. As a result, RET can react to energy-transition information while also transmitting shocks that originate from the broader crypto-asset environment.

This institutional structure also implies that spillovers may be asymmetric in the tails. A positive dirty-energy shock can weaken low-carbon assets when it is interpreted as a signal of energy-security pressure, geopolitical stress or delayed decarbonization. A negative dirty-energy shock, however, does not necessarily produce an equivalent rise in low-carbon assets, because falling fossil-fuel prices may also reflect weaker aggregate demand or a temporary decline in substitution incentives. Similarly, high EUA prices can transmit strongly to DE when they signal credible regulatory tightening and higher expected compliance costs, whereas ordinary EUA movements may have limited effects when the policy environment is perceived as stable. The same logic applies to RET, whose response depends not only on clean-energy fundamentals but also on the state of crypto-market sentiment. Accordingly, we formulate two hypotheses.

H1: *Cross-market connectedness among DE, EUA and RET is stronger in the tails of the return distribution than in normal market states*.

H2: *The direction and configuration of spillovers differ across institutional regimes*.

4. Methodologies

To capture the state-dependent transmission of shocks between dirty energy and decarbonization-aligned assets, we employ the quantile-on-quantile connectedness framework originally formalized by Gabauer & Stenfors (2024) [37]. This methodology allows the dependence structure to vary simultaneously across the quantiles of both markets, thereby overcoming the restrictive assumption embedded in linear and mean-based spillover models that transmission occurs symmetrically around central tendencies. The introduction to our methodology begins with the QVAR(p) model, as follows:

$$\boldsymbol{x}_t = \boldsymbol{\mu}(\tau) + \sum_{j=1}^{p} \boldsymbol{B}_j(\tau)\boldsymbol{x}_{t-j} + \boldsymbol{u}_t(\tau) \tag{1}$$

$\boldsymbol{x}_t$ and $\boldsymbol{x}_{t-j}$ are $K \times 1$ dimensional endogenous variable vectors, τ is a vector of quantiles which are between [0,1], p stands for the lag length of the QVAR, $\boldsymbol{\mu}(\tau)$ is a $K \times 1$ dimensional conditional mean vector, $\boldsymbol{B}_j(\tau)$ is a $K \times K$ dimensional QVAR coefficient matrix, and $\boldsymbol{u}_t(\tau)$ demonstrates a $K \times 1$ dimensional error vector with a $K \times K$ dimensional variance–covariance matrix, $D(\tau)$. In order to compute the generalized forecast error variance decomposition (GFEVD) proposed, the QVAR is transformed to a QVMA using the Wald representation theorem:

$$\boldsymbol{x}_t = \boldsymbol{\mu}(\boldsymbol{\tau}) + \sum_{j=1}^{p} \boldsymbol{B}_j(\boldsymbol{\tau})\boldsymbol{x}_{t-j} + \boldsymbol{u}_t(\boldsymbol{\tau}) = \boldsymbol{\mu}(\boldsymbol{\tau}) + \sum_{i=0}^{\infty} \boldsymbol{A}_i(\boldsymbol{\tau})\boldsymbol{u}_{t-i}(\boldsymbol{\tau}) \tag{2}$$

Subsequently, the H-step ahead GFEVD represents the impact a shock in series j has on series i, which is formulated as follows:

$$\phi^{g}_{i\leftarrow j,\tau}(H) = \frac{\sum_{f=0}^{H-1}\left(\mathbf{e}_i'\mathbf{A}_f(\tau)D(\tau)\mathbf{e}_j\right)^2}{\mathbf{H}_k(\tau)\sum_{f=0}^{H-1}\left(\mathbf{e}_i'\mathbf{A}_f(\tau)D(\tau)\mathbf{A}_f(\tau)'\mathbf{e}_i\right)} \tag{3}$$

$$gSOT_{i\leftarrow j,\tau}(F)=\frac{\phi^{g}_{i\leftarrow j,r}\left(F'\right)}{\sum_{j=1}^{k}\phi^{g}_{i+j,\tau}(F)} \tag{4}$$

where $\boldsymbol{e}_i$ is a $K \times 1$ dimensional zero vector with unity on its ith position. As the row sum of $\phi gen\ i{\leftarrow}j, \boldsymbol{\tau}$ is not equal to unity, Diebold and Yılmaz (2014) suggested normalizing $\phi geni{\leftarrow}j, \boldsymbol{\tau}(D)$ by dividing it by the row sum to obtain the scaled GFEVD, $gSOTi{\leftarrow}j, \boldsymbol{\tau}(H)$ [38].

