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Network interconnections among DeFi, NFTs, AI tokens, and renewable energy: driving factors, measurements, and portfolio implications

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ABSTRACT

This study investigates the role of artificial intelligence (AI) tokens in dynamic interactions, diversification, and hedging capabilities, in relation to non-fungible tokens (NFTs), decentralised finance (DeFi) tokens, and renewable energy assets. Using the Time-Varying Parameter Vector Autoregressive (TVP-VAR) model, we examine return, volatility, and higher-order spillovers across both time and frequency domains. The results show that NFTs serve as persistent channels for the transmission of return and volatility shocks, driven by their speculative nature. AI and renewable tokens primarily absorb systemic risk due to their lower liquidity and niche adoption. DeFi tokens play flexible roles, shifting between transmitters and receivers across market regimes. The results demonstrate asset-specific idiosyncrasies and that volatility spillovers are generally stronger than return spillovers. Frequency-domain analysis highlights that digital tokens dominate short-term spillovers, while renewable assets absorb shocks across horizons. However, higher-order moment results reveal that extreme risk linkages shift transmission channels. Our results also confirm that oil market (OVX) shocks drive short-term return connectedness, CBOE volatility (VIX) volatility, and policy uncertainty (EPU) significantly impact return linkages. The results of our portfolio analysis show that AI tokens form the core of diversification, NFTs provide short-term speculative hedging, and renewable assets, particularly solar-linked tokens, act as low-cost stabilisers, underscoring the need for active rebalancing under different market regimes. These findings provide meaningful implications for policymakers, regulators, and portfolio managers for strengthening systemic risk oversight and considering asset-specific idiosyncrasies in investment strategies.

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AI tokens; NFTs; DeFi; renewable energy markets; TVP-VAR; portfolio implications

1. Introduction

In today's fourth industrial revolution, artificial intelligence (AI) has become a beacon of transformation across various industries. Unprecedented technological advancements are transforming multiple industries, including accounting, financial services, healthcare, intelligent manufacturing, energy, robotics, and autonomous driving (Zeng et al. 2024).

Over the past five decades, human intervention in the financial industry has gradually declined as technological innovation has reshaped global capital markets. The financial services infrastructure has also integrated emerging technologies such as Web 3.0, blockchain, and mobile applications. More recently, AI has occupied a central role (Gunay et al. 2023). In the finance domain, AI enhances market efficiency and productivity by optimising risk-reward assessments, strengthening fraud detection, and improving financial advisory processes. Its influence extends beyond traditional financial assets to digital assets such as cryptocurrencies and tokens.

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Machine learning algorithms can process large-scale data to identify predictive patterns, forecast asset movements, and design trading strategies in highly volatile environments (Han et al. 2026). AI-driven blockchain analytics and fraud-detection frameworks can provide critical safeguards for investors. At the same time, rising investments in AI initiatives by major technology firms reflect growing confidence in AI's capacity to generate sustained financial value.

Recently, unconventional financial asset markets, like digital tokens, have attracted portfolio investors due to their diversification opportunities (Odusami and Akinsomi 2024). Since its inception in 2008, cryptocurrencies have been envisioned as an alternative to traditional financial systems, facilitating peer-to-peer electronic transfers. However, they have rapidly evolved into a distinct class of financial assets (Raza, Sharif, and Anwar 2025; Zadeh and Romagnoli 2024) owing to the versatility of blockchain technology. In recent years, two notable markets have emerged within the blockchain ecosystem. One such market is non-fungible tokens (NFTs), which represent a transformative shift in digital ownership.

By leveraging blockchain technology, NFTs tokenise digital content such as artworks, music, and virtual real estate, imbuing them with uniqueness and provenance in the digital realm. Another such market is decentralised finance (DeFi), where assets embody blockchain's decentralised ethos by offering financial services through smart contracts, circumventing traditional intermediaries. These services include lending, borrowing, and trading, executed autonomously across blockchain networks (Dowling 2022). The rise of DeFi introduces novel pathways for global financial inclusion and innovation, challenging conventional financial systems. Each of these developments represents a distinct evolution within the broader blockchain ecosystem, influencing investor strategies (Gunay et al. 2023).

Regarding cryptocurrencies, their high energy consumption is a barrier to the adoption of sustainable, low-carbon solutions. Mining cryptocurrencies is a leading cause of carbon emissions and global warming. The high energy consumption is due to computationally intensive consensus mechanisms, which contribute to increased CO_2 emissions and, in turn, to climate change (Zhang et al. 2023). Although previous studies have explored the relationship between fossil fuel markets and crypto assets, research examining renewable energy assets and digital assets remains limited. Exploring their linkages to digital assets is important for understanding how the breakthrough development of blockchain affects renewable energy markets.

Furthermore, the relationship between AI, renewable energy, and digital assets holds substantial economic and environmental significance. AI is transforming the energy industry through smart grids, predictive maintenance, and efficiency optimisation, facilitating the integration of renewable sources (Qin et al. 2024). Heightened awareness of climate change has accelerated investments in renewable energy technologies to foster green innovation (Lundgren et al. 2018). However, the rapid growth of cryptocurrency and token markets has also raised sustainability concerns due to their high energy consumption. Some studies show that AI-driven models, such as artificial neural networks, can enhance forecasting of energy production, demand, and carbon emissions, thereby improving energy planning and the development of low-emission infrastructure (Pan et al. 2024). Furthermore, AI tokens such as SingularityNET and Fetch.AI have emerged as vehicles for investors seeking exposure to the expanding AI sector. Understanding these evolving linkages is crucial, as AI continues to drive efficiency and sustainability in the energy sector. Digital assets are evolving toward greener technologies, aligning technological innovation with long-term economic and environmental objectives.

