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ESG Crypto-Assets and Environmental Signals in the Energy Transition: A Quantile-Frequency Perspective

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ABSTRACT

This study examines the dynamic interconnectedness between ESG-oriented crypto-assets, traditional cryptocurrencies, equity markets, and environmental attention related to digital assets, within the context of the global energy transition. Using a quantile-frequency connectedness framework, the analysis captures heterogeneous spillover effects across market regimes and investment horizons, focusing on systemic risk and sustainable portfolio design. The results indicate significant linkages between ESG crypto-assets and conventional cryptocurrencies, especially under extreme market conditions. ESG digital assets offer diversification and hedging benefits during bearish phases, while displaying predictive influence on equity markets in bullish states. Environmental attention on cryptocurrencies, considered as a behavioral proxy, reveals weak and unstable connectedness patterns, suggesting its limited systemic role. Spillovers are mainly concentrated at short-term frequencies, highlighting the long-term diversification potential of ESG crypto-assets. From a portfolio perspective, connectedness-minimizing strategies outperform traditional variance-based approaches under stable conditions, achieving better risk-adjusted outcomes. These findings provide practical insights for investors and policymakers by underlining the value of incorporating ESG-oriented digital assets into sustainable investment frameworks. The study contributes to the ongoing discussion on integrating climate-conscious instruments into financial systems while addressing systemic risk transmission in the digital asset space during the global energy transition.

Keywords: ESG, Crypto Assets, Cryptocurrency Environment Attention, Quantile-frequency Connectedness, Portfolio Risk Management
JEL Classifications: C32, G4, G11, G15

1. INTRODUCTION

Sustainable finance has surged into the mainstream of global markets over the past decade, reflecting investors' increasing focus on Environmental, Social, and Governance (ESG) considerations (Sharma & Kautish, 2023; Raghavendra Babu et al., 2024). By 2024, more than $3.56 trillion in assets, representing 6.8% of professionally managed funds worldwide, were allocated to sustainable investments (Morgan Stanley Institute for Sustainable Investing, 2024). This trend is reshaping capital markets and has increasingly extended into blockchain assets. Green cryptocurrencies have emerged as sustainable options, aiming to mitigate the ecological footprint associated with traditional cryptocurrencies (Del Sarto et al., 2024; Rana et al., 2025). Often operating on energy-efficient proof-of-stake (PoS) blockchain protocols, these assets offer an eco-friendly alternative to traditional energy-intensive proof-of-work (PoW) systems.

The crypto assets ecosystem is adapting to align with sustainable finance principles, giving rise to a subset of digital assets and platforms oriented towards environmental stewardship. Several newer crypto platforms were "ESG" from inception, such as Cardano, Algorand, and Tezos (Rana et al., 2025). Moreover, Celo, a green DeFi token, focuses on global financial inclusion and carbon offsetting (Abbas & Najam, 2024). Likewise, MakerDAO, a major decentralized finance (DeFi) protocol governing the DAI stablecoin, has charted a sustainability-focused course (Chatzinikolaou and Vlados, 2024). These green crypto assets have begun to attract attention from ethically minded investors and traditional markets, raising questions about their financial behavior and interactions with other assets.

The intersection of blockchain assets and sustainability is a nascent but rapidly growing subject of academic inquiry. The interconnectedness between green and traditional cryptocurrencies, as well as their spillover effects, has been studied. ESG assets tend to be net receivers of spillovers (Özkan et al., 2024; Shao et al., 2025), and the connectedness is stronger in extreme market conditions (Attarzadeh & Balcilar, 2022). ESG-aligned DeFi assets exhibit moderate returns and volatilities interconnected with traditional commodities and sustainable investments (Oben et al., 2025). This suggests that while there is some level of connection, ESG DeFi assets can still offer diversification benefits. The analysis of interconnectedness between green cryptocurrencies and the stock market reveals that green cryptocurrencies function as net receivers of return and volatility spillovers, while serving as strong diversifiers for green stocks and effective hedges against ESG equities across varying market conditions (Alharbi et al., 2025). However, despite these initial insights, essential questions remain regarding the dynamic interaction among ESG cryptos and their linkage to traditional markets under different market regimes. While investor environmental sentiment may influence the pricing of green crypto assets, this area remains largely underexplored. The Index of Cryptocurrency Environmental Attention (ICEA) reflects the degree of media attention to the environmental impact of cryptocurrencies, reflecting rising concerns over their energy-intensive mining processes (Wang et al., 2022; Qing et al., 2025). Early evidence shows that surges in environmental attention correspond to heightened volatility in crypto and green asset markets (Patel et al., 2024), suggesting that a proper analysis of green cryptocurrencies should account for such behavioural factors and integrate how environmental news and sentiment propagate through the system.

Against this backdrop, the current understanding of risk transmission involving ESG crypto assets remains limited. We address these gaps using a quantile-frequency framework introduced by Chatziantoniou et al. (2022) to explore the nexus among ESG cryptos, traditional cryptocurrencies, the stock market, and the ICEA index. This method captures system dynamics across different time horizons and market conditions. Moreover, this study explores portfolio management using approaches proposed to derive optimal asset weights and assess hedge effectiveness.

1.1. Contribution of the Paper

This study offers three main contributions to the existing literature. First, it contributes to the literature by examining a novel set of ESG-aligned blockchain-based crypto assets and their dynamic interrelationships with traditional and crypto benchmarks under extreme stress events. We specifically investigate whether ESG-aligned crypto assets (spanning cryptocurrencies, DeFi, and DAO governance tokens) exhibit distinct connectedness behavior and hedging performance during a major systemic shock (PoS & ESG Rise (2020–2021), SEC vs Crypto in 2023, ETFs Approval in 2023)) and recent geopolitical shocks (the Russia–Ukraine war of 2022 and Middle East tensions in 2023). Second, the study investigates the marginal effect of environmental attention, proxied by the ICEA index, on systemic connectedness among ESG-aligned crypto assets, uncovering behavioural finance spillovers driven by shifts in environmental concern. Third, this study applies advanced spillover measurement techniques by employing the Quantile Frequency Connectedness Approach (QFCA) (Chatziantoniou et al., 2022), which captures connectedness dynamics across different frequencies and market conditions. The quantile-frequency framework allows us to gauge whether connectedness patterns change in the tails of the return distribution and over short- versus long-run horizons. In addition, this study investigates the portfolio implications of various strategies, following Broadstock et al. (2022). This dual methodology allows us to evaluate the hedging effectiveness and risk-minimization properties of ESG-aligned crypto assets under varying connectedness states.

The results should interest portfolio managers seeking diversification in the age of sustainable investing and policymakers monitoring the financial stability implications of the burgeoning green digital finance sector.

1.2. Organization of the Paper

The remainder of this paper is as follows: Section 2 presents the theoretical background and the literature review; Section 3 details the methodology; Section 4 describes the data; Section 5 reports and discusses the empirical findings; and finally, Section 6 concludes the study.

2. THEORETICAL BACKGROUND AND LITERATURE REVIEW

2.1. Theoretical Background

This study is grounded in an interdisciplinary theoretical foundation that integrates modern portfolio theory, time-varying connectedness models, behavioral finance, and environmental economics. Each strand offers a distinct but complementary lens for examining the dynamics of ESG crypto assets and their response to systemic and behavioral factors.

Modern portfolio theory (Markowitz, 1952) posits that diversification across uncorrelated or negatively correlated assets can optimize the risk-return trade-off. However, in crisis conditions, correlations between assets tend to increase sharply, compromising diversification benefits, a phenomenon known as correlation breakdown (Forbes & Rigobon, 2002). In response, researchers have increasingly adopted connectedness frameworks to capture the dynamic transmission of market shocks across assets.

The spillover index developed by Diebold & Yilmaz (2012) marked a significant advancement in quantifying inter-asset risk transmission. Later, Baruník & Křehlík (2018) extended this model into the frequency domain, allowing differentiation between short-term and long-term spillovers. Further refinement came with Chatziantoniou et al. (2022), who introduced a quantile-frequency decomposition, integrating asymmetry in market states. These tools are especially useful in analyzing high-volatility, speculative environments like crypto markets, where transmission mechanisms vary across quantiles and frequencies.

Behavioral finance contributes by recognizing that investor decisions are shaped by sentiment, attention, and media narratives. Behavioral factors can dominate in crypto markets where valuation fundamentals are less transparent. The ICEA, developed by Wang et al. (2022), serves as a behavioral sentiment index that captures public attention toward the environmental implications of cryptocurrencies, particularly concerns over energy usage and carbon emissions. Integrating such indicators allows for a richer, multidimensional understanding of asset interdependence.

Environmental economics further justifies the study of green crypto assets through the lens of externalities. Traditional proof-of-work cryptocurrencies impose environmental costs through high energy consumption. In contrast, proof-of-stake-based assets aim to internalize environmental costs by offering energy-efficient alternatives. This aligns with Pigouvian correction theories (Pigou & Aslanbeigui, 2017), which advocate for pricing externalities to correct market inefficiencies. By incorporating such assets into portfolio strategies and connectedness models, researchers can explore how environmentally aligned financial instruments behave under stress and contribute to sustainable finance.

2.2. Literature Review

2.2.1. Connectedness dynamics in the crypto ecosystem

Cryptocurrency connectedness is influenced by liquidity, volatility, external shocks, and asset-specific characteristics, with direct implications for systemic risk and portfolio construction. Hasan et al. (2022) identified short-term liquidity clustering, with Bitcoin, Litecoin, and Ripple as primary transmitters. Regarding volatility, Hasan et al. (2021) found Ripple and Binance Coin to be key sources of spillovers, while Bitcoin and Litecoin mainly absorbed shocks, especially during the COVID-19 crisis.

External events such as pandemics and crashes reshape spillover patterns. Studies by Attarzadeh and Balcilar (2022), Giannellis (2022), and Kumar et al. (2022) reported a temporary decline in connectedness during crises, followed by a post-crisis rebound that enhanced hedging effectiveness. Amirzadeh et al. (2025) and Vidal-Tomás (2021) highlighted the growing influence of Ethereum in speculative periods, with both Bitcoin and Ethereum driving directional spillovers. Furthermore, Hasan et al. (2021) emphasized the importance of higher-moment connectedness, particularly skewness and kurtosis, among BTC, ETH, and LTC, underscoring complex dependence structures beyond simple mean-volatility measures. Complementing this, Assaf et al. (2024) found that large-cap cryptocurrencies often act as systemic transmitters, while decentralized finance (DeFi) tokens tend to play a shock-absorbing role during high-uncertainty periods.

The interdependence between cryptocurrencies and traditional financial assets remains limited under normal conditions. However, during market stress, these linkages intensify. For instance, Chen and Yu (2024) and Zeng et al. (2020) explored this dynamic. They noted that cryptocurrencies may serve as effective hedging instruments or portfolio diversifiers during downturns, challenging the assumption of crypto assets as isolated from mainstream finance.

Environmental and sustainability concerns are also emerging as relevant factors in the spillover structure. Yuan et al. (2022) analyzed the dynamic linkage between Bitcoin and energy consumption, revealing that energy-intensive cryptocurrencies contribute to systemic interactions with ESG assets. Similarly, Khan et al. (2025) investigated the nonlinear connectedness between conventional and sustainable crypto-assets, highlighting that climate-related shocks propagate distinctly within crypto markets, emphasizing the growing relevance of green finance and energy-efficient protocols.

In sum, crypto connectedness is dynamic and influenced by market regimes, asset characteristics, and sustainability considerations, offering important insights for investors and policymakers.

2.2.2. Green crypto assets in sustainable portfolios

Green crypto assets are increasingly considered for sustainable portfolios due to their diversification potential and environmental compatibility. They align with ESG principles and offer financial resilience, making them attractive to sustainability-focused investors. Analyzing volatility dynamics, Mukul et al. (2025) found that Stellar exhibits asymmetric volatility, with adverse shocks having more substantial impacts, underscoring the need for careful risk management. Similarly, Ghaemi Asl et al. (2024) observed increased co-movement between Bitcoin, Stellar, and green financial assets during bull markets, suggesting their growing relevance in ESG investing.

Ali et al. (2024) highlighted that Cardano and Tezos offer diversification benefits and better risk-adjusted returns than non-green cryptos, owing to their energy-efficient PoS mechanisms. Rana et al. (2025) further emphasized their reduced environmental footprint, enhancing their appeal for sustainable finance. However, challenges remain. Meyer et al. (2024) noted persistent concerns over the environmental impact of energy-intensive cryptos, driving interest in cleaner alternatives. Iuga et al. (2024) showed that green cryptos like Cardano can stabilize portfolios during stress, while Ionela et al. (2023) classified them as medium-risk due to macro-financial exposure and regulatory ambiguity.