The scaled GFEVD is at the heart of the connectedness approach and is used to compute the total directional connectedness *TO* (*FROM*) others. While the TO total directional connectedness illustrates the effect series i has on all others, the *FROM* total directional connectedness illustrates the impact all series have on series i. These connectedness measures can be calculated as follows,

$$S^{gen,to}_{i\to\bullet,\tau}=\sum_{k=1,i\neq j}^{K} gSOT_{k\leftarrow i,\tau} \tag{5}$$

$$S^{\text{gen, from}}_{i\leftarrow\bullet,\tau}=\sum_{k=1,i\neq j}^{K} gSOT_{i\leftarrow k,\tau} \tag{6}$$

The difference between the *TO* and *FROM* total directional connectedness results in the NET total directional connectedness of series i,

$$S^{\text{gen, net}}_{i,\tau}=S^{\text{gen,to}}_{i\to ?,\tau}-S^{\text{gen, from}}_{i\leftarrow ?,\tau} \tag{7}$$

where $S^{gen,net} > 0$ ($S^{gen,net} < 0$) indicates that series i is influencing all other series more (less) than being influenced by them and is therefore considered as a net transmitter (receiver) of shocks.

Finally, the adjusted total connectedness index (*TCI*) of Chatziantoniou et al. (2021), which ranges between [0,1] is computed by [39]:

$$TCI_{\tau}(H)=\frac{K}{K-1}\sum_{k=1}^{K}S^{\text{gen,from}}_{k\leftarrow\bullet,\tau}\equiv\frac{K}{K-1}\sum_{k=1}^{K}S^{\text{gen,to}}_{k\leftarrow ?,\tau}. \tag{8}$$

This measure computes the degree of network connectedness. Hence, the higher the *TCI*, the higher the market risk. In order to distinguish how shock transmission behaves under symmetric versus asymmetric market states, we separate quantile spillovers into two configurations: direct quantiles, where both assets occupy similar return regions such as lower–lower, median–median or upper–upper, and reverse quantiles, where the return positions differ across markets, including lower–upper or upper–lower combinations. This classification differentiates synchronized market regimes from contrasting-state conditions in which portfolio rebalancing, hedging incentives, or regulatory cost pass-through may generate inverted transmission patterns. The dominance between the two regimes is evaluated using ΔTCI, defined as the difference between direct and reverse connectedness at each point in time.

5. Data

This study utilizes a dataset comprising daily observations from 2021 to 2024. The starting point of this sample window coincides with the full implementation of Phase IV of the EU ETS, which introduces a more stringent linear reduction factor and a revised Market Stability Reserve. These institutional reforms significantly strengthened the price-discovery role of EU Allowance (EUA) futures and contributed to the emergence of a more financially integrated carbon market. To capture carbon-market behavior, we use the EUA futures price obtained from the Wind database. Futures prices are preferred to spot prices because they exhibit higher liquidity and provide a more accurate signal of market-based assessments of carbon-policy stringency. DE is proxied by the S&P Commodity Producers Oil & Gas Exploration & Production Index (This index is also sourced from the investment websites: https://www.investing.com/ (accessed on 20 January 2025)). This index tracks firms whose core activities lie in crude oil and natural gas extraction, and is therefore closely aligned with the primary sources of global fossil-fuel supply. Its suitability as a dirty-energy indicator is reinforced by the fact that crude oil and natural gas together account for roughly 60% of global primary energy consumption. This dominant share means that developments in the oil and gas sector effectively summarize broader fossil-fuel market conditions, making the index a concise and theoretically grounded proxy for dirty energy in the global energy system. RET is one of the relatively visible crypto assets associated with decentralized energy-market infrastructure and digital coordination in the clean-energy sector. Unlike carbon-offset tokens, whose value is more directly linked to claims on avoided or removed emissions, RET is closer to the category of energy-infrastructure or power-system coordination tokens. Its price therefore reflects not only expectations about renewable-energy digitalization, but also the liquidity conditions and speculative sentiment of the broader crypto market (See the IEA reports: https://www.iea.org/reports/world-energy-balances-overview/world (accessed on 20 January 2025)). Additionally, all variables are transformed into returns series using log-differences, ensuring comparability across assets and eliminating potential scale effects in level series.