The motivation for focusing on digital assets like NFTs, DeFi, AI tokens, and renewable energy markets stems from their growing interconnections and influence on financial markets. The recent technological developments have introduced transformative dynamics into financial markets, reshaping ownership structures, transactional frameworks, and investment strategies (Cheraghali et al. 2024). Within the blockchain industry, NFTs and DeFi are two significant developments redefining ownership in the digital financial world. Furthermore, AI tokens serve as an interesting signal of participation in underlying technologies reshaping industries across the financial and energy sectors. Thus, the rapid advancements in AI technology present promising opportunities for higher returns. However, they also require a thorough analysis given their evolving nature and impact on investment processes. Constantly growing technological processes are changing the landscape of these connected fields. It is also important to explore the opportunities associated with their application and analyse how they affect market environments.

On the other hand, the energy market plays a crucial role in global economic stability and environmental impact, which is an area of particular concern. The rise in AI technology has driven increased energy demand, with tech companies reporting higher emissions from data centres powering AI applications. For instance, Lin and Lan (2024) emphasise the need to monitor the interconnections and volatility spillovers among these sectors, particularly in uncertain economic times. Thus, exploring the role of AI tokens in network connections and portfolio management, alongside renewable energy, NFTs, and DeFi, is crucial for understanding the future of investment strategies in the era of technological and environmental sustainability.

This study makes several key contributions to the existing literature. First, this study extends the existing literature by advancing the understanding of interconnections among emerging digital and sustainability-linked assets. Prior research has extensively studied the hedging or diversification benefits of traditional cryptocurrencies relative to equities, commodities, and bonds (Raza, Ahmed, and Aloui 2022). Our work shifts attention to AI tokens, DeFi assets, NFTs, and renewable energy assets. Together these represent the new frontier of digital and sustainable finance, rather than examining these assets in isolation. For instance, Raza, Sharif, and Anwar (2025) examine DeFi portfolio performance; our paper offers a unified analysis that captures their collective behaviour within the same financial ecosystem. This integration enables a deeper understanding of how technology-driven and sustainability-oriented tokens co-move, transmit shocks, and shape cross-market interdependence.

Our paper expands the perspective by analysing return and volatility spillovers between AI, NFTs, DeFi, and renewable energy assets during both pre-war and war periods, thereby capturing the extent to which geopolitical shocks influence interconnections among digital assets. Similarly, earlier studies on green finance (Karkowska and Urjasz 2023; Reboredo 2018) emphasise risk mitigation within clean energy or green bond markets. However, our paper innovatively links renewable energy assets to AI- and blockchain-based financial systems, revealing a new dimension of sustainable digital interdependence.

We also extend the existing methodological framework by applying the time-varying parameter VAR (TVP-VAR) to examine interconnection in the frequency domain (short-, medium-, and long-term) and at higher-order moments (skewness and kurtosis). This integrated approach reveals how short- and long-term spillovers evolve across different geopolitical regimes and distributional assumptions. Moreover, by linking these dynamics to the pre-war and war periods, we offer a more policy-relevant understanding of how shocks affect the resilience of digital assets and portfolios. By incorporating higher-order moment interrelations, we capture asymmetries and tail dependencies that traditional mean-based analyses often ignore. This contribution is particularly important because it reveals how extreme events and persistent shocks affect digital asset networks differently, thereby enhancing our understanding of digital financial markets under distributional properties and geopolitical conditions.

Furthermore, amid global financial uncertainty and ongoing policy changes that continue to affect investment behaviour, there is increasing recognition of how macroeconomic volatility shapes the interplay between emerging digital finance and renewable energy resources (Li, Mo, and Nie 2023). Accordingly, this paper explores the role of stock market volatility (VIX), oil market volatility (OVX), currency market fluctuations (ECV), and policy uncertainty (EPU) in the network dynamics of AI tokens, DeFi, NFTs, and renewable energy assets on a short-term, medium-term, and long-term basis. This multi-frequency approach provides a broader picture of the propagation of market shocks across these time horizons.

Lastly, this research paper provides meaningful portfolio strategies by evaluating the diversification potential of AI tokens, NFTs, DeFi, and renewable energy assets across geopolitical regimes. To estimate the optimal portfolio weights and hedge ratios for the pre-war and war periods, we use overall bivariate portfolios and horizon-specific multivariate portfolios. This strategy enables us to determine the performance of asset combinations during different periods of market stress and identify the most efficient combinations to minimise portfolio risk.

The subsequent sections are organised as follows: Section 2 introduces the theoretical background and key related literature. Section 3 outlines the data and methodology employed in this study. Section 4 covers the findings of connectedness, portfolios, and the determinants of connectedness. Section 5 concludes the study and outlines key implications.