From a portfolio perspective, Ali et al. (2024) and Patel et al. (2024) confirmed that green cryptos enhance diversification and reduce downside risk during market shocks. Nonetheless, broader adoption depends on regulatory clarity, as Marín-Rodríguez et al. (2023) and Morgan (2022) stressed. In summary, green cryptocurrencies present promising tools for sustainable investing, though their effective integration requires addressing volatility, regulatory risks, and evolving market dynamics.

2.2.3. Environmental sentiment and behavioral spillovers in crypto finance

Environmental sentiment increasingly shapes spillover dynamics in cryptocurrency markets. Umar et al. (2022; 2023) showed that dirty assets act as key transmitters of return and volatility, particularly during periods of systemic stress, with spillovers intensifying in response to rising environmental concern, as measured by the ICEA index.

Behavioral aspects reinforce this effect. Ghazouani et al. (2024) found that social media discussions negatively correlate with Bitcoin volatility, although Empirical indicators, including electricity consumption, exert a stronger and more consistent influence on price dynamics. Akyildirim et al. (2024) and Lin et al. (2023) demonstrated that positive sentiment from social media significantly amplifies volatility spillovers, highlighting the role of investor psychology in market transmission.

Asset characteristics also shape these dynamics. Iuga et al. (2024) reported that clean cryptocurrencies like Cardano contribute to market stability, whereas Bitcoin displays stronger and asymmetric volatility responses to environmental sentiment. While its dominance in return spillovers has declined, Akyildirim et al. (2021) found that Bitcoin remains central in sentiment-driven connectedness.

These findings underscore the joint influence of environmental sentiment and investor behavior in shaping crypto market risk. Clean cryptocurrencies may serve as effective hedging tools in ESG portfolios, reinforcing the importance of sustainability in digital asset analysis.

2.2.4. Connectedness and portfolio optimization strategies

Connectedness is fundamental to portfolio optimization, offering insights into diversification and systemic risk. Torrente and Uberti (2021) linked connectedness metrics to diversification measures, while Maggi et al. (2020) showed that Advanced strategies leveraging multilayer connectedness networks showed their predictive power for financial crises.

Advanced strategies using multilayer networks (linear, nonlinear, and tail) improve performance. Wang et al. (2024) demonstrated that low-centrality and ρ-based strategies outperform benchmarks. Mehta and Yang (2022) found that the diversification ratio (DR) performs well under stress, and Ben Amar et al. (2025) confirmed the resilience of minimum connectedness portfolios during major shocks.

Machine learning enhances these models. Wójcik (2023) showed that DRL improves returns in volatile markets, and ML-based connectedness matrices yield more robust allocations than traditional correlations. Empirical studies confirm these advantages. Yan et al. (2024) used network-based ROE and DuPont metrics to optimize portfolios. AlGhazali et al. (2025) showed that connectedness varies across market states, with green bonds and commodities offering effective hedges.

Despite the growing literature on crypto assets, green finance, and behavioral sentiment, their interconnected dynamics, particularly those involving ESG-aligned digital assets and environmental attention proxies, remain underexplored. This research addresses this gap by using quantile-frequency connectedness analysis to assess how ESG crypto assets interact with each other, with traditional markets, and with behavioral sentiment signals under systemic and geopolitical shocks. It further integrates these insights into portfolio optimization strategies, offering new empirical evidence on the risk mitigation effectiveness of ESG-aligned digital assets.

3. METHODOLOGY

This research applies the quantile frequency connectedness approach (QFCA), developed by Chatziantoniou et al. (2022), to assess connectedness over time horizons and quantiles. In addition, it explores the portfolio implications using different portfolio approaches introduced by Broadstock et al. (2022).

3.1. Quantile Frequency Connectedness Approach

This study employs the QFCA, enabling a comprehensive analysis of connectedness dynamics across different quantiles over short- and long-term horizons. The approach begins with Quantile Vector Autoregression (QVAR) estimation of order p, as follows:

$$v_t = \mu_t(\tau) + \sum_{j=1}^{p} \Phi_j(\tau) v_{t-j} + \varepsilon_t(\tau) \quad (1)$$

where v_t and v_{t-j} (j = 1,…,p) are N×1 vectors of endogenous variables, τ denotes the quantile, p is the lag order, $\mu_t(\tau)$ is the N×1 conditional mean vector and $\Phi_j(\tau)$ is the N×N coefficient matrix. Using Wold's theorem, the QVAR(p) model is expressed in its infinite-order form, QVAR(∞):

$$v_t = \mu_t(\tau) + \sum_{i=0}^{\infty} \Gamma_i(\tau) \Pi(\tau)_{t-i} \quad (2)$$

Let $\Gamma_I(\tau)$ represent the moving average lag coefficient matrices. Frequency domain is assessed through the frequency response function, defined as $\Gamma\left(e^{-i\omega}\right) = \sum_{h=0}^{\infty} e^{-i\omega h} \Gamma_h$, where $i = \sqrt{-1}$ and ω represents the frequency. The spectral density of z_t at frequency ω is then obtained via the Fourier transform of the QVAR(∞) process.

$$SD_y(\omega) = \sum_{h=-\infty}^{\infty} E\left(z_t z_{t-h}\right) e^{-i\omega h} = \Gamma\left(e^{-i\omega}\right) \Pi_t \Gamma'\left(e^{+i\omega}\right) \quad (3)$$

Subsequently, the Generalized Forecast Error Variance Decomposition (GFEVD), introduced by Koop et al. (1996) and Pesaran and Shin (1998), is calculated. This constitutes a central component of the connectedness framework, as it measures the share of forecast error variance of variable i attributable to shocks originating from variable j.

$$\Gamma_{ij}(w) = \frac{\left(\Sigma(\tau)\right)_{jj}^{-1} \sum_{h=0}^{\infty} \left(\left(\Gamma_\tau\right)\left(e^{-i\omega h}\right) \Pi(\tau)\right)_{ij}^{2}}{\sum_{h=0}^{\infty} \left(\left(\Gamma_\tau\right)\left(e^{-i\omega h}\right) \Gamma(\tau)\left(e^{-i\omega h}\right)\right)_{ii}} \quad (4)$$

$$\tilde{\Gamma}_{ij}(w) = \frac{\Gamma_{ij}(w)}{\sum_{i=1}^{N} \Gamma_{ij}(w)} \quad (5)$$

Given that $\sum_{i=1}^{N} \tilde{\Gamma}_{ij}(w) = 1$ and $\sum_{i,j=1}^{N} \tilde{\Gamma}_{ij}(w) = N$, the spectral density of variable i at frequency w reflects the shock contribution from variable j. To analyze connectedness across frequency bands, short- or long-term, rather than at a single frequency,

$\tilde{\Gamma}_{ij}(w)$ values are integrated over a frequency interval $d = (a, b) \subset (-\pi,\pi)$, yielding $\tilde{\Psi}_{ij}(d) = \int_a^b \tilde{\Gamma}_{ij}(w)dw$. The Net Pairwise Directional Connectedness (NPDC) index is then defined as:

$$NPDC_{ij}(d) = \left[\tilde{\Gamma}_{ij}(d) - \tilde{\Gamma}_{ji}(d)\right] \tag{6}$$

A positive (negative) NPDC implies that series *j* has a stronger (weaker) influence on series *i* than vice versa.

The total directional connectedness 'to others' estimates the extent to which shocks from series *i* are transmitted to all other series *j*:

$$TO_i(d) = \sum_{j=1, i\neq j}^{N} \tilde{\Gamma}_{ji}(d) \tag{7}$$

The total directional connectedness 'from others' measures the proportion of shocks transmitted to series *i* by all other series and is computed as:

$$FROM_i(d) = \sum_{j=1, i\neq j}^{N} \tilde{\Gamma}_{ij}(d) \tag{8}$$

The net directional connectedness captures the net effect by calculating the difference between the contributions to others and from others, indicating whether series *i* acts predominantly as a transmitter or receiver of shocks:

$$NET_i(d) = TO_i(d) - FROM_i(d) \tag{9}$$

A positive (negative) value of $NET_i(d)$ implies that series *i* is a net shock transmitter (or receiver) within the system. Ultimately, the Total Connectedness Index (TCI) summarizes the degree of overall interconnectedness in the system and is given by:

$$TCI(d) = N^{-1}\sum_{i=1}^{N} TO_i(d) = N^{-1}\sum_{i=1}^{N} FROM_i(d) \tag{10}$$

3.2. Portfolio Selection Approaches

In addition to the quantile frequency connectedness analysis, this paper investigates the portfolio implications of various strategies, following Broadstock et al. (2022), to compute optimal asset allocations and evaluate hedging performance.

The weights of the Minimum Variance Portfolio (MVP), as defined by Markowitz (1952), are calculated as follows:

$$\omega_{vt} = \frac{v_t^{-1} I}{I v_t^{-1} I} \tag{11}$$

I is the identity matrix, and v_t is the conditional variance–covariance at t.

The weights for the Minimum Correlation Portfolio (MCP), as conceptualized by Christoffersen et al. (2014), are obtained using:

$$\omega_{Ct} = \frac{R_t^{-1} I}{I R_t^{-1} I} \tag{12}$$

where Rt represents an m × m dimensional conditional correlation matrix.

The weights for the Minimum Connectedness Portfolio (MCoP), as formulated by Broadstock et al. (2022), are given by:

$$\omega_{COt} = \frac{PCI_t^{-1} I}{IPCI_t^{-1} I'} \tag{13}$$

where PCIt represents pairwise connectedness indices.

Hedge effectiveness, assessed using the method of Ederington (1979), and Antonakakis et al. (2020), is measured as follows:

$$HE = 1 - \frac{Var(R_p)}{Var(R_u)} \tag{14}$$

Where *Var* (R_p) denotes the hedged portfolio variance, while *Var* (R_u) refers to the unhedged asset variance.

4. DATA DESCRIPTION

This study investigates the quantile time-frequency dependence and portfolio implications among ESG-aligned crypto Assets, traditional cryptocurrencies, conventional markets, and attention to the cryptocurrency environment. Two green cryptocurrencies utilizing energy-efficient PoS mechanisms are selected: Cardano (ADA) and Algorand (ALGO). Moreover, Tezos (XTZ) is used as a green blockchain platform that leverages liquid PoS. Celo (CELO) and MakerDAO's governance token (MKR) constitute the ESG-aligned DeFi⁄DAO tier, representing application- and governance-layer tokens that incorporate sustainability objectives at the protocol level: Celo maintains an on-chain reserve that systematically retires verified carbon credits, whereas MKR holders allocate DAI-system revenues to renewable-energy receivables in pursuit of a net-zero treasury target. Bitcoin (BTC), the largest cryptocurrency by market capitalization, is a benchmark for comparing the performance of ESG crypto assets against the broader crypto market. The S&P 500 Index (SP500) serves as a broad proxy for stock market performance, allowing for an analysis of how ESG cryptos correlate with traditional markets. Data for crypto assets and benchmark assets are obtained from Yahoo Finance. The ICEA, which measures global attention to cryptocurrency-related environmental concerns, provides the behavioral environmental signal, with data from Cryptocurrency Indices.

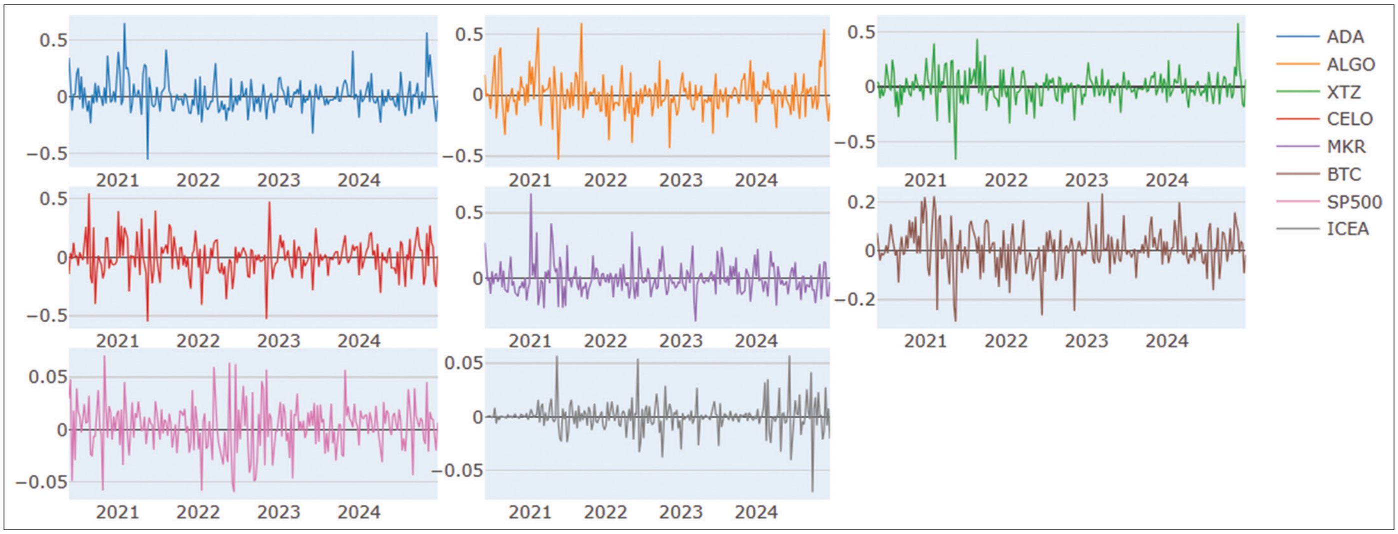
This study uses weekly closing price data from May 18, 2020, to December 23, 2024. This period is characterized by key economic