Table 1 reports the descriptive statistics for the return series of DE, the EUA, and the RET. All three assets exhibit similar unconditional mean returns of approximately 0.001, although their higher-moment characteristics differ substantially. RET displays by far the greatest return variability, with a variance of 0.006, consistent with the elevated volatility typically observed in crypto-asset markets relative to traditional energy and carbon assets. All three return distributions exhibit negative skewness, indicating a tendency toward more pronounced downside movements, while kurtosis values exceed the Gaussian benchmark, particularly for RET, suggesting the presence of heavy tails and extreme fluctuations. Figure 1 plots these log-return series over the sample period and shows that all three fluctuate around zero, with periods of calm interspersed with clusters of large shocks. DE and EUA display several pronounced spikes, while RET exhibits more frequent but relatively localized jumps, visually corroborating the volatility clustering and heavy-tail behavior documented in Table 1. The Jarque–Bera (*JB*) statistics strongly reject the null hypothesis of normality for each series, further confirming the non-Gaussian nature of returns. Unit-root tests based on the Elliott–Rothenberg–Stock (*ERS*) statistic support the stationarity of all return series, validating their suitability for connectedness and quantile-based dependence analysis. The $Q(20)$ statistic for DE is significant at the 1% level, pointing to short-run autocorrelation in returns. Moreover, the $Q^2(20)$ statistics for squared returns are significant at the 1% level across all assets, indicating persistent volatility clustering.

Table 1. Descriptive statistics for return series.

	DE	EUA	RET
Mean	0.001	0.001	0.001
Variance	0.000	0.001	0.006
Skewness	−0.354	−0.443	−0.038
Kurtosis	1.616	4.825	9.449
JB	136.815 ***	1057.842 ***	3925.378 ***
ERS	0.000	0.000	0.000
Q(20)	28.011 ***	14.244	13.578
$Q^2(20)$	111.825 ***	172.796 ***	64.272 ***

Notes: *** represents significance at the 1%.

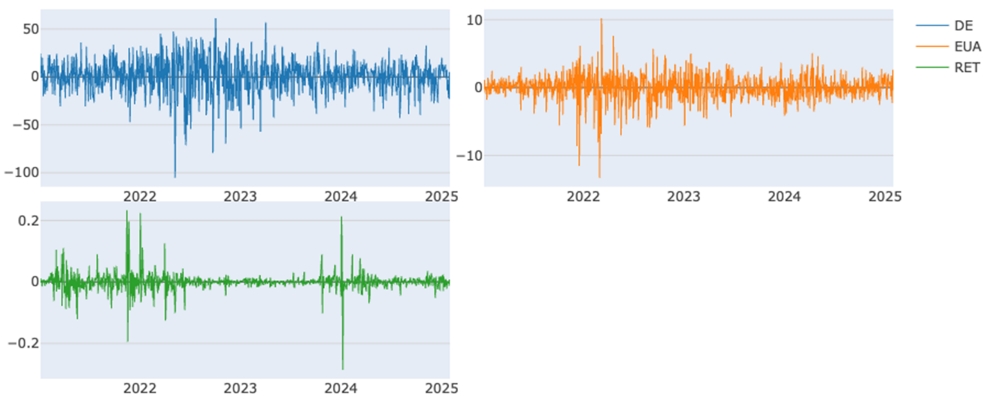

Figure 1. The trends of return series.