2. Theoretical background and related literature

2.1. Theoretical background

The interconnections among DeFi tokens, NFTs, and renewable energy assets can be theoretically grounded in financial contagion theory and ecological modernisation theory (EMT). Financial contagion theory suggests that shocks in one financial market can flow to other markets due to interconnected investor behaviour, common liquidity constraints, or psychological herding effects (King and Wadhwani 1990). In the context of blockchain-based markets, DeFi and NFTs share overlapping investor bases and technological infrastructures, which amplifies the potential for spillovers and synchronous price movements. When uncertainty or speculation increases in a digital segment, such as DeFi lending protocols, it can quickly affect NFT valuations through behavioural contagion and portfolio rebalancing. Similarly, as renewable energy assets are becoming increasingly integrated into digital asset markets through tokenisation and blockchain-based sustainability platforms, contagion pathways emerge. This perspective is supplemented by the Ecological Modernisation theory (Mol 2002), which serves as a theoretical bridge to the Fourth Industrial Revolution (4IR). While the 4IR focuses on the disruptive power of decentralisation and artificial intelligence, EMT describes how environmental challenges are addressed through such technological innovation and institutional restructuring. In this regard AI tokens and blockchain protocols represent the digital infrastructure of 4IR that facilitates the goals of ecological modernisation. With the increasing integration of renewable energy equities into the broader investment ecosystem, their financial behaviour partly aligns with the markets of digital innovation. As renewable energy firms increasingly adopt digital technologies and operate within innovation-driven financial systems, the valuation dynamics of their equities may partially align with digital innovation markets. This convergence reflects a broader investor preference for sustainable, technology-driven portfolios, in which renewable energy and digital assets co-move in response to shared macroeconomic signals and ESG-driven capital flows. These theories together show that the connections among DeFi, NFTs, AI, and renewable energy assets arise from shared investor behaviour, common technologies, and the growing focus on sustainable investments in modern financial markets.

2.2. Related literature

Cryptocurrencies have attracted significant academic and market attention due to their potential for portfolio diversification and liquidity, as well as growing criticism of their volatility and environmental impact. In this regard, evidence in existing literature documents that incorporating cryptocurrencies into traditional asset portfolios can reduce downside risk and enhance diversification benefits, though this varies across assets (Nadarajah and Chu 2017). Similarly, in another study, Zhang et al. (2021) find that cryptocurrencies with higher downside risk yield greater expected returns. Moreover, macroeconomic conditions, particularly economic policy uncertainty, play a crucial role in determining cryptocurrency returns, especially in emerging markets like China (Colombo 2013). Likewise, Chen, Qin, and Zhang (2022) emphasise that the cryptocurrency market reacts asymmetrically to global economic shocks, as evidenced by its interactions with other financial systems.

With the adoption of blockchain technology in the energy sector, it is becoming increasingly linked to digital and green investments. In this regard, Kuang (2021) emphasises the potential for diversification between energy assets and renewable energy stocks, noting their interrelationship. Yi, Xu, and Wang (2018) also report that volatility relationships among cryptocurrencies exhibit cyclical movements and growing spillovers, indicating increasing interdependence over time. In line with digital finance, the literature on green financial assets emphasises their role in mitigating environmental risks and strengthening portfolio performance. For example, Reboredo (2018) shows that green bonds provide effective diversification opportunities to energy investors. In contrast, Karkowska and Urjasz (2023) show that renewable energy equities offset risks in non-clean sectors, though with only a small contribution to overall risk reduction. In addition, Yuan et al. (2023) report that, in bearish markets, the information spillover from clean energy and green economy assets is high, indicating increased systemic interconnectedness.

Building on this body of research, a few recent studies have examined the average and dynamic connections between sustainability-related assets and new equity markets. For example, Ali et al. (2025) examine ESG and BRICS equity markets, which exhibit time-varying spillovers that a static framework cannot capture. Such dynamics are also reflected in those of commodity-related assets, including minerals and the Global South market, where asymmetric structures of dependency and directional connectedness are shifting (Ali et al. 2024). Both these studies emphasise the importance of robust time-varying models to understand the heterogeneity and temporal dynamics of interconnections among digital, green, and traditional financial markets.

On the interaction between blockchain technology and energy markets, various methodologies have been applied, including the DCC-GARCH model (Corbet et al. 2023) and the TVP-VAR model (Primiceri 2005). Following Antonakakis et al. (2018 & 2020), our study applies the Time-Frequency TVP-VAR approach. This method is superior to fixed-coefficient VAR models because it does not use a random rolling window. It also does not emphasise the extreme point, and retains baseline information. Our research thus adds significantly to existing literature on DeFi, NFTs, and cryptocurrencies. We agree with the stance of Dowling (2022) that suggests DeFi and NFTs are remarkable improvements on the traditional blockchain concept, offer better alternatives to traditional financial instruments. We argue that research on AI-based assets remains limited, with only a few studies addressing their financial interconnections (Anwer et al. 2026; Guo et al. 2026). While these studies document the importance of technology-related assets for portfolio diversification and their potential safe-haven properties, gaps remain in understanding their spillover effects on other emerging digital assets.

Building on this strand of literature, some recent contributions have deepened our understanding of connectedness within and across digital asset classes. For instance, Raza, Sharif, and Anwar (2025) explore the potential of portfolio optimisation with DeFi tokens using a dynamic R-vine copula-based mean-CVaR framework. Their results indicate that DeFi tokens exhibit nonlinear, time-varying dependence structures with other asset classes, suggesting that traditional linear models cannot fully capture their risk–return dynamics. Their findings study also show that adding DeFi tokens to diversified portfolios can improve risk-adjusted returns, especially during periods of increased market uncertainty.

It has also been argued that in existing literature a comprehensive analysis integrating digital assets, renewable energy equities, and AI tokens within a unified connectedness framework is largely limited (Reboredo 2018). However, given the rapid technological advancements and their influence on financial markets, mean-based models are insufficient to capture important fluctuations and emerging trends. To this end, we implement a temporal model that enables more nuanced exploration of the evolving linkages among these asset classes. By adopting this approach, our study provides deeper insights into the interactions among digital assets, AI tokens, and renewable energy markets over time, offering valuable implications for both investors and policymakers.