Table 1: Summary statistics

Statistics	ADA	ALGO	XTZ	CELO	MKR	BTC	SP500	ICEA
Mean	0.010	0.001	−0.003	−0.004	−0.005	0.010*	0.003*	0.000
Variance	0.019	0.023	0.018	0.022	0.013	0.007	0.001	0.129
Skewness	0.908***	0.494***	−0.005	−0.046	1.314***	0.305*	−0.063	−0.305
Kurtosis	3.880***	12.484***	3.915***	1.856***	4.901***	1.364***	0.548*	5.889***
JB	182.767***	71.172***	152.668***	34.378***	308.028***	22.208***	3.145	346.033***
ERS	−2.973***	−6.363***	−5.218***	−6.087***	−2.923***	−5.502***	−1.540	−9.607***
IQ (20)	15.050	18.321	24.358***	11.350	12.541	19.902**	10.645	31.238***
IQ2 (20)	16.677*	15.168	17.461**	15.925*	16.552*	24.275***	47.535***	24.180***

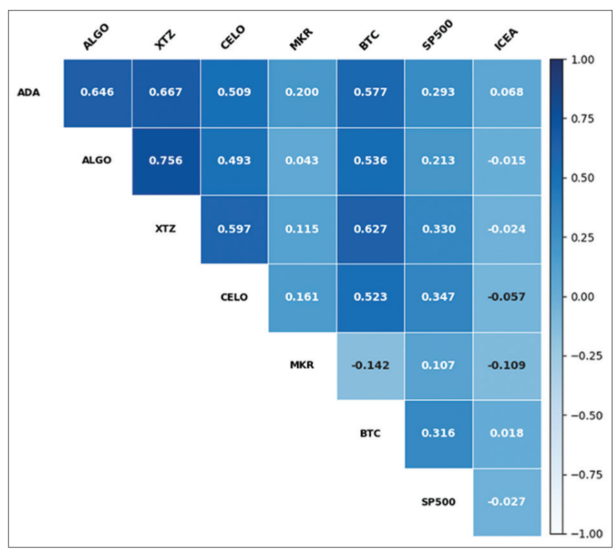
***,**,*Indicate significance at the 1%, 5%, and 10% levels

Figure 1: Plots of the sample returns



and geopolitical events, including PoS & ESG Rise (2020- 2021), Post-Terra Collapse (2022), Russia–Ukraine conflict (2022), SEC vs Crypto (2023), and ETFs Approval (2023). All price data are transformed into logarithmic returns to ensure statistical stability and comparability across series. Figure 1 illustrates the dynamics of the weekly return series, providing strong evidence of volatility clustering. It demonstrates the high volatility and fat-tail behavior of Bitcoin, Cardano, and Algorand, which exhibit a pronounced sensitivity to market fluctuations and geopolitical tensions, thereby emphasizing their speculative nature. Meanwhile, ICEA remained stable initially, then became more volatile from 2021. Summary statistics of the return series are reported in Table 1. All assets display asymmetric and fat-tailed distributions. The Jarque–Bera test confirms non-normality at the 1% significance level. In most cases, the Elliott–Rothenberg–Stock (ERS) test rejects the unit root hypothesis, indicating stationarity in the return series. Furthermore, the Q-statistics reveal significant autocorrelation in several return series. Figure 2 plots the correlation matrix of all return series. Positive correlations are observed across most markets. Notably, green crypto assets show high correlations with each other and with BTC, suggesting significant co-movement within the broader crypto market. In contrast, MKR shows weak or negative correlations with the remaining series, highlighting its potential as a hedging instrument. The ICEA Index shows no significant positive correlation with the assets, weak linear correlations with ADA and BTC, and negative correlations with the others. Observed patterns of volatility clustering, non-normality, autocorrelation, and varying dependence structures justify using a quantile-frequency connectedness approach, which offers a refined assessment of systemic interlinkages across market regimes and tail events.

Figure 2: Pairwise correlation matrix



5. RESULTS AND DISCUSSION

5.1. Static Quantile-frequency Connectedness Analysis

The analysis begins with estimating static quantile-frequency connectedness measures over total, short, and long-horizon components. These measures are computed at τ = 0.5 (Table 2), 0.05 (Table 3), and 0.95 (Table 4), capturing normal, bearish, and bullish market states, respectively. Values above parentheses denote total connectedness, whereas those in parentheses represent short- and long-term components. The quantile-based results are further contrasted with the mean-based connectedness estimates obtained through the frequency decomposition framework proposed by Baruník and Křehlík (2018), providing additional insights into nonlinear and tail-specific spillover dynamics. The results are summarized in Table 5. The average Total Connectedness Index (TCI) is estimated at 55.00, signifying that over half of Cross-market spillovers explain the forecast error variance in the system. The TCI computed at the median quantile is closely aligned, with a value of 52.80. However, a sharp increase is observed in the distributional tails. Specifically, the TCI reaches 84.11 at the extreme lower quantile (τ = 0.05) and peaks at 86.88 in the extreme upper quantile (τ = 0.95). These results reveal that systemic interconnectedness intensifies considerably under extreme market regimes. Notably, the TCI is higher at the upper quantile, suggesting that uncertainty propagation across green assets is more pronounced during positive returns than during downturns. This finding aligns with recent studies (Chen et al., 2022; Liu et al., 2024; Zhang et al., 2023), which conclude that risk spillovers and uncertainty may escalate more severely during bullish conditions, confirming the asymmetric nature of systemic risk. Furthermore, the divergence between quantile-specific and mean-based measures underscores connectedness's nonlinear and regime-dependent behavior. Relying exclusively on mean-based metrics may underestimate the systemic risk during extreme market events. These findings advocate for the integration of tail-specific connectedness analysis in assessing financial contagion and portfolio risk

Table 2: Median-based quantile-frequency connectedness (τ =0.5)

	ADA	ALGO	XTZ	CELO	MKR	BTC	SP500	ICEA	FROM
ADA	34.54 (28.82; 5.72)	15.06 (12.31; 2.76)	16.34 (13.12; 3.22)	12.53 (10.19; 2.34)	2.78 (2.38; 0.39)	12.8 (10.18; 2.61)	3.27 (2.52; 0.75)	2.69 (2.43; 0.26)	65.46 (53.14; 12.32)
ALGO	15.85 (12.95; 2.9)	35.14 (29.95; 5.19)	17.63 (14.65; 2.98)	13.36 (10.79; 2.57)	2.1 (1.71; 0.39)	10.26 (8.49; 1.78)	2.71 (2.16; 0.55)	2.95 (2.54; 0.41)	64.86 (53.29; 11.57)
XTZ	15.31 (12.52; 2.79)	16.12 (13.49; 2.63)	31.67 (26.79; 4.87)	15.05 (12.12; 2.92)	1.58 (1.35; 0.23)	13.06 (10.92; 2.14)	4.02 (3.32; 0.7)	3.2 (2.75; 0.45)	68.33 (56.46; 11.87)
CELO	13.09 (10.57; 2.52)	13.33 (11.09; 2.24)	16.4 (13.75; 2.65)	36.99 (31.01; 5.98)	2.42 (1.82; 0.6)	10.53 (8.74; 1.78)	4.89 (4.06; 0.83)	2.36 (1.95; 0.41)	63.01 (51.99; 11.03)
MKR	5.84 (4.54; 1.29)	3.25 (2.77; 0.48)	3.12 (2.41; 0.71)	3.76 (3.34; 0.42)	68.93 (57.1; 11.83)	6.81 (5.26; 1.55)	2.82 (2.18; 0.65)	5.46 (4.62; 0.84)	31.07 (25.12; 5.95)
BTC	14.2 (11.87; 2.32)	11.02 (9.18; 1.84)	15.28 (12.63; 2.65)	10.92 (9.03; 1.88)	4.16 (3.22; 0.94)	37.32 (31.04; 6.28)	4.44 (3.86; 0.58)	2.66 (2.17; 0.49)	62.68 (51.97; 10.71)
SP500	6.02 (4.67; 1.35)	3.93 (3.33; 0.6)	7.13 (5.75; 1.38)	7.63 (6.58; 1.06)	4.0 (3.7; 0.3)	5.84 (4.88; 0.95)	61.75 (53.42; 8.32)	3.71 (3.13; 0.58)	38.25 (32.04; 6.22)
ICEA	5.04 (4.43; 0.61)	3.31 (3.08; 0.23)	4.35 (4.11; 0.24)	3.76 (3.53; 0.23)	4.74 (3.76; 0.98)	4.83 (4.46; 0.37)	2.69 (2.53; 0.17)	71.27 (64.74; 6.54)	28.73 (25.91; 2.82)
TO	75.33 (61.55; 13.79)	66.01 (55.24; 10.77)	80.25 (66.43; 13.83)	67.0 (55.58; 11.42)	21.78 (17.95; 3.83)	64.13 (52.94; 11.19)	24.85 (20.63; 4.22)	23.03 (19.6; 3.44)	TCI 52.80 (43.74; 9.06)
Net	9.87 (8.41; 1.47)	1.15 (1.95; −0.80)	11.92 (9.97; 1.96)	3.99 (3.59; 0.39)	−9.29 (−7.17; −2.12)	1.45 (0.97; 0.48)	−13.40 (−11.41; −2.00)	−5.70 (−6.31; 0.62)	

Table 3: Extreme lower quantile-based frequency Connectedness (τ =0.05)

	ADA	ALGO	XTZ	CELO	MKR	BTC	SP500	ICEA	FROM
ADA	14.05 (11.98; 2.07)	11.93 (10.03; 1.90)	13.04 (10.82; 2.23)	13.34 (10.44; 2.90)	11.15 (10.00; 1.15)	13.53 (10.93; 2.60)	12.81 (10.11; 2.70)	10.15 (8.94; 1.22)	85.95 (71.25; 14.69)
ALGO	11.53 (9.69; 1.84)	14.61 (12.39; 2.23)	13.31 (11.15; 2.16)	13.09 (10.37; 2.72)	11.08 (9.86; 1.22)	13.06 (10.61; 2.46)	13.00 (9.92; 3.08)	10.31 (9.08; 1.24)	85.39 (70.68; 14.71)
XTZ	11.30 (9.75; 1.56)	12.39 (10.67; 1.72)	14.81 (12.69; 2.12)	13.50 (10.89; 2.60)	11.41 (10.37; 1.04)	13.21 (11.20; 2.01)	12.44 (9.97; 2.47)	10.95 (9.86; 1.09)	85.19 (72.70; 12.48)
CELO	11.02 (9.18; 1.83)	12.02 (9.92; 2.10)	13.18 (10.99; 2.20)	15.82 (12.48; 3.34)	10.28 (9.03; 1.25)	13.70 (11.00; 2.69)	13.36 (10.14; 3.22)	10.62 (9.08; 1.54)	84.18 (69.34; 14.84)
MKR	10.86 (9.12; 1.74)	11.25 (9.31; 1.93)	12.02 (9.99; 2.03)	12.75 (9.85; 2.91)	17.76 (14.98; 2.77)	12.04 (9.40; 2.63)	12.67 (9.73; 2.94)	10.66 (9.06; 1.60)	82.24 (66.46; 15.79)
BTC	11.28 (9.65; 1.63)	12.11 (10.23; 1.88)	13.05 (10.97; 2.08)	13.16 (10.50; 2.66)	11.04 (9.91; 1.14)	15.84 (12.99; 2.85)	13.04 (10.09; 2.95)	10.48 (9.15; 1.33)	84.16 (70.50; 13.66)
SP500	10.78 (8.87; 1.91)	11.07 (9.17; 1.90)	11.91 (9.91; 2.00)	12.67 (9.93; 2.74)	12.23 (10.83; 1.40)	13.01 (10.49; 2.51)	17.23 (13.54; 3.69)	11.11 (9.62; 1.48)	82.77 (68.82; 13.95)
ICEA	10.13 (8.41; 1.72)	11.16 (9.36; 1.79)	11.67 (9.79; 1.88)	12.20 (9.81; 2.39)	12.44 (11.21; 1.23)	12.53 (9.94; 2.59)	12.86 (9.99; 2.87)	17.01 (14.41; 2.61)	82.99 (68.50; 14.49)
TO	76.89 (64.65; 12.24)	81.92 (68.69; 13.23)	88.18 (73.61; 14.57)	90.72 (71.79; 18.93)	79.62 (71.21; 8.42)	91.07 (73.58; 17.49)	90.18 (69.95; 20.23)	74.28 (64.79; 9.50)	TCI 84.11 (69.78; 14.33)
Net	−9.06 (−6.60; −2.45)	−3.47 (−1.99; −1.48)	2.99 (0.91; 2.09)	6.54 (2.45; 4.09)	−2.62 (4.75; −7.37)	6.91 (3.08; 3.83)	7.41 (1.13; 6.28)	−8.71 (−3.71; −4.99)	