6. Empirical Results

In this section, we analyze the state-dependent relationships between DE and two decarbonization-related assets, namely EUA futures and RET, using a quantile-on-quantile connectedness approach. Prior to estimating the connectedness measures, we determine the optimal lag order through the Bayesian Information Criterion (BIC), which selects a lag length of 1 for all quantile specifications. This is also consistent with the relatively short memory of return series and helps preserve estimation degrees of freedom in the rolling-window quantile framework. The analysis further employs a rolling-window scheme with a width of 200 daily observations, allowing the connectedness structure to evolve over time and reflect changes in underlying market conditions (Robustness checks using an alternative DE proxy and alternative rolling-window lengths yield qualitatively similar results, which are available from the authors upon request). Following Gabauer and Stenfors (2024), we adopt a forecast horizon of 20 steps, which balances the need to capture forward-looking spillover effects with the constraint of maintaining estimation precision [37].

6.1. Average Dynamic Quantile-on-Quantile Total Directional Connectedness

Figure 2 presents the quantile-on-quantile total connectedness index (TCI) for the DE–EUA and DE–RET pairs across the joint distribution of returns. A clear and consistent pattern emerges from both panels. Connectedness reaches its highest levels when DE and the corresponding asset lie simultaneously in the upper or lower tails of their return distributions. These regions exhibit TCI values that exceed 60 in several cells, indicating that spillover transmission becomes markedly stronger when markets experience extreme upward or downward movements. This pattern aligns with the established literature on quantile dependence, which highlights that financial and energy markets tend to exhibit stronger connectedness under extreme conditions [39,40]. In contrast, TCI values are considerably weaker in the center of the distribution, which suggests that average market states are associated with limited cross-market influence.

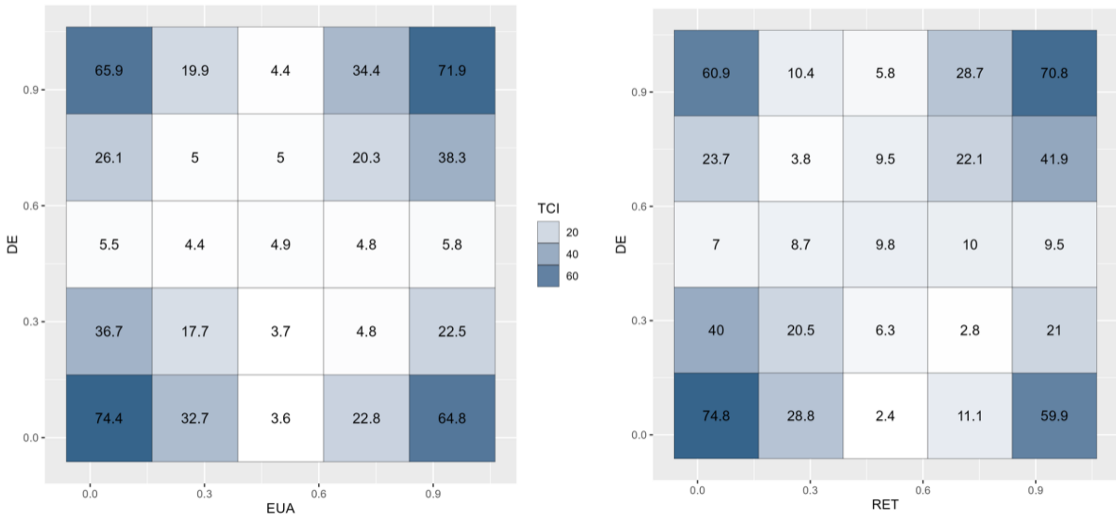

Figure 2. Average dynamic quantile-on-quantile total directional connectedness.