3. Data and methodology

3.1. Data

In this study, we use daily data of the chosen blockchain-based digital assets and renewable energy equities. Three types of tokens are used to reflect the blockchain market: non-fungible tokens (NFTs), decentralised finance (DeFi) tokens, and tokens related to artificial intelligence (AI). NFTs denote digital assets that represent ownership of unique objects stored on a blockchain network. Whereas DeFi tokens are utilised in DeFi applications, and AI tokens are meant to facilitate blockchain-based artificial intelligence ecosystems. Specifically, three NFTs, Decentraland (MANA), Tezos (XTZ), and Enjin Coin (ENJ), are included due to their high liquidity, large market capitalisation relative to other NFT projects, and established role in metaverse and digital ownership applications. From the DeFi sector, Chainlink (LINK), Maker (MKR), and Basic Attention Token (BAT) are selected based on their consistent trading volumes, active use cases in smart contracts and decentralised applications, and broad market relevance. In line with recent research emphasising the growing role of AI tokens in the blockchain ecosystem, SingularityNET (AGIX), Fetch.AI (FET), and Ocean Protocol (OCEAN) are considered as leading AI tokens because of their market capitalisation, ecosystem development, and representation of blockchain-based AI assets (Jiang et al. 2022). In the case of renewable energy, three sector-specific equities are used as a proxy: Solar Energy Initiat (SNRY), Global Wind Energy (WNDY), and NASDAQ OMX Bio/Clean Fuels (Biofuel). These represent distinct renewable energy segments of biofuel, solar, and wind. The data is separated into two subsamples: the pre-war period (the timeframe between September 24, 2019, and February 24, 2022) and the period of the war (between February 25, 2022, and April 23, 2024) to reflect the effect of geopolitical events on the market dynamics (Jiang et al. 2022).

3.2. Methodology

This study employs the Time-Varying Parameter Vector Autoregression (TVP-VAR) model within a time-frequency connectedness framework to capture the dynamics of return and volatility spillovers among AI tokens, NFTs, DeFi assets, and renewable energy markets. Unlike the traditional VAR or rolling-window approaches based on Diebold and Yilmaz (2012 & 2014), which assume constant relationships and use arbitrary fixed windows, the TVP-VAR model accounts for structural changes, regime shifts, and parameter evolution over time, thereby improving spillover estimations. The optimal lag length is selected withstandard information criteria (AIC and BIC), and parameter updates are performed using a Kalman filter. Spillover effects are measured using the forecast error variance decomposition, which quantifies about how much of the forecast uncertainty in one asset is explained by shocks in other assets, allowing us to trace the magnitude and direction of interconnections across markets. Appendix A gives details for the parameters of the connectedness approaches.

To further enrich the analysis, we apply the frequency decomposition method of Baruník and Křehlík (2018), which separates connectedness into short-, medium-, and long-term components. This allows us to see whether spillovers are more dominant in the short run for speculative traders or in the long-run for institutional investors and strategic allocation of assets. By jointly considering time- and frequency-domain perspectives, this framework provides a comprehensive picture of how return- and volatility-transmission mechanisms evolve across investment horizons in emerging digital and sustainable markets. In this study, the return series for each asset is calculated using logarithmic returns, defined as the natural logarithm difference between consecutive closing prices, i.e. $\mathrm{r_t} = \ln(\mathrm{P_t})\text{-}\ln\,(\mathrm{P_{t-1}})$, where $\mathrm{P_t}$ denotes the asset price at time t. This transformation ensures that returns are stationary and comparable across assets with different price scales. Volatility is measured by the squared returns, capturing fluctuations in asset prices over time and reflecting the risk associated with each asset.

3.2.1. TVP-VAR model

As explained earlier, this study employs the Time-Varying Parameter Vector Autoregression (TVP-VAR) framework to analyse the evolving spillover linkages among assets, including NFTs, DeFi, AI tokens, and renewable energy assets. The model specification follows the Bayesian Information Criterion (BIC) for optimal lag determination, with one lag selected to balance the model fit and parsimony:

$$z_t = B_t z_{t-1} + u_t, \quad u_t \sim N(0, S_t) \tag{1}$$

$$vec(B_t) = vec(B_{t-1}) + v_t, \;\; v_t \sim N(0, R_t) \tag{2}$$

In this framework, $\mathrm{z_t}$ denotes a $\mathrm{K} \times 1$ vector of asset returns, while $\mathrm{B_t}$ represents the $\mathrm{K} \times \mathrm{K}$ matrix of time-varying coefficients. The matrix $\mathrm{S_t}$ captures the dynamic variance-covariance structure, and ν_{t} is the innovation term with its own variance-covariance matrix $\mathrm{R_t}$. To trace the transmission of shocks across assets, the model relies on the generalised forecast error variance decomposition (GFEVD) proposed by Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998).

$$z_t = \sum_{i=1}^{p} B_{i,t} z_{t-i} + u_t = \sum_{j=0}^{\infty} A_{j,t} u_{t-j}, \tag{3}$$