Table 4: Extreme upper quantile-based frequency Connectedness (τ =0.95)

	ADA	ALGO	XTZ	CELO	MKR	BTC	SP500	ICEA	FROM
ADA	13.43	13.00	10.62	10.70	13.11	11.42	11.35	16.38	86.57
	(11.34; 2.08)	(10.46; 2.54)	(9.60; 1.02)	(9.14; 1.56)	(11.68; 1.43)	(10.15; 1.26)	(10.12; 1.23)	(14.58; 1.80)	(75.74; 10.84)
ALGO	12.70	13.29	10.68	10.97	13.02	11.59	11.12	16.63	86.71
	(10.82; 1.88)	(10.68; 2.62)	(9.70; 0.98)	(9.44; 1.52)	(11.75; 1.28)	(10.37; 1.21)	(9.95; 1.17)	(14.79; 1.84)	(76.82; 9.88)
XTZ	12.96	12.32	11.25	10.89	13.22	11.58	11.08	16.70	88.75
	(11.34; 1.61)	(10.22; 2.09)	(10.29; 0.97)	(9.65; 1.24)	(12.04; 1.18)	(10.44; 1.14)	(10.10; 0.99)	(15.01; 1.69)	(78.80; 9.95)
CELO	12.98	12.85	10.79	11.39	13.30	11.69	11.05	15.96	88.61
	(11.15; 1.83)	(10.49; 2.35)	(9.88; 0.91)	(9.88; 1.51)	(12.05; 1.25)	(10.58; 1.12)	(9.99; 1.06)	(14.38; 1.58)	(78.51; 10.10)
MKR	12.28	12.63	10.58	11.01	14.07	11.29	11.55	16.59	85.93
	(10.79; 1.48)	(10.52; 2.11)	(9.73; 0.85)	(9.83; 1.19)	(12.80; 1.27)	(10.23; 1.06)	(10.56; 0.98)	(14.96; 1.63)	(76.62; 9.31)
BTC	12.45	12.30	10.82	11.11	13.56	11.80	11.33	16.64	88.20
	(11.06; 1.40)	(10.54; 1.76)	(9.99; 0.83)	(9.91; 1.20)	(12.37; 1.18)	(10.70; 1.10)	(10.38; 0.95)	(15.09; 1.55)	(79.34; 8.86)
SP500	12.36	12.00	10.46	10.99	13.77	11.42	12.36	16.65	87.64
	(10.92; 1.44)	(10.09; 1.91)	(9.71; 0.75)	(9.80; 1.19)	(12.56; 1.21)	(10.38; 1.04)	(11.40; 0.96)	(15.14; 1.50)	(78.59; 9.05)
ICEA	12.50	12.16	10.56	11.09	13.38	11.34	11.59	17.38	82.62
	(10.81; 1.69)	(9.98; 2.18)	(9.68; 0.88)	(9.71; 1.38)	(12.10; 1.28)	(10.19; 1.15)	(10.50; 1.09)	(15.43; 1.96)	(72.96; 9.65)
TO	88.22	87.26	74.50	76.76	93.35	80.32	79.07	115.55	TCI 86.88
	(76.89; 11.33)	(72.30; 14.96)	(68.28; 6.22)	(67.47; 9.28)	(84.54; 8.81)	(72.33; 7.99)	(71.60; 7.47)	(103.95; 11.60)	(77.17; 9.71)
Net	1.65	0.55	−14.25	−11.85	7.42	−7.88	−8.57	32.93	
	(1.15; 0.49)	(−4.52; 5.08)	(−10.52; −3.73)	(−11.04; −0.82)	(7.92; −0.50)	(−7.01; −0.87)	(−6.99; −1.58)	(30.99; 1.95)	

Table 5: Mean-based quantile-frequency connectedness

	ADA	ALGO	XTZ	CELO	MKR	BTC	SP500	ICEA	FROM
ADA	31.49	15.61	16.23	12.68	3.20	14.25	3.43	3.10	68.51
	(26.36; 5.14)	(12.77; 2.83)	(13.35; 2.88)	(10.18; 2.50)	(2.62; 0.58)	(11.36; 2.89)	(2.68; 0.76)	(2.90; 0.21)	(55.86; 12.65)
ALGO	16.28	32.45	18.00	13.47	1.93	11.94	3.04	2.89	67.55
	(13.63; 2.65)	(27.55; 4.90)	(15.17; 2.83)	(10.99; 2.48)	(1.49; 0.44)	(9.93; 2.01)	(2.32; 0.71)	(2.56; 0.33)	(56.11; 11.43)
XTZ	15.53	16.47	29.53	15.16	1.59	14.22	4.38	3.13	70.47
	(13.12; 2.40)	(13.88; 2.59)	(25.44; 4.10)	(12.35; 2.80)	(1.34; 0.25)	(11.87; 2.35)	(3.59; 0.79)	(2.68; 0.45)	(58.84; 11.63)
CELO	13.26	12.68	16.86	35.73	2.62	11.42	5.35	2.07	64.27
	(10.95; 2.32)	(10.32; 2.36)	(13.92; 2.94)	(29.96; 5.77)	(2.10; 0.52)	(9.33; 2.09)	(4.37; 0.98)	(1.67; 0.40)	(52.65; 11.62)
MKR	6.53	2.61	2.94	4.04	68.09	7.26	3.50	5.02	31.91
	(5.51; 1.02)	(2.31; 0.30)	(2.61; 0.33)	(3.84; 0.20)	(56.77; 11.33)	(5.92; 1.34)	(2.87; 0.63)	(4.37; 0.66)	(27.44; 4.46)
BTC	13.80	12.53	16.60	11.44	3.53	34.77	4.87	2.47	65.23
	(11.63; 2.16)	(10.39; 2.14)	(13.76; 2.84)	(9.30; 2.14)	(2.88; 0.65)	(29.01; 5.76)	(4.16; 0.71)	(2.05; 0.42)	(54.17; 11.06)
SP500	6.04	4.35	7.70	8.19	3.92	6.56	60.82	2.43	39.18
	(5.03; 1.01)	(3.60; 0.75)	(6.41; 1.29)	(7.03; 1.16)	(3.73; 0.18)	(5.78; 0.78)	(53.60; 7.21)	(2.07; 0.36)	(33.64; 5.54)
ICEA	6.07	3.68	5.02	3.91	6.11	5.66	2.41	67.14	32.86
	(5.22; 0.85)	(3.50; 0.19)	(4.80; 0.22)	(3.70; 0.22)	(5.00; 1.11)	(5.28; 0.38)	(2.23; 0.18)	(60.66; 6.48)	(29.71; 3.15)
TO	77.50	67.93	83.35	68.89	22.89	71.31	26.98	21.11	TCI 55.00
	(65.10; 12.40)	(56.77; 11.16)	(70.02; 13.33)	(57.39; 11.50)	(19.17; 3.72)	(59.48; 11.83)	(22.22; 4.75)	(18.29; 2.82)	(46.05; 8.94)
NET	9.00	0.39	12.88	4.62	−9.02	6.08	−12.21	−11.75	
	(9.24; -0.25)	(0.66; −0.27)	(11.17; 1.70)	(4.74; −0.12)	(−8.27; −0.74)	(5.31; 0.77)	(−11.42; −0.79)	(−11.42; −0.33)	

management, particularly in markets dominated by ESG-oriented digital assets.

In addition, the frequency-domain breakdown presented in parentheses demonstrates that short-term transmission channels dominate the system's spillover structure. Short-run connectedness dominates long-run connectedness across normal and extreme market states. These ratios, ranging from nearly fivefold to eightfold, indicate that shocks are transmitted primarily over short horizons. This findings corroborate those of Wang et al. (2024), suggesting that a fluctuation within the system predominantly affects short-term dynamics, implying greater potential for diversification in the long term for investors.

The indices of TO and FROM measure the directional connectedness between assets, with TO indicating how much an asset influences others and FROM showing how much it is influenced. The averaged TO and FROM connectedness measures indicate that sustainable crypto assets and the traditional crypto market are the most interconnected, while ICEA and the S&P 500 exhibit relatively weaker linkages. The limited interactions between crypto assets and the broad stock market suggest diversification potential. However, under bearish and bullish market conditions, spillovers increase significantly, which supports previous findings (Ustaoglu, 2023; Shao et al., 2025) and indicates that diversification benefits tend to decline during periods of systemic stress.

The NET connectedness index, measured as the gap between TO and FROM measures, captures each asset's net role in transmitting systemic shocks. The findings suggest that a series' influence may vary across various quantile levels. In particular, in a bullish market situation, green crypto assets act as the primary transmitters. In contrast, the stock market is a net receiver of chocs, indicating that investors can use green crypto assets to predict the stock market's movements. Nevertheless, in a bearish market condition, ESG crypto assets tend to be net receivers of spillovers from the system, while stocks are the primary transmitters. ESG cryptos provide diversification to the stock market and perform well as hedging tools against stocks.

Under normal market conditions, the ICEA shows weak interdependence with green cryptocurrencies, traditional cryptocurrencies, and stock markets, opening up opportunities to reduce exposure to systematic risk. Therefore, ICEA can be a strong diversifier, particularly for sustainability-conscious industries. Moreover, when market sentiment is low and volatility is muted during bearish market conditions, ICEA functions as a net receiver, reflecting global environmental concerns without notably affecting other assets. In contrast, under bullish market conditions, marked by high volatility and optimistic sentiment, ICEA acts as a net transmitter, exerting influence as environmental issues gain prominence, driven by growing awareness of the environmental impact of crypto assets.

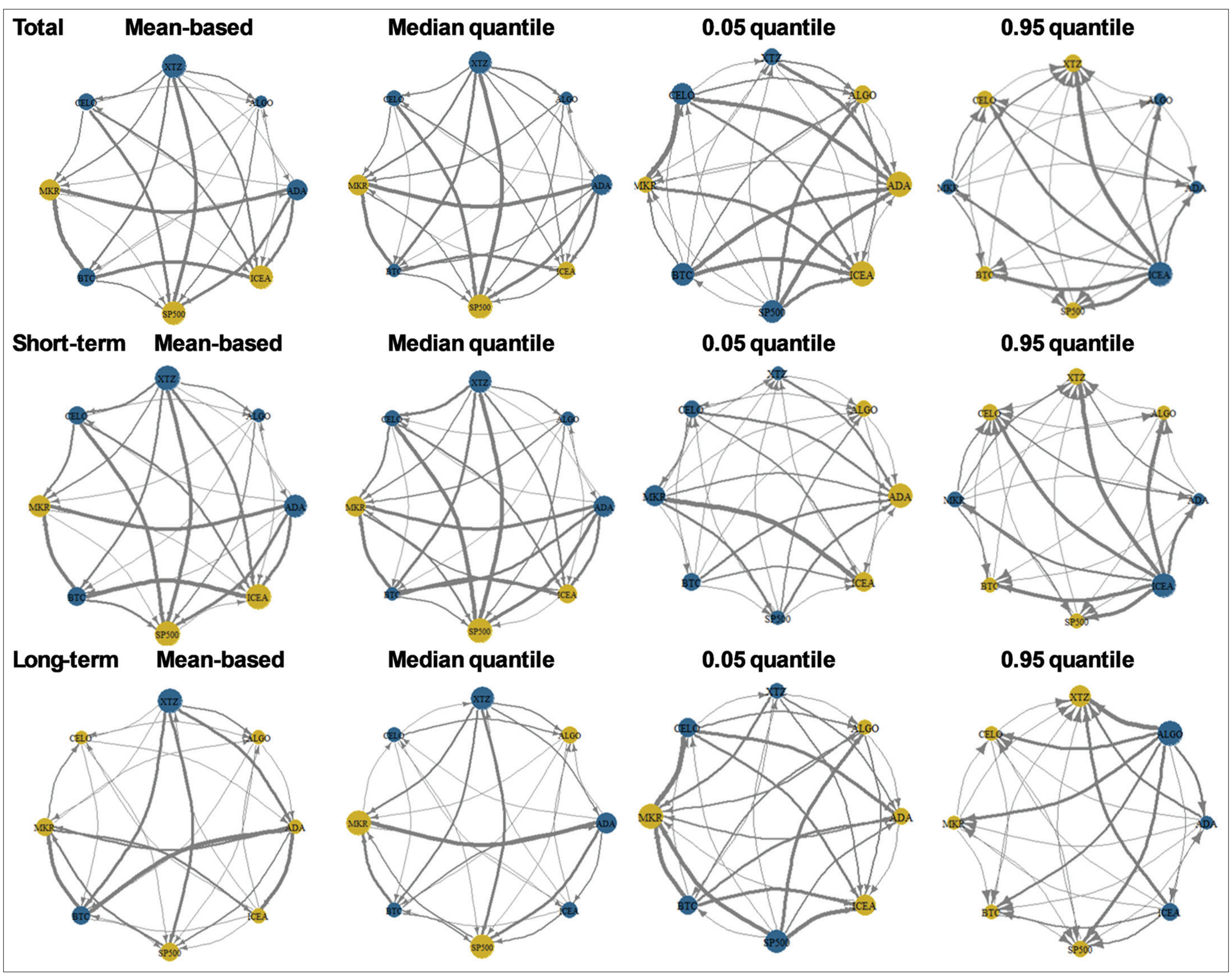
Figure 3 depicts the networks showing net pairwise directional spillovers across aggregate, short-, and long-horizon periods across varying market conditions. Blue nodes represent net transmitters, while yellow nodes denote net receivers. Node dimensions and arrow thickness convey spillover dynamics. ADA and XTZ are key net transmitters at the mean-based level in the short term, while ICEA, MKR, and S&P500 are more passive. In the long term, BTC and XTZ dominate spillover transmission, whereas ICEA, MKR, ALGO, and S&P500 remain mainly on the receiving end. The median network shows a similar structure, with ADA, BTC, and XTZ as transmitters, and ICEA, MKR, and S&P500 as receivers. Under extreme conditions, the structure shifts: ADA and ALGO act as net receivers during negative returns. ICEA consistently absorbs shocks in downturns, reflecting its reactive nature. Conversely, ICEA becomes a leading transmitter in bullish regimes, especially in the short term. Portfolio managers can use ICEA to adjust asset allocation and hedge strategies, optimizing diversification and leveraging environmental signals.