Although the two panels share the same broad structure, several distinctions deserve attention. For the DE–EUA pair, the most intensive spillovers are observed at the joint upper tail and the joint lower tail, reflecting the sensitivity of the carbon market to large movements in fossil-fuel related shocks. The DE–RET pair displays a similar concentration of high TCI values in the tails, but the magnitude is slightly more dispersed across surrounding quantiles, which suggests that renewable-energy tokens react not only to extreme dirty-energy shocks but also to broader fluctuations in market sentiment. Both heatmaps reveal another notable feature. Directly aligned quantile combinations ([τ_1 = 5%, τ_2 = 5%], … ,[τ_1 = 95%, τ_2 = 95%]) generate significantly stronger connectedness than opposite-tail combinations, such as lower-upper ([τ_1 = 5%, τ_2 = 95%]) or upper-lower ([τ_1 = 95%, τ_2 = 5%]) cases. This indicates that synchronized market states amplify spillovers, while opposing market states limit the degree of cross-market transmission. A further asymmetry is observed in the reversely related quantiles. When DE is situated in a high quantile and EUA or RET is in a low quantile, the TCI values are larger than in the opposite configuration. This suggests that extreme positive movements in dirty-energy markets transmit more strongly to downturns in decarbonization-related assets than the reverse, a pattern that is consistent with the view that fossil-fuel shocks continue to exert dominant influence over emerging clean-energy instruments. As the strong positive shocks to dirty-energy prices often coincide with elevated geopolitical risk or policy uncertainty, which trigger reassessments of the cost of decarbonization [41]. These reassessments can depress valuations in carbon and renewable-token markets more forcefully than declines in fossil-fuel prices boost them, because upside shocks to DE strengthen its cash-flow prospects in the short run while simultaneously highlighting transition risk in competing low-carbon assets.

6.2. Net Quantile-on-Quantile Total Connectedness

Figure 3 presents the distribution of net spillovers across the joint quantiles for the DE–EUA and DE–RET pairs. The DE–EUA panel displays a clear pattern in which DE tends to be a net receiver in several upper quantiles of EUA, particularly when EUA is located in its highest quantile range and DE lies in the middle of its distribution. These negative values indicate that the influence transmitted from EUA to DE exceeds the influence transmitted in the opposite direction [42]. A plausible explanation relates to the institutional features of the EU ETS. When EUA reach elevated levels, the cost of acquiring emissions allowances rises accordingly. Firms engaged in fossil-fuel production face higher marginal compliance costs [43,44], which can constrain operational decisions and weaken the ability of dirty energy to transmit shocks outward. As a result, EUA exhibits stronger influence over DE in high-quantile states. Beyond compliance channels, expectation formation also contributes to the observed directionality. A high-EUA environment often signals tighter future regulation and lower demand for fossil fuels over the medium horizon [45]. Such expectations are capitalized into fossil-energy valuations more rapidly than the effect of fossil-price fluctuations on carbon. Put differently, EUA in the upper quantile acts as a forward-looking policy signal, whereas DE serves as a current-fundamentals asset. This asymmetry in temporal information content strengthens spillovers from EUA to DE but weakens the reverse channel.