The J-step ahead GFEVD can be specified as:

$$\phi_{\mathrm{ij,t}}(\mathrm{J}) = \frac{\sigma_{\mathrm{jj}}^{-1} \sum_{\mathrm{h=0}}^{\mathrm{J-1}} \left(\mathrm{e_i^{\prime} A_{j,t}} \Sigma_{\mathrm{t}} \mathrm{e_j}\right)^2}{\sum_{\mathrm{k=1}}^{\mathrm{N}} \sigma_{\mathrm{kk,t}}^{-1} \sum_{\mathrm{j=0}}^{\mathrm{J-1}} \left(\mathrm{e_i^{\prime} A_{j,t}} \Sigma_{\mathrm{t}} \mathrm{e_k}\right)^2}, \tag{4}$$

The normalised GFEVD, $\Phi_{\mathrm{ij,t}}(\mathrm{J})$ ensures that the rows sum to unity as follows:

$$\bar{\phi}_{\mathrm{ij,t}}(\mathrm{J}) = \frac{\phi_{\mathrm{ij,t}}(\mathrm{J})}{\sum_{\mathrm{j=1}}^{\mathrm{N}} \phi_{\mathrm{ij,t}}(\mathrm{J})} \text{ with } \sum_{j=1}^{N} \bar{\phi}_{ij,t}(j) = 1 \text{ and } \sum_{i,j=1}^{N} \bar{\phi}_{ij,t}(j) = N \tag{5}$$

Based on this framework, various connectedness indices are computed as:

$$TCI_t(J) = \frac{\sum_{j=1}^{N} \overleftarrow{\phi}_{i,j}(J)}{\overline{\sum_{i=1}^{N}\sum_{J=1}^{N} \phi_{i,j}(J)}} * 100 \tag{6}$$

$$FROM_{i\leftarrow *,t} = \frac{\sum_{j=1,i\neq j}^{N} \overleftarrow{\phi}_{i,j}(J)}{\sum_{i=1,j=1}^{N} \overleftarrow{\phi}_{i,j}(J)} * 100 \tag{7}$$

$$TO_{i\rightarrow *,t} = \frac{\sum_{j=1,j\neq i}^{N} \overleftarrow{\phi}_{j,i}(J)}{\sum_{i=1,j=1}^{N} \overleftarrow{\phi}_{j,i}(J)} * 100 \tag{8}$$

$$NET_{i,t} = TO_{i\rightarrow *,t} - FROM_{j\leftarrow *,t}(J) \tag{9}$$

3.2.2. Frequency TVP-VAR model

To capture how financial markets react to shocks at different horizons, this study integrates the time-varying parameter VAR framework of Antonakakis et al. (2020). This combined approach generates a dynamic frequency response function of the form $B_t(e^{iw}) = \sum_{h=0}^{H-1} e^{iwh}B_{h,t}$, where $i = \sqrt{-1}$ and ω denotes the frequency domain. The generalised causal spectrum is then computed over the range $\omega \in (-\pi, \pi)$, which allows the decomposition of spillover effects into short-, medium-, and long-term components:

$$f_t(\omega)_{jk} = \frac{|\theta_j' B_t(e^{iw})\Sigma_t\theta_j|^2}{|(\theta_j' B_t(e^{i\omega})\Sigma_t B_t'(e^{-i\omega})\theta_j)|} \tag{10}$$

In this setting, $f_t(\omega)_{jk}$ denotes the portion of fluctuations in the j_{th} variable at frequency ω that can be attributed to innovations originating from the kth variable. For any given frequency band $d = (a, b)$. The spillover effects are quantified through the generalised forecast error variance decomposition (GFEVD), which isolates the contribution of shocks across different horizons within the VAR framework.

$$\Phi_{jk,t}(d) = \frac{1}{2\pi}\int_d W_{j,t}(w)(f_t(w))_{jk}d\omega \quad \ldots \tag{11}$$

$$W_{j,t}(\omega) = \frac{|\theta_j' B_t(e^{iw})\Sigma_t B_t'(e^{-iw})\theta_j|}{\frac{1}{2\pi}\int_{-\pi}^{\pi} |(\theta_j' B_t(e^{i\lambda})\Sigma_t B_t'(e^{-i\lambda})\theta_j)| d\lambda} \tag{12}$$

Once the GFEVD is derived over the frequency band $d = (a, b)$ and connectedness indices can be computed to capture the strength and direction of spillovers across markets. The TCI measures the overall degree of spillovers transmitted within the system and is given as:

$$\bar{\Phi}_{jk,t}(d) = \frac{\Phi_{jk,t}(d)}{\sum_{k=1}^{N}\Phi_{jk,t}(d)} \tag{13}$$

To further examine directional effects, we compute indices showing how much spillover a variable receives from others and how much it transmits. The spillovers received from all other variables are captured as:

$$TCI_t(d) = \left(\frac{\sum_{j=1,k=1}^{N} \Phi^{\sim}_{jk,t}(d)}{\sum_{j=1,k=1}^{N} \Phi^{\sim}_{jk,t}(d)} \right) * 100 \tag{14}$$

$$FROM_{j \leftarrow *,t}(d) = \left(\frac{\sum_{k=1,j \neq k}^{N} \Phi^{\sim}_{jk,t}(d)}{\sum_{j=1,k=1}^{N} \Phi^{\sim}_{jk,t}(d)} \right) * 100 \tag{15}$$

$$TO_{j \rightarrow *,t}(d) = \left(\frac{\sum_{k=1,k \neq j}^{N} \Phi^{\sim}_{kj,t}(d)}{\sum_{j=1,k=1}^{N} \Phi^{\sim}_{jk,t}(d)} \right) * 100 \tag{16}$$

$$NET_{j,t}(d) = TO_{j \rightarrow *,t}(d) - FROM_{j \leftarrow *,t}(d) \tag{17}$$

These measures together provide a comprehensive view of system-wide, directional, and bilateral connectedness across different frequency bands, enabling us to distinguish short-term effects from long-term linkages.