5.2. Dynamic connectedness

5.2.1. Total connectedness dynamics

Figure 4 compares the TCI from the median quantile QFVAR model and the mean−based approach (Baruník & Křehlík, 2018). The black area shows total connectedness, with red and green

Figure 3: Quantile-frequency networks of net pairwise connectedness



indicating short- and long-term components. Both methods exhibit broadly similar trends, with pronounced increases around geopolitical and regulatory developments such as the Russia–Ukraine conflict and crypto ETF authorizations during late 2024, which triggered a notable rise in short-term spillovers. Short-term dynamics dominate throughout, reflecting the high reactivity of ESG crypto assets and behavioral signals to shocks. Long-term components remain more stable and subdued. However, the mean-based TCI at long-term horizons exceeds the quantile-based measure at several points (mid-2021, late 2022, end-2024), likely due to OLS's sensitivity to extremes, as Chatziantoniou et al. (2022) explained. This divergence highlights the risk of overestimating systemic connectedness using mean-based models alone and underscores the value of quantile-based approaches. These insights motivate the transition to a time–quantile perspective. Figure 5 illustrates heatmaps of total, short-term, and long-term connectedness (TCIs) across quantiles and over time. Warmer colors indicate more substantial spillovers. Total connectedness peaks in the distribution tails, confirming that systemic risk flares during crashes and speculative surges. Short-run spillovers rise sharply at these extremes and closely track major shocks such as China's 2021 mining ban, the 2022 Russia-Ukraine conflict, and the 2024 spot ETF approvals. Long-run connectedness appears only sporadically around these macro events. Outside such windows, cross-asset correlations stay low, preserving long-term diversification.

5.2.2. Net directional connectedness

5.2.2.1. Net total directional connectedness over time and quantiles

Figure 6 displays the evolution of net directional connectedness for each variable across time and quantiles. Red areas signal that a variable acts as a net transmitter of shocks, while blue areas indicate net receivers. The color intensity reflects the magnitude of connectedness. The visual patterns reveal that the roles of the variables shift considerably across time and quantile levels, highlighting notable asymmetries in their systemic behavior. To better understand these regime-dependent dynamics, the sample is divided into four phases: (1) PoS & ESG Rise: (study outset until May 2022), (2) Post-Terra Collapse, Inflationary Pressures,

Figure 4: Frequency-based dynamic connectedness at mean-based and median-based quantiles

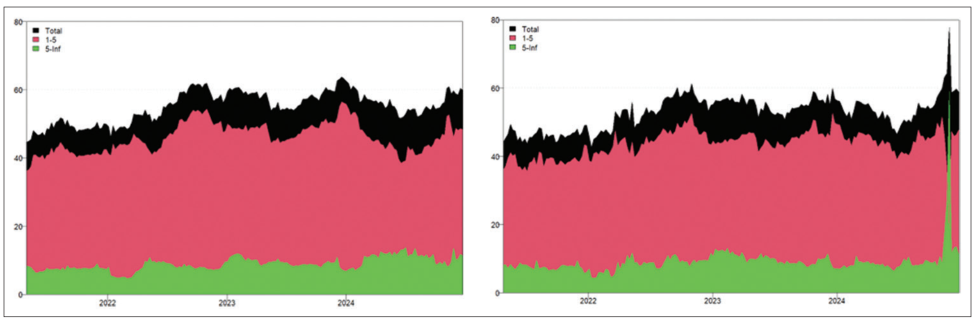


Figure 5: Total, short-term, and long-term connectedness across time and quantiles

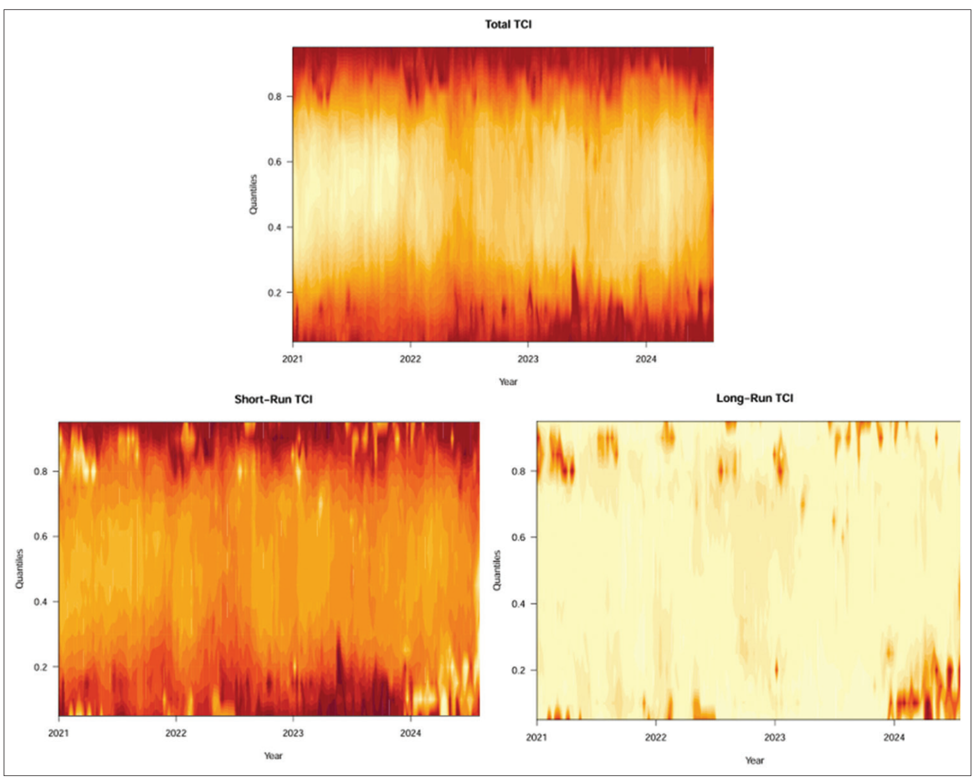
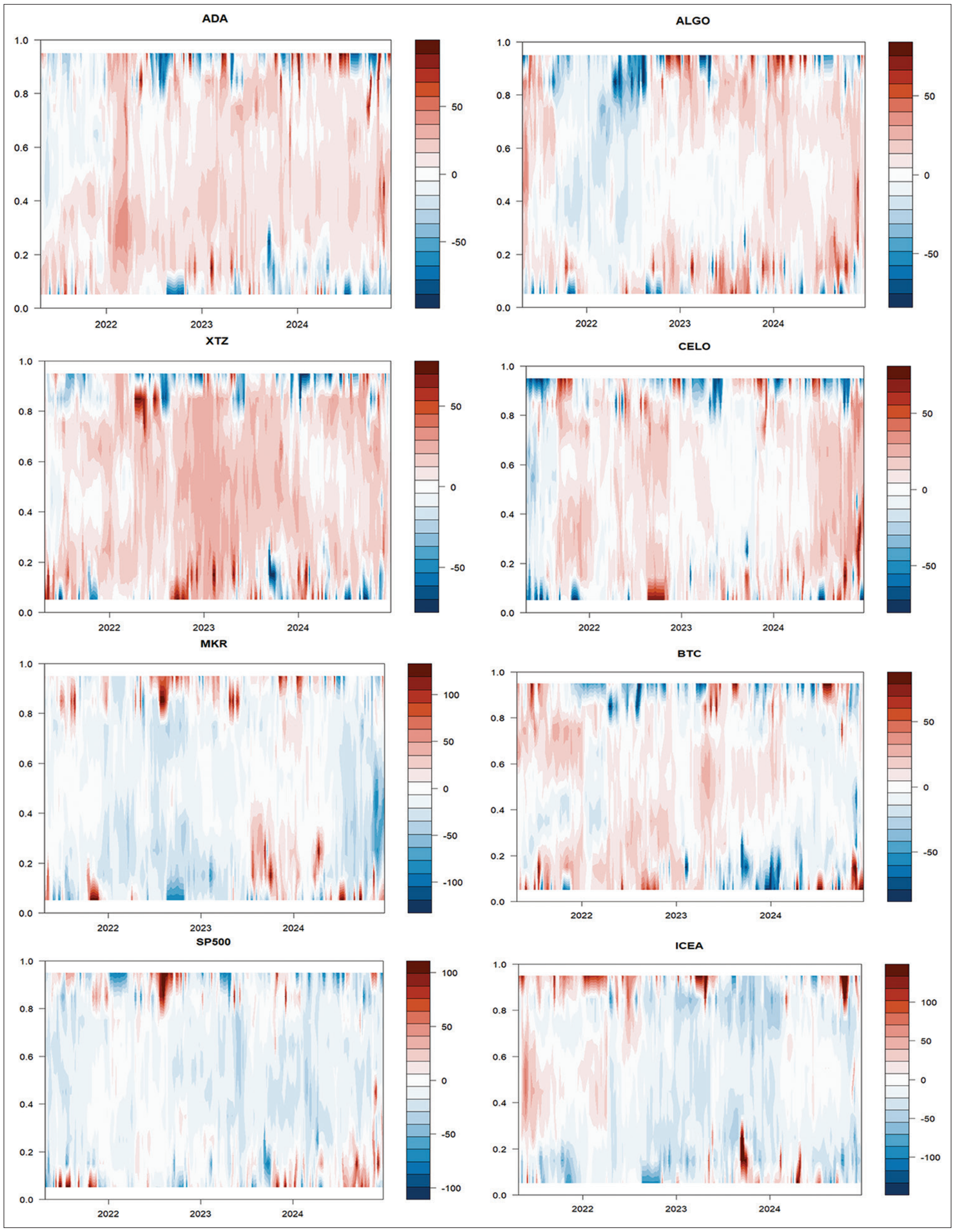


Figure 6: Net directional connectedness of each variable across time and quantiles



Russia–Ukraine conflict (May 2022 until Feb 2023), (3) SEC vs Crypto (Feb 2023 until July 2023), and (4) ETFs Approval and Pre-halving Rally (July 2023 until Dec 2024). Across the four event-based phases, transmission patterns shift markedly. Phase 1 sees ADA, CELO, and XTZ as transmitters, while ALGO maintains a moderate receiver role. BTC exhibits a mixed profile, and MKR remains neutral. SP500 consistently behaves as a structural receiver. Phase 2 retains this structural asymmetry but intensifies defensive behaviors: ALGO becomes a strong receiver, ADA switches between reception and transmission, while CELO and XTZ continue transmitting shocks. BTC absorbs shocks at higher quantiles but transmits at the center. MKR and SP500 act as stable net receivers. Phase 3 marks a widespread amplification of transmission roles. Most ESG cryptos become dominant transmitters under regulatory stress. BTC and SP500 maintain moderate and passive roles, respectively. MKR remains a systemic stabilizer. Phase 4 shows more differentiated behaviors. ADA, ALGO, and BTC exhibit mixed dynamics, receiving shocks at extreme quantiles while transmitting during rallies. CELO stays a persistent transmitter, while XTZ alternates between mild reception and transmission. MKR and SP500 continue acting as net receivers. The ICEA index predominantly acts as a net receiver of informational pressures related to environmental concerns in the cryptocurrency sphere, particularly during heightened uncertainty or ESG-driven portfolio reallocations. The few transmission episodes observed at extreme quantiles correspond to periods of intense environmental media attention, such as the FTX collapse, SEC actions, and greenwashing narratives, during which the ICEA temporarily amplifies systemic behavioral effects without assuming a sustained role as a contagion driver.