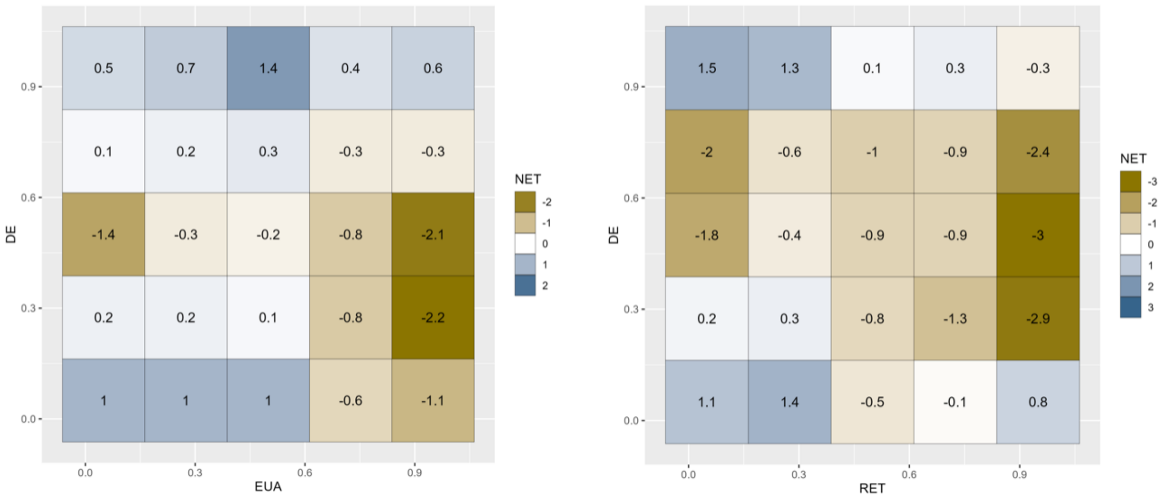

Figure 3. Average dynamic quantile-on-quantile net total connectedness.

The DE–RET panel exhibits a similar but more pronounced pattern. The more irregular connectedness pattern of RETs may reflect the fact that RET prices are not governed solely by clean-energy fundamentals. In tail states, liquidity fragmentation, retail-driven trading, leverage and speculative sentiment can magnify price responses, while sudden shifts in attention may weaken the link between RET prices and energy-transition fundamentals. Across much of the quantile grid, DE acts as a net receiver rather than a net transmitter, and several regions contain substantially negative values. This indicates stronger spillovers originating from the renewable-energy token market. Unlike EUA, RETs are not anchored to regulated scarcity [46], which allows their valuation to move more freely than prices in the carbon or DE markets. This higher elasticity of expectation makes RETs a generator of shock waves rather than merely a recipient, particularly when digital-asset momentum become dominant drivers of price formation. Oher possible explanation is that RET valuations incorporate expectations about long-term technology adoption that shape the future trajectory of low-carbon investment [47–49]. These expectations can shift market sentiment away from traditional fossil-fuel assets, thereby reducing the influence of DE on RET while amplifying the reverse transmission channel. In addition, fossil-fuel markets face increasing regulatory restrictions [50,51], which further weaken their ability to generate outward spillovers.

6.3. Dynamic Direct and Reverse Quantile-on-Quantile Connectedness

Figure 4 displays the evolution of directly related and reversely related quantile-on-quantile connectedness for the DE–EUA and DE–RET pairs over the sample period. The green line reports the TCI associated with direct quantile combinations, which represent cases in which DE and the corresponding asset lie in similar parts of their return distributions. The red line shows the TCI associated with reverse quantile combinations, where the two series occupy opposite parts of their distributions, such as lower–upper or upper–lower quantiles. The blue line represents the difference between these two measures and indicates which type of quantile configuration dominates at a given point in time [37,52].

Figure 4. Dynamic directly-related and reversely-related quantiles total connectedness.

For the DE-EUA pair, reverse connectedness remains above direct connectedness for most of the sample period, indicating that spillovers are more pronounced when the two markets are located in contrasting regions of their conditional distributions. This pattern is consistent with the institutional role of the EU ETS under Phase IV, in which allowance prices embody expectations about regulatory scarcity, future abatement costs, and the credibility of the emissions-cap trajectory. When EUA occupies an upper-tail state while DE remains in a lower or more moderate state, the carbon market may transmit a policy-cost signal to fossil-fuel-related assets. Higher allowance prices raise expected compliance costs for emissions-intensive activities, but the extent to which these costs can be passed through depends on demand conditions, market power, and regulatory credibility. Incomplete pass-through implies that part of the adjustment is capitalized into the valuation of fossil-fuel producers, thereby strengthening the transmission from EUA to DE in opposite-state configurations. The reverse configuration can be interpreted through a policy-expectation channel. When DE moves into an upper-tail state while EUA remains weak, the market may be pricing an energy-security shock or a short-run improvement in fossil-fuel profitability that temporarily dominates decarbonization concerns. Such episodes may also generate expectations that policymakers will place greater weight on energy affordability and supply stability, thereby moderating the perceived immediacy of regulatory tightening. This does not imply a reversal of the long-run decarbonization path, but it may weaken the contemporaneous influence of carbon prices and increase the relative importance of fossil-fuel fundamentals. The persistent dominance of reverse connectedness in the DE-EUA system therefore reflects the asymmetric interaction between compliance-cost pass-through and policy-expectation adjustment [53].