3.3. Portfolio analyses

Using the TVP-VAR conditional variance and covariance, we conduct a portfolio analysis. We compute the optimal bivariate portfolio weights as follows:

$$W_{xy,t} = \frac{h_{y,t} - h_{xy,t}}{h_{x,y} - 2h_{xy,t} + h_{y,t}} \tag{18}$$

$$\mathrm{W}_{\mathrm{xy,t}} = \begin{cases} 0, \ \mathit{If}\ \mathrm{W}_{\mathrm{xy,t}} < 0 \\ \mathrm{W}_{\mathrm{xy,t}}, \ \mathit{If}\ 0 \leq \mathrm{W}_{\mathrm{xy,t}} \leq 1 \\ 1, \ \mathit{If}\ \mathrm{W}_{\mathrm{xy,t}} > 1 \end{cases} \tag{19}$$

In this framework, $W_{xy,t}$ denotes the proportion of asset x (e.g. an AI token) in a one-dollar portfolio consisting of asset x and asset y (e.g. a renewable energy asset) at time t. The term $h_{xy,t}$ captures the conditional covariance between x and y. In contrast, $h_{x,t}$ and $h_{y,t}$ illustrates the conditional variances of each asset, respectively. To evaluate the risk-mitigating role of digital assets, we compute the hedge ratio following Kroner and Sultan (1993):

$$\beta_{xy,t} = \frac{h_{xy,t}}{h_{y,t}} \tag{20}$$

Here $\beta_{xy,t}$ reflects the extent to which exposure in asset y (e.g. renewable energy) can be hedged by taking an offsetting position in asset x (e.g. an NFT or DeFi token). Furthermore, to assess the performance of these hedging strategies, the hedging effectiveness is calculated in line with Ku and Chen (2007), which compares the variance of hedged and unhedged portfolios, providing a measure of how effectively risk is reduced through diversification.

$$HE = \frac{Var_U - Var_H}{Var_U} \tag{21}$$

In this formulation, Var_U represents the variance of the unhedged portfolio (which holds a single asset in isolation), while Var_H corresponds to the variance of the portfolio after applying the hedging strategy (a combination of digital assets and renewable energy markets)[1] The value of hedging effectiveness (HE) reflects the degree of risk reduction, with larger values indicating stronger risk mitigation. An HE = 1 denotes a perfectly effective hedge, which implies that portfolio volatility has been eliminated through diversification.

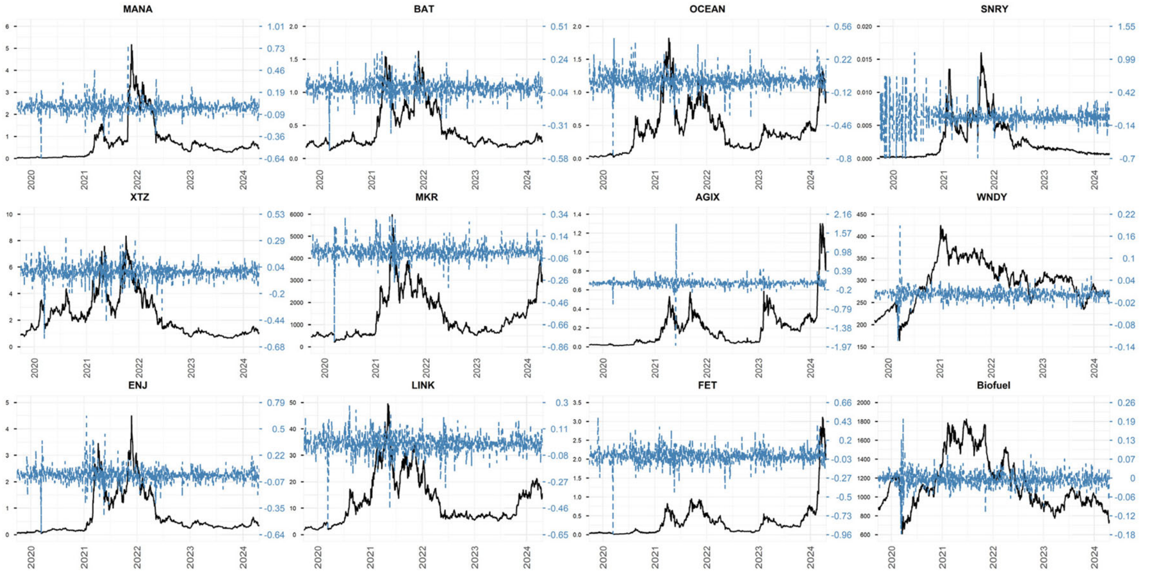


Figure 1. Line graphs of markets.

Note: This figure shows the line graph of the prices (black solid line) and returns (blue dotted line) of the twelve markets under study during the full sample period (September 09, 2019, to April 23, 2024).

Based on our spillover index, we also compute a multivariate portfolio and measure its performance across short-, medium-, and long-term horizons, as developed by Broadstock, Chatziantoniou, and Gabauer (2022). The MCP weight is calculated as follows:

$$\omega_{C_t} = \frac{PCI_t^{-1} I}{I PCI_t^{-1} I} \tag{22}$$

where ω_{C_t} indicates the weight of the least interconnected asset in the portfolio, PCI_t is the pairwise connectedness index matrix at time t, and I is the identity matrix.