5.2.2.2. Frequency-based net directional connectedness

To examine net directional connectedness across frequencies, we split the spillover metrics into short- and long-run components;

the estimates appear in Figure 7. The short-term connectedness largely mirrors the patterns in Figure 6, confirming that short-term dynamics primarily drive transmitter or receiver roles, while long-term structures either reinforce or moderate these effects. ADA acts as a strong short-term transmitter, with a structural shift after early 2022, coinciding with the Terra-LUNA collapse and the escalation of regulatory scrutiny. ALGO behaves defensively in the early periods but becomes a partial transmitter following systemic shocks. XTZ consistently transmits shocks across both horizons, particularly intensifying during the post-FTX liquidity crisis. CELO remains a persistent transmitter, reflecting its vulnerability during ESG sentiment shifts and DeFi market stress. In contrast, MKR maintains a stable net receiver role, absorbing shocks during turbulent phases, notably the Russia–Ukraine crisis and the crypto regulatory wave in 2023. From a portfolio perspective, the persistent long-term transmission roles of ADA, CELO, and XTZ suggest greater systemic risk exposure. At the same time, ALGO's mixed profile and MKR's resilience make them suitable for hedging strategies in sustainable crypto portfolios. In the short run, ICEA consistently acts as a net receiver, especially in the extreme quantiles, highlighting its role as a behavioral signal that absorbs shocks during stress episodes. In the long run, the connectedness weakens, with sparse and transient transmission at upper quantiles, suggesting limited systemic influence. ICEA functions as a short-term sentiment absorber rather than a long-term contagion driver.

5.2.3. Pairwise directional connectedness

5.2.3.1. Pairwise directional connectedness at median quantile

Figure 8 illustrates the bilateral net directional spillovers among the series. ADA acts predominantly as a persistent net transmitter to ALGO, while short-horizon spillovers remain weak and oscillating. With total connectedness near zero at the median quantile, the pair retains short-run diversification benefits despite ADA's rising long-run influence. ADA and ALGO acted as net receivers from CELO until 2023, then shifted to moderate transmitters. However, low spillover levels suggest these assets still offer diversification potential. ADA briefly transmits shocks to XTZ during early 2022, reflecting speculative pressures, but the relationship stabilizes as narratives shift. ALGO shows mild persistence around the Terra-LUNA collapse and late 2024, linked to broader DeFi market stress. XTZ is a modest short-run transmitter to CELO after 2022, driven by ESG repositioning, with minimal long-term impact. Crypto assets exhibit a broadly consistent connectedness pattern with MKR, maintaining relatively neutral relationships until mid-2023. Following major regulatory shifts (MiCA, SEC actions) and Bitcoin ETF approvals, these assets progressively became net transmitters of shocks to MKR, with spillover intensity rising sharply by late 2024, weakening MKR's traditional defensive role. The pairwise connectedness between ESG crypto assets and Bitcoin reveals heterogeneous spillover dynamics. ADA, ALGO, and XTZ shift from mild receivers to moderate transmitters, with spillover intensity peaking in late 2024 amid ETF approvals

Figure 7: Dynamic net connectedness by variable, horizon, and quantile

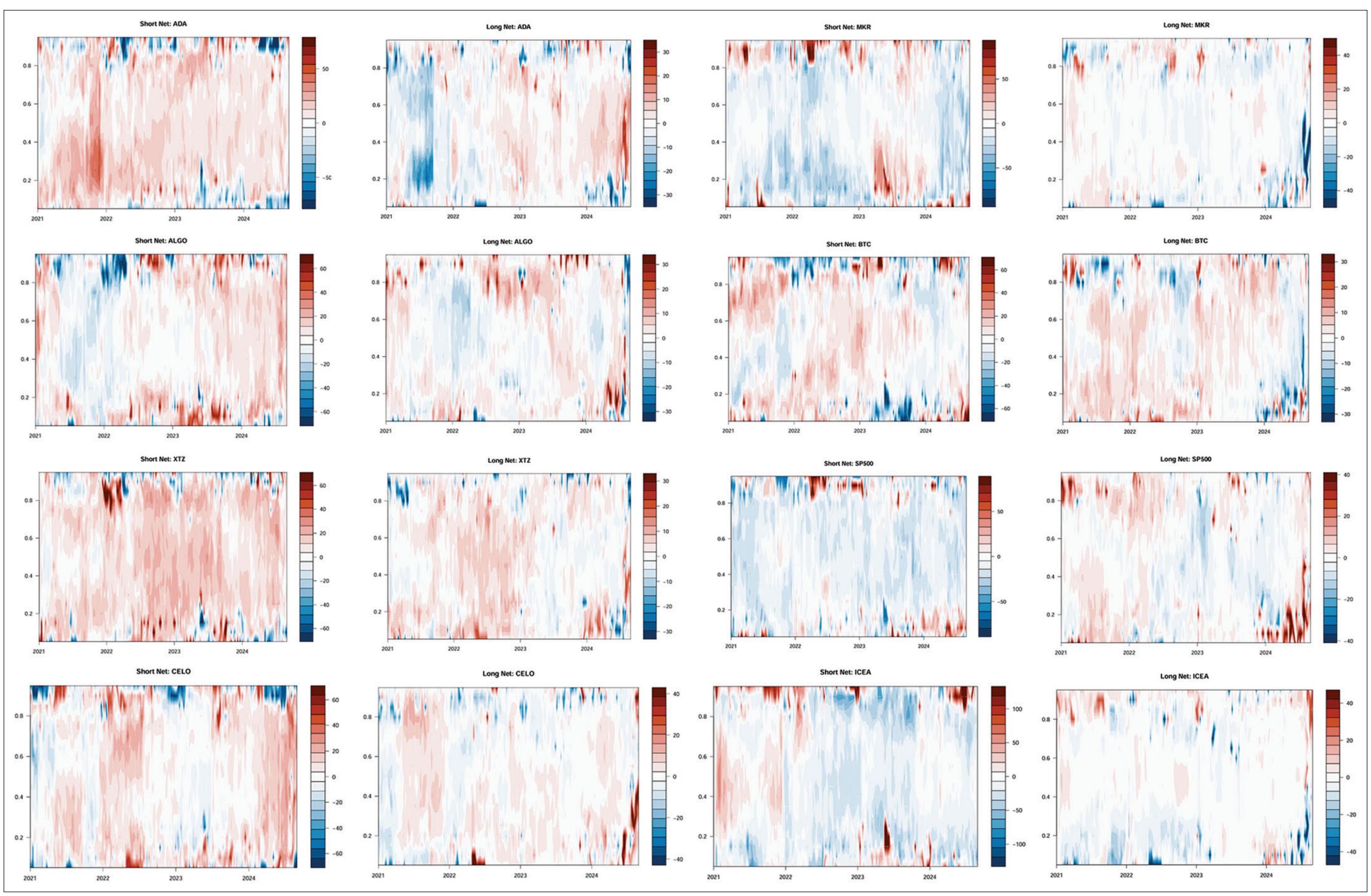
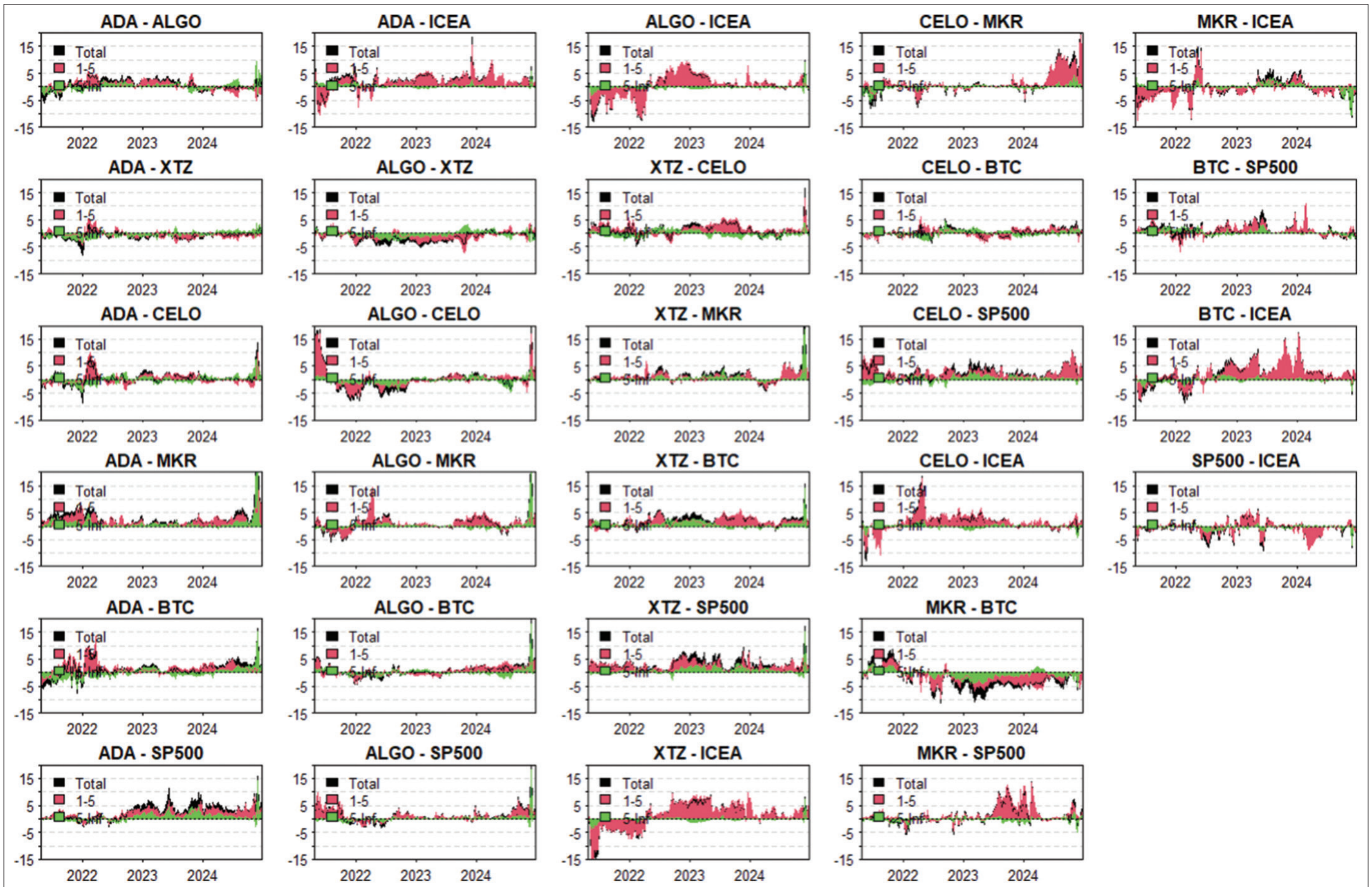


Figure 8: Pairwise directional connectedness by frequency at the median quantile



and pre-halving speculation. CELO remains largely neutral with occasional mild transmission. MKR consistently acts as a net receiver, reinforcing its role as a systemic stabilizer rather than a contagion source. From mid-2022, green crypto assets (ADA, ALGO, XTZ, CELO) increasingly transmit shocks to the SP500, with spillovers peaking by late 2024 amid greater financial integration following MiCA implementation and Bitcoin ETF approvals. MKR shows only a brief transmission episode in 2023 before reverting to a neutral, defensive role toward traditional equities.

The ICEA initially behaved as a spillover transmitter, later transitioning to a net receiver by early 2022, following heightened ESG scrutiny, regulatory tightening, and growing instability in the crypto market. Events like stablecoin concerns and the Terra-LUNA collapse reshaped ICEA into a reactive behavioral indicator. Since then, crypto-assets like ADA, XTZ, and BTC have increasingly transmitted shocks to ICEA, with peaks between early 2022 and mid-2023. ICEA primarily functions as a behavioral thermometer, absorbing shifts in environmental sentiment within the crypto-financial ecosystem.