Although reverse connectedness generally remains above the direct measure, the gap between them narrows considerably during several intervals, and the ΔTCI series fluctuates around zero for extended periods. These patterns suggest that the connectedness between DE and RET is more sensitive to broad shifts in market sentiment and to changes in expectations surrounding clean-energy adoption and digital-asset valuations. This behavior resonates with the findings of Wang et al. (2024), who document that direct and reverse quantile connectedness between gold and the U.S. yield-curve spread varies significantly over time rather than remaining anchored to a single dominant configuration [54].

7. Conclusions

The empirical analysis documents a highly nonlinear and state-dependence transmission structure linking dirty energy to two key decarbonization-related assets. Using a quantile-on-quantile connectedness framework, this study uncovers three central features of this interaction. First, spillovers are sharply concentrated in the joint tails of the return distributions, indicating that the propagation of shocks between fossil-fuel markets, carbon prices, and renewable-energy tokens is fundamentally amplified under extreme market states rather than during normal conditions. Second, the net connectedness patterns show that dirty energy is predominantly a net receiver of shocks from both EUA and RET, especially when carbon prices or renewable-energy token valuations reach elevated quantiles. Third, the dynamic evolution of direct and reverse spillover configurations reveals distinct modes of market interaction. For the DE–EUA pair, reverse connectedness consistently dominates, suggesting that carbon price movements exert a disproportionate influence when the two markets occupy opposite quantile states. However, the dominance alternates over time for the DE–RET pair.

The findings of this study have several implications for investors and policymakers who operate at the intersection of dirty markets, carbon markets, and emerging digital clean-energy assets. For investors, the concentration of spillovers in the joint tails highlights that transition-related risks are strongly nonlinear and become most pronounced during market stress. Approaches that rely on average dependence or linear correlation measures are therefore insufficient for portfolios that combine fossil-fuel exposures with carbon-linked or renewable-energy digital assets. Incorporating tail-sensitive and state-dependent metrics into risk management can provide a more accurate assessment of potential contagion. Moreover, the fact that dirty energy behaves largely as a net receiver of shocks suggests that EUA and RET markets increasingly embed forward-looking information about regulatory tightening and clean-energy adoption. Monitoring these markets as leading indicators can help investors anticipate shifts in transition risk and improve hedging performance.

For policymakers, the amplification of spillovers under extreme conditions underscores the need for closer monitoring of cross-market transmission channels. The strong influence of carbon prices on fossil-fuel markets, particularly when the two series diverge in their distributional states, highlights the importance of transparent communication regarding allowance allocation, emissions-cap trajectories, and compliance schedules within the EU ETS. Clear regulatory signals can help reduce uncertainty-driven volatility and improve the stability of transition-relevant price discovery. The more variable spillover patterns observed between dirty energy and renewable-energy tokens point to a distinct regulatory challenge. Since RET valuations combine technological fundamentals with elements of digital-asset speculation, their influence can shift rapidly with changes in sentiment. Enhancing disclosure standards for token design, verification procedures, and governance arrangements would help mitigate informational frictions and reduce excessive volatility. Greater coordination among carbon-market regulators and digital-asset supervisory frameworks may further ensure that price signals across markets remain coherent with long-term decarbonization objectives.

The relatively short sample period is a limitation of this study. Since the sample is concentrated in the post-2021 period, the estimated connectedness may partly reflect the specific conditions of EU ETS Phase IV, the European energy crisis, monetary tightening, and crypto-market volatility. Future research with longer samples could further examine the persistence of these spillover patterns.

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L.P.: conceptualization, methodology, software, writing—original draft preparation, writing—reviewing and editing; J.Q.: data curation, visualization, investigation. Both authors have read and agreed to the published version of the manuscript.

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The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

During the preparation of this work, the authors used ChatGPT to polish the article. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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