3.4. *Preliminary analyses*

Figure 1 shows the time series structure of prices and returns in black and blue lines. Regarding the behaviour of digital assets, there are notable similarities and differences between them and the energy market during the pre-Russia-Ukraine war period, with fluctuations in BAT, ENJ, and XTZ being particularly evident. Furthermore, digital asset and AI token prices, such as Biofuel, LINK, and MANA, remain bearish before the war, except for FET, which remains stable. During the war period, prices rose, except for AGIX, which showed stability. However, we observe visible fluctuations starting in Q3 of 2021. The second considerable spike is detected in the first months of 2023, caused by the Russia-Ukraine war (Balsalobre-Lorente, Sinha, and Murshed 2023). As for energy assets, it has been revealed that two energy token prices have been moving in tandem, except for SNRY, over the full sample period. Nevertheless, the prices of WNDY and Biofuel have risen since the first quarter of 2023. This increase aligns with the crypto market bubble prevalent in the first quarter of 2023, as evidenced by Hairudin and Mohamad (2024).

The time-varying returns indicate that all the markets exhibit volatility clustering at different time horizons. Increased market volatility has resulted from the conflict's eruption, disrupting energy supplies, impacting commodity prices, and leading to generalised economic uncertainty. Furthermore, the maximum volatility levels are observed after 2022 across all markets except FET, suggesting that the Russia-Ukraine war has significantly impacted digital assets and other energy markets.

Table 1. Descriptive statistics of sample markets.

	Mean	Max	Min	Std.Dev.	Skewness	Kurtosis	Jarque.Bera
Panel A: Full Sample							
MANA	0.264	77.85	−62.98	8.023	0.702	18.0	10278.2
XTZ	0.015	32.94	−60.73	6.895	−0.892	12.4	4194.4
ENJ	0.168	64.02	−62.42	7.901	0.246	14.4	5912.0
BAT	0.051	30.18	−51.5	6.479	−0.413	9.6	2036.7
MKR	0.173	34.06	−81.82	6.914	−0.975	24.0	20317.5
LINK	0.198	28.97	−61.75	6.885	−1.064	12.0	3893.1
OCEAN	0.336	43.86	−78.79	8.652	−0.488	12.1	3834.8
AGIX	0.352	186.59	−193.26	12.156	−0.255	112.1	542550.7
FET	0.372	47.9	−95.98	9.211	−0.832	16.0	7786.1
SNRY	0.1	109.86	−69.32	15.488	0.51	12.7	4313.3
WNDY	0.022	18.89	−12.58	1.499	0.957	31.6	37340.8
Biofuel	−0.014	20.05	−18.2	2.569	−0.317	12.2	3868.4
Panel B: Pre-War							
MANA	0.787	77.85	−62.98	9.369	0.733	16.53	4485.18
XTZ	0.21	32.94	−60.73	8.184	−0.845	10.84	1556.18
ENJ	0.55	64.02	−62.42	9.356	0.334	12.85	2360.71
BAT	0.247	30.18	−51.5	7.376	−0.332	9.42	1008.66
MKR	0.251	34.06	−81.82	7.881	−1.319	25.21	12104.81
LINK	0.35	28.97	−61.75	7.851	−1.193	11.85	2033.80
OCEAN	0.486	43.86	−78.79	9.802	−0.517	11.72	1868.09
AGIX	0.26	186.59	−193.26	14.32	−0.511	108.53	269604.51
FET	0.314	47.9	−95.98	10.085	−1.289	18.45	5941.55
SNRY	0.54	109.86	−69.32	19.554	0.397	9.18	941.05
WNDY	0.063	18.89	−12.58	1.656	1.254	38.33	30375.76
Biofuel	0.055	20.05	−18.2	2.863	−0.486	13.72	2804.35
Panel C: War							
MANA	−0.33	35.62	−35.41	6.103	0.003	9.25	833.54
XTZ	−0.207	16.57	−34.73	5.047	−0.988	7.96	607.28
ENJ	−0.266	20.52	−30	5.804	−0.621	6.41	281.42
BAT	−0.17	20.96	−25.03	5.277	−0.726	6.01	237.71
MKR	0.085	27.31	−32.17	5.626	0.2	7.32	402.00
LINK	0.026	19.11	−31.24	5.593	−0.588	7.02	373.56
OCEAN	0.165	31.9	−38.38	7.132	−0.401	8.77	724.08
AGIX	0.456	49.02	−28.68	9.11	1.01	8.17	656.59
FET	0.437	40.02	−39.67	8.115	0.219	6.64	286.35
SNRY	−0.398	36.77	−33.65	8.841	0.33	4.95	90.07
WNDY	−0.024	5.02	−4.23	1.298	0.13	4.43	45.22
Biofuel	−0.092	8.21	−9.03	2.188	0.064	4.05	24.07

Notes: This table reports summary statistics for daily returns across all variables for three different sample periods. Full sample (September 24, 2019, to April 23, 2024), Pre-War (September 24, 2019, to February 24, 2022), and War period (February 25, 2022, to April 23, 2024) in 1a, 1b, and 1c, respectively. *Denotes significance at 1%. Note: Std.Dev. denotes standard deviation.

Table 1 contains the statistical properties of AI tokens, digital assets, and renewable energy markets. It is evident that the average returns for all the markets under consideration are positive for the entire sample period, and FET achieves the highest returns. Furthermore, energy equities, except Biofuel, show positive returns across the sample period considered in our analysis.