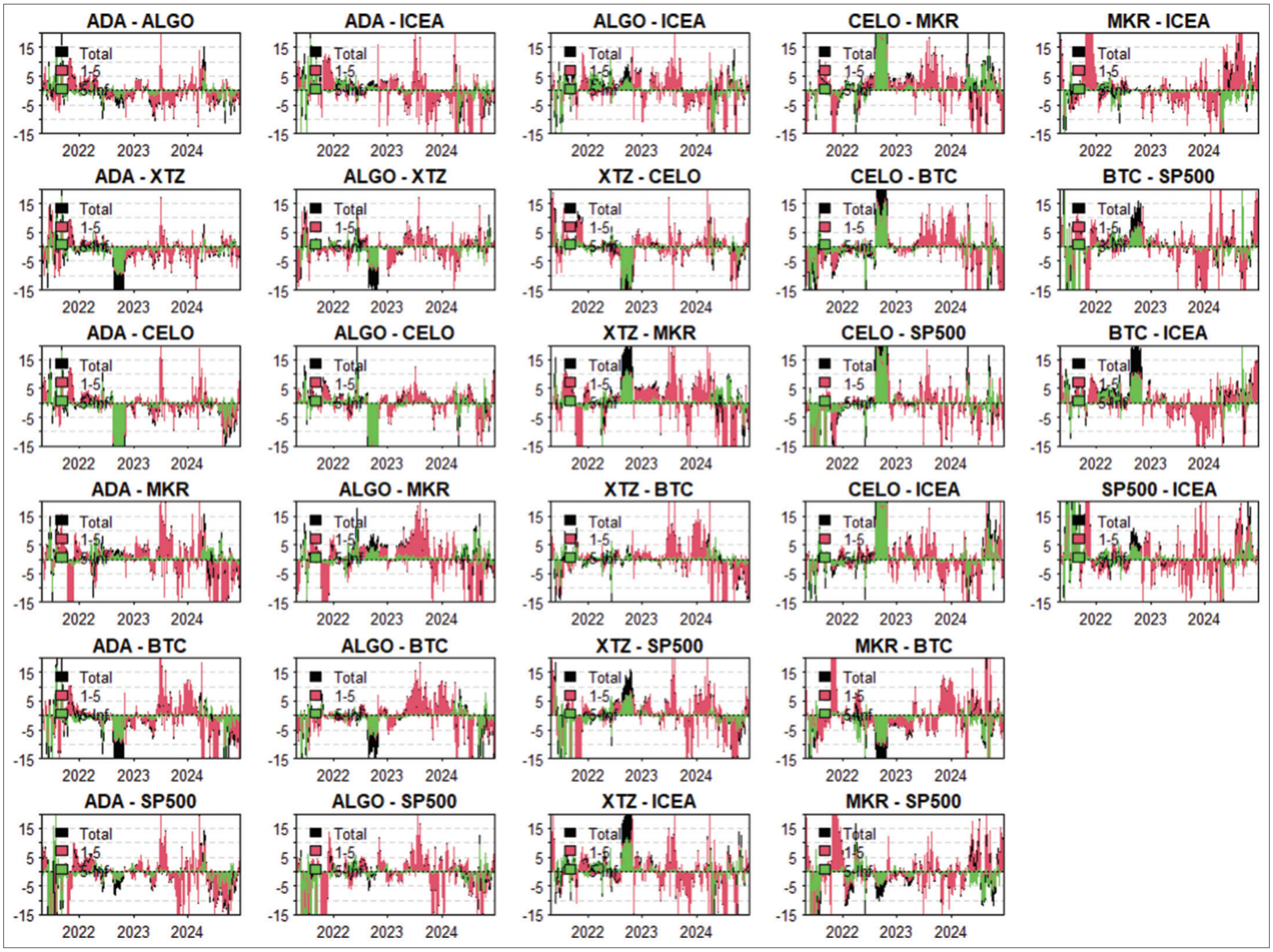
5.2.3.2. Pairwise directional connectedness at extreme quantiles

Figures 9 and 10 display the Pairwise directional connectedness at the extreme lower and upper quantiles. The connectedness measures show considerable volatility across both figures, with noticeable differences in magnitude, thereby confirming the asymmetry previously discussed. Specifically, at the extreme lower quantile, green crypto-assets such as ADA and ALGO predominantly act as net receivers of downside shocks from both Bitcoin and the S&P 500, particularly from 2021 to mid-2023. This pattern highlights their limited hedging capacity under financial distress and emphasizes Bitcoin's dominant contagion role alongside spillovers from traditional equity markets. It also reflects the market's early prioritization of liquidity and scale over ESG alignment. These findings corroborate Shao et al. (2025), who indicate that traditional cryptocurrencies significantly influence green cryptocurrencies. In contrast, at the extreme upper quantile, these assets shift into mild net transmitters of upside shocks, initially toward Bitcoin and subsequently toward the equity market, especially between mid-2023 and mid-2024. This transition suggests that during speculative or optimistic phases, investor enthusiasm for ESG narratives and PoS protocols temporarily enhances the influence of sustainable crypto assets within broader financial markets.

5.3. Portfolio Strategy Implications

Alongside the analysis of quantile frequency connectedness, this subsection explores portfolio implications by implementing portfolio strategies proposed by Broadstock et al. (2022). This study employs the MVP (Minimum Variance), MCP (Minimum Correlation), and MCoP (Minimum Connectedness) portfolio approaches to assess their hedge effectiveness (HE) in enhancing risk-adjusted returns under changing market conditions. Figure 11

Figure 9: Pairwise directional connectedness by frequency at the extreme lower quantile (τ = 0.05)



depicts the performance of the three portfolio strategies. The MVP portfolio exhibits a smooth and consistent upward trajectory, confirming its effectiveness in delivering stable returns through risk minimization. In contrast, the MCP and MCoP portfolios reveal greater volatility, with marked surges and declines around late 2021 and mid-2023, reflecting their heightened sensitivity to changing correlation and connectedness patterns. These fluctuations are likely associated with significant systemic events such as the post-COVID speculative boom and MiCA regulatory developments, which significantly reshaped cross-asset dynamics. Although MCP and MCoP outperformed MVP before mid-2022, the MVP strategy reasserted its dominance, underscoring its superior resilience. This transition coincides with the market disruptions triggered by the Russia–Ukraine conflict and the early phases of global monetary tightening, strengthening the role of variance-based strategies in mitigating systemic risk. Table 6 offers a detailed comparison of asset allocations and hedging effectiveness across the three portfolio strategies. Under the MVP strategy, the portfolio exhibits an intense concentration in the S&P 500, confirming its perceived stability in variance-based optimization. ESG crypto assets like ADA, XTZ, and CELO are excluded, while ALGO, MKR, and BTC receive minor allocations. However, all exhibit strong hedge effectiveness (HE ≥ 0.91), especially ADA, ALGO, and XTZ. Conversely, the S&P 500 shows a negative HE, reflecting its poor hedging performance under stress. In the MCP strategy, MKR, BTC, ALGO, and SP500 receive the largest weights, aiming to reduce pairwise correlations. CELO and ADA are marginally included, while XTZ is excluded. Most ESG cryptos offer moderate hedge effectiveness, but SP500 shows a sharply negative HE, indicating weak hedging performance. In the MCoP strategy, MKR, SP500, and ALGO receive the highest allocations, followed by BTC and CELO. ADA is modestly weighted, while XTZ is excluded. Most ESG crypto assets achieve solid hedge effectiveness, confirming their role in minimizing systemic risk. SP500 again shows a strongly negative correlation, indicating poor hedging capacity in connectedness-based optimization.

Figure 12 depicts the dynamic allocation of assets within the portfolios. Across the analyzed timespan, allocations to ESG cryptos remain generally limited under MVP, consistent with their higher volatility profiles and the strategy's emphasis on minimizing total risk. However, the MCP and MCoP display more adaptive behavior, suggesting that these strategies respond

Figure 10: Pairwise directional connectedness by frequency at the extreme upper quantile (τ = 0.95)

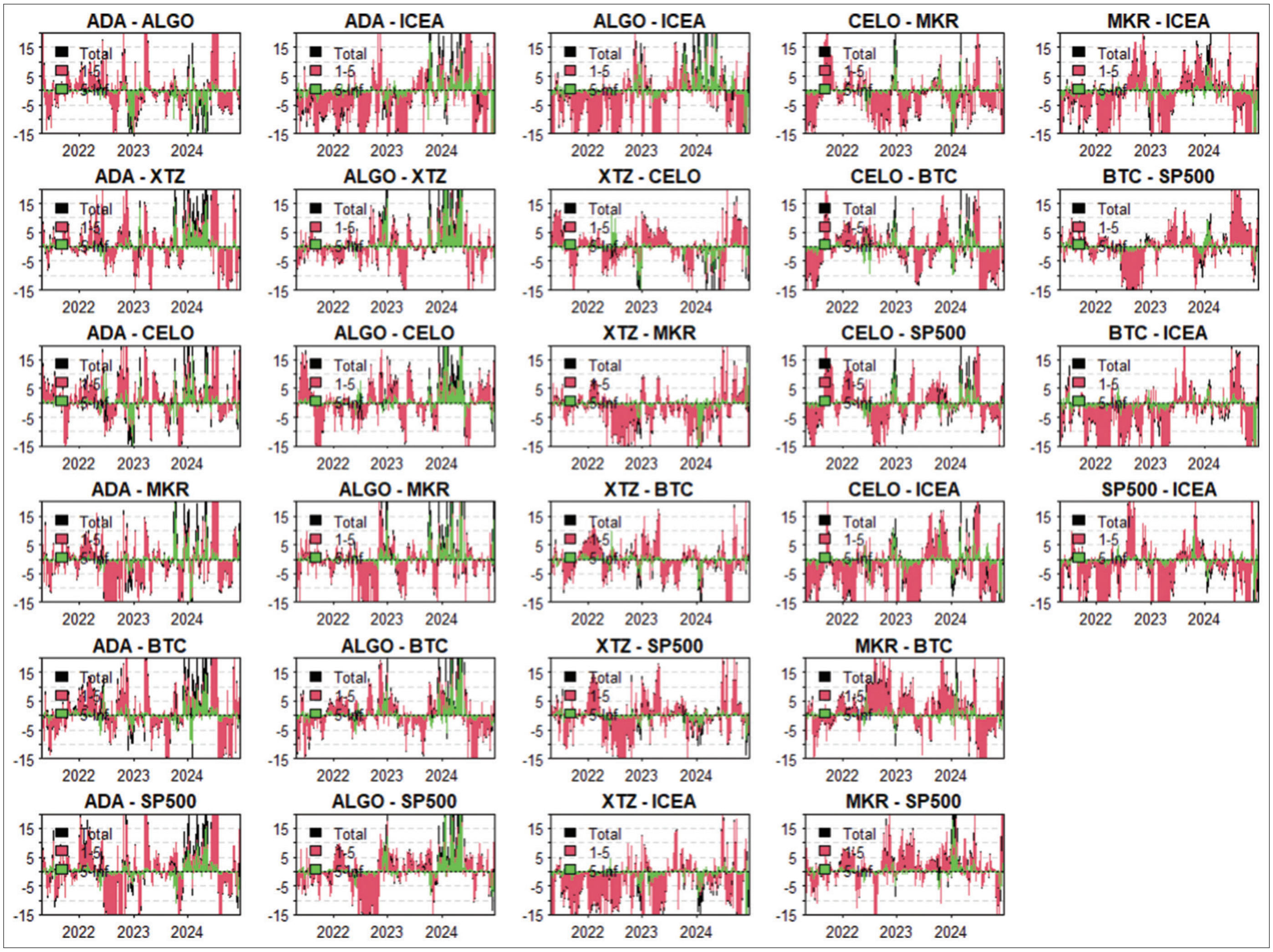
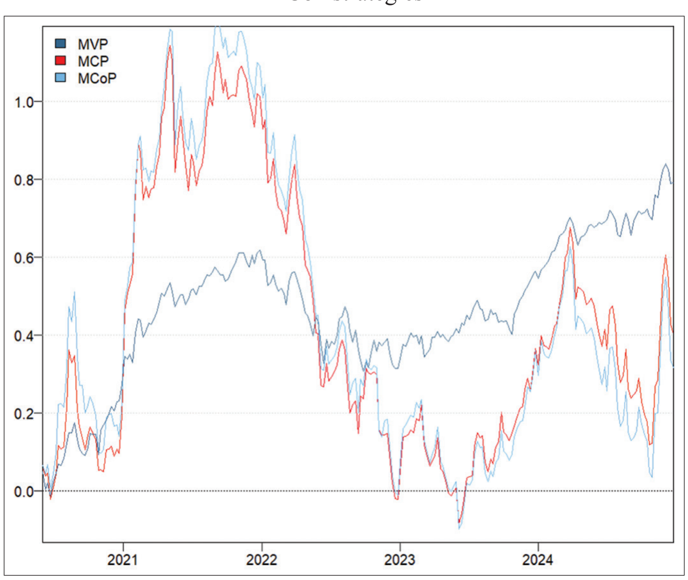


Figure 11: Cumulative portfolio returns based on MVP, MCP, and MCoP strategies



more sensitively to evolving co-movement structures among ESG-aligned digital assets. Notable reallocations occur after China's 2021 regulatory crackdown on crypto and the growing criticism of the environmental footprint of PoW protocols, reflecting increased investor appetite for sustainable blockchain alternatives. Overall, the analysis validates the core objective of this study by demonstrating that connectedness dynamics strongly influence optimal portfolio decisions. The observed differences across the portfolio strategies reinforce the value of quantile-frequency connectedness approaches in identifying systemic risks and guiding strategic ESG asset allocation under changing market conditions.

5.4. Robustness Test

To ensure the robustness of the QVAR-based connectedness results, all analyses were replicated with alternative rolling window sizes of 100 weeks. As shown in Figure 13, the Total Connectedness Indices (TCIs) exhibit similar patterns to those observed with the 50-day window (). Likewise, net connectedness and inter-asset spillovers remain consistent across specifications. These findings indicate that the interconnectedness among ESG blockchain assets, traditional cryptocurrencies, conventional markets, and the ICEA index is stable for window size and frequency decomposition parameters modifications, confirming the robustness of the analysis.

Figure 12: Dynamic Multivariate Portfolio Weights

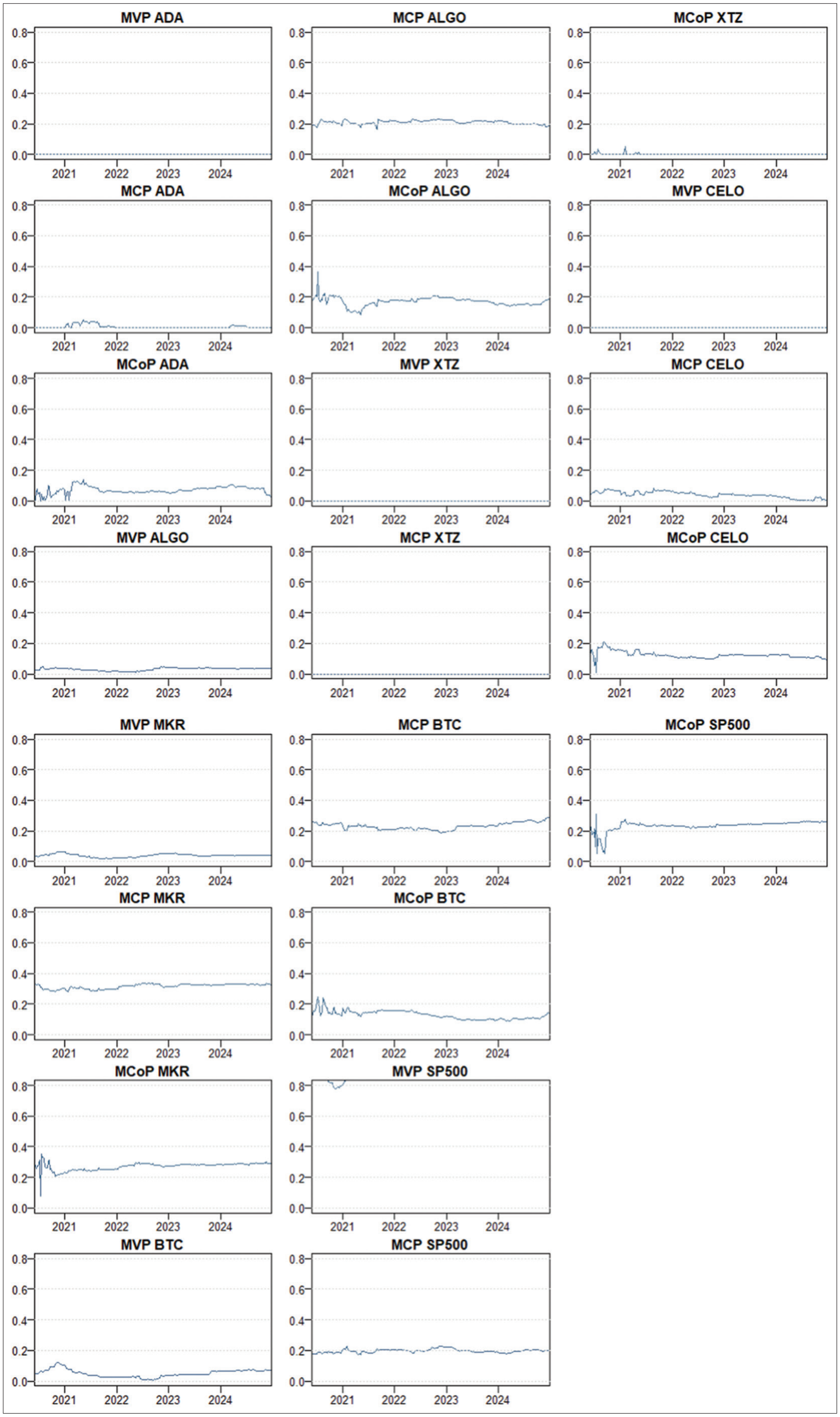


Figure 13: Total, short-term, and long-term connectedness over time and quantiles with rolling window sizes 100

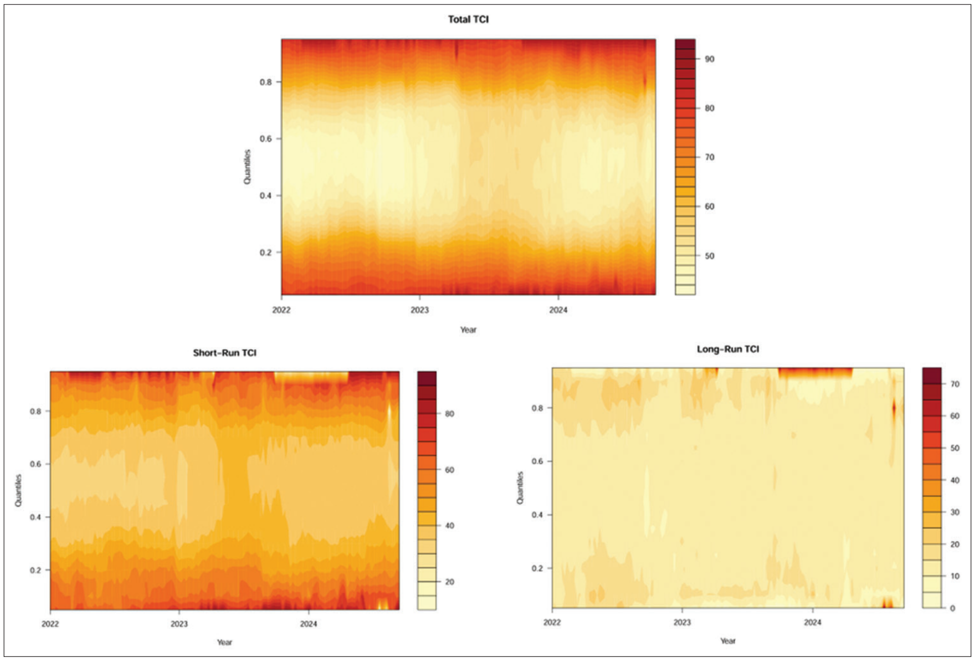


Table 6: Multivariate portfolio weights based on MVP, MCP, and MCoP strategies.

	Mean	Std. Dev.	5%	95%	HE	P-value
	Minimum variance portfolio					
ADA	0.00	0.00	0.00	0.00	0.97	0.00
ALGO	0.03	0.01	0.01	0.04	0.97	0.00
XTZ	0.00	0.00	0.00	0.01	0.97	0.00
CELO	0.00	0.00	0.00	0.00	0.97	0.00
MKR	0.04	0.01	0.02	0.05	0.96	0.00
BTC	0.05	0.02	0.01	0.09	0.91	0.00
SP500	0.88	0.04	0.82	0.93	-0.14	0.30
	Minimum correlation portfolio					
	Mean	**Std. Dev.**	**5%**	**95%**	**HE**	**P-value**
ADA	0.01	0.01	0.00	0.04	0.80	0.00
ALGO	0.21	0.01	0.19	0.23	0.83	0.00
XTZ	0.00	0.00	0.00	0.02	0.78	0.00
CELO	0.04	0.02	0.00	0.07	0.83	0.00
MKR	0.32	0.02	0.29	0.33	0.71	0.00
BTC	0.23	0.02	0.20	0.27	0.45	0.00
SP500	0.20	0.01	0.18	0.22	-6.36	0.00
	Minimum connectedness portfolio					
	Mean	**Std. Dev.**	**5%**	**95%**	**HE**	**P-value**
ADA	0.07	0.02	0.03	0.11	0.78	0.00
ALGO	0.17	0.03	0.11	0.21	0.82	0.00
XTZ	0.00	0.00	0.00	0.00	0.76	0.00
CELO	0.12	0.02	0.10	0.17	0.81	0.00
MKR	0.27	0.03	0.23	0.29	0.68	0.00
BTC	0.13	0.03	0.09	0.17	0.40	0.00
SP500	0.23	0.03	0.19	0.26	-7.06	0.00

6. CONCLUSION

ESG blockchain assets have emerged as a growing class of environmentally aligned digital instruments, bridging blockchain innovation with sustainability goals. Understanding their connectedness with conventional assets and cryptocurrencies is essential to assess systemic risk and diversification potential. To deepen this analysis, the inclusion of the cryptocurrency environmental attention adds a behavioral lens by linking environmental attention to asset interdependencies. Accordingly, we analyzed a system comprising ESG crypto assets, traditional cryptocurrencies, the stock market, and the ICEA, using a quantile-frequency connectedness approach combined with a portfolio optimization framework.

The main findings are as follows. The static analysis shows that ESG cryptos and traditional cryptocurrencies exhibit significant spillover effects, particularly during extreme market conditions. Weak linkages between ESG digital assets and the stock market indicate potential diversification benefits when investing in sustainable digital assets. However, this interconnectedness intensifies under extreme market conditions. In a bullish market, ESG crypto assets are the leading transmitters. In contrast, the stock market acts as a net receiver of spillovers, indicating that investors can use the ESG blockchain market to predict the stock market's movements. Nevertheless, ESG crypto assets act as net receivers of spillovers in a bearish situation, while stocks are the dominant transmitters. In this context, ESG cryptos provide diversification to the stock market and act as effective hedging instruments against stocks.

The ICEA index remains largely decoupled from green blockchain assets. Its interdependence is weak and time-varying, making ICEA an effective diversifier in the system and providing new avenues for reducing systematic risk in investment portfolios. Moreover, when market sentiment is low and volatility is muted under bearish market conditions, ICEA functions as a net receiver, reflecting global environmental concerns without notably affecting other assets. In contrast, during bullish market conditions, marked by high volatility and optimistic sentiment, ICEA acts as a net transmitter, exerting influence as environmental issues gain prominence, driven by growing awareness of the environmental impact of crypto assets.

Moreover, the connectedness is stronger during episodes of market instability, notably the Russia–Ukraine conflict and the crypto ETF approvals, than during normal market conditions. In addition, connectedness among assets exhibits asymmetric and heterogeneous patterns across quantiles and investment horizons, with spillovers intensifying during periods of market turmoil. This regime-dependent behavior highlights the need to capture tail-specific dynamics rather than relying solely on a single frequency or quantile. Incorporating quantile-specific measures offers a more accurate estimation of connectedness and supports more robust portfolio risk management in ESG-driven digital markets. Furthermore, frequency-based connectedness analysis reveals that shocks are concentrated mainly in the short term, suggesting enhanced long-term diversification opportunities for investors. Finally, investment strategies that reduce connectedness outperform variance-based portfolios and offer valuable diversification benefits, especially under stable conditions. Their effectiveness varies with market regimes, highlighting the importance of integrating these strategies into a dynamic portfolio optimization framework.

These findings entail meaningful implications for both investors and policymakers. For investors, ESG digital assets present meaningful diversification and hedging opportunities, particularly when integrated into dynamic portfolio strategies that account for market regimes and systemic connectedness. The weak and time-varying linkage of ICEA with other assets enhances its appeal as a behavioral diversifier, especially under heightened environmental concerns. The effectiveness of minimum connectedness portfolios in reducing systemic risk underscores the value of incorporating spillover dynamics, rather than relying solely on variance-based approaches. For policymakers, the results highlight the need to monitor how sustainability-driven digital assets interact with traditional markets and public sentiment. Given the shifting role of green assets across market states, regulatory frameworks should aim to enhance transparency and stability in ESG-oriented crypto markets while supporting innovation in green decentralized finance.

This study, however, is subject to certain limitations. It focuses on a specific set of ESG crypto assets, and the ICEA, while novel, may not capture the full spectrum of environmental sentiment. Additionally, while powerful, the quantile-frequency connectedness framework is constrained by the choice of quantile bands and frequency windows. Future research could expand the asset universe to include additional ESG-related tokens or sectors such as green AI or tokenized carbon credits. Moreover, integrating macroeconomic variables, regulatory shocks, or global policy indicators could provide a richer understanding of the drivers of connectedness in sustainable finance. Finally, exploring time-varying portfolio strategies using machine learning or regime-switching models would offer promising avenues for optimizing ESG portfolios in increasingly complex financial environments.

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