Before the war, AI tokens and renewable energy markets produced positive returns. However, during the war period, all energy markets, including BAT, ENJ, XTZ, and MANA, show negative returns. Such a deviation indicates that the risk and return characteristics of energy markets differ significantly from those of AI and digital assets during crises. The results also show high volatility in overall returns across the various markets. The JB test suggests non-stationary markets. Furthermore, based on kurtosis, the markets exhibit leptokurtic distributions, indicating a high likelihood of large movements and highlighting the role of higher-order connections among markets. Therefore, it is crucial to recognise the interactions at higher-order moments across markets, making these findings essential for effective risk management and investment strategies.

4. Empirical results and discussion

4.1. Static returns and volatility spillover analyses

Table 2 shows the time-invariant return connectedness among AI tokens, NFTs, DeFi tokens, and energy markets across the full sample, the pre-war period, and the war period. The average connectedness (TCI) is 62.46% and 65.21% during the war period, confirming that systemic shocks increase co-movement across asset classes (Ali et al. 2024). This aligns with the well-known fact that crises amplify financial contagion through herding behaviour and liquidity constraints. NFTs like XTZ, ENJ, and MANA are strong net transmitters of spillovers. NFTs' speculative demand and sentiment-driven pricing make them highly sensitive to global shocks and efficient in transmitting risks across digital markets (Wang 2022). Economically, NFTs behave like high-beta assets in traditional markets; they are priced largely on expectations and momentum rather than cash flows or fundamentals, making them prime channels of risk transmission when global uncertainty rises. In crises, investors typically liquidate speculative positions first, intensifying contagion across interconnected tokens. Their role as transmitters is more pronounced during crises, as speculative assets tend to experience sharp repricing and contagion effects that spread to other correlated tokens. On the other hand, AI tokens (AGIX and FET) are consistently net receivers of spillovers. This aligns with Danielsson and Uthemann (2025), who also find that AI-driven assets absorb shocks rather than transmitting them. One reason is that AI tokens are still relatively niche assets with limited liquidity and market depth, which means their prices respond to shocks elsewhere rather than driving system-wide dynamics. Their role as a receiver also highlights their dependence on broader digital market sentiment and technological adoption cycles rather than independent market fundamentals.

Energy assets (SNRY, WNDY, Biofuel) are weakly connected and primarily act as net receivers. Their low spillover suggests they remain decoupled from the mainstream digital asset market, given their limited market capitalisation. Energy assets are often linked to real-sector fundamentals rather than to speculative trading (Ferrer et al. 2018). However, during crises, they absorb shocks transmitted from NFTs and DeFi, as investors may use them as secondary diversification channels when speculative tokens collapse. DeFi tokens exhibit heterogeneous behaviour in the network. For instance, LINK switches from receivers to transmitters during the war period, reflecting their increased market influence amid geopolitical uncertainty and portfolio rebalancing. In contrast, MKR and LINK consistently act as receivers due to lower trading volumes and liquidity constraints during crises, which reduce their capacity to transmit shocks. These differences highlight token-specific idiosyncrasies. For example, MKR's governance-focused structure may be associated with comparatively lower spillover sensitivity within the network. In contrast, LINK's oracle function and FET's broad platform applications increase their short-term market impact. This is consistent with portfolio rebalancing theory, in which investors shift into perceived resilient assets (e.g. AI and DeFi platforms with broader applications), thereby increasing their short-term market influence. When liquidity is reallocated, tokens that are passive in normal periods can become shock transmitters under stress. Reallocation of liquidity can temporarily turn passive tokens into active transmitters during market stress (Ghosh et al. 2023). On the other hand, tokens like MKR and LINK switch to receivers, as liquidity shortages and reduced trading activity in crises can mute their ability to transmit shocks (Chen, Qin, and Zhang 2022).

Our results show that NFTs are structural transmitters driven by speculative trading dynamics, while AI tokens and energy assets are absorbers due to niche adoption and lower liquidity. DeFi assets can play different roles depending on macroeconomic and geopolitical conditions. This not only confirms digital asset contagion but also shows how crises reshape the transmission channels across emerging token classes, as earlier findings suggest that spillover intensity and direction are state-dependent (Saeed, Bouri, and Alsulami 2021).

Table 3 illustrates the static volatility interconnections among digital assets and energy markets across the full sample, the pre-war period, and the war period. The TCI for volatility over the full sample is 65.39%, higher than that for returns (62.46%), indicating that volatility spillovers are stronger than return spillovers, suggesting that risk transmission among these assets is more intense than price co-movement. Economically, this implies that while return movements reflect moderate integration, shocks to market uncertainty and risk propagate more widely across assets. In the sub-sample analysis, the TCI rises to 72.69% before the war and drops to 61.54% during the war. The lower TCI during the war suggests that volatility spillovers became more uneven across markets. This pattern indicates a shift of capital toward safer digital assets, such as stablecoins and established

Table 2. Static return spillovers.

	MANA	XTZ	ENJ	BAT	MKR	LINK	OCEAN	AGIX	FET	SNRY	WNDY	Biofuel	FROM
Panel A: Full Sample													
MANA	26.43	9.78	13.24	11.42	6.37	4.93	7.91	6.72	7.86	0.94	2.05	2.34	73.57
XTZ	9.69	24.59	10.35	11.76	7.1	8.17	8.5	7.31	7.5	0.66	2.12	2.26	75.41
ENJ	12.27	10.19	24.69	11.69	6.47	5.61	8.51	6.75	7.73	0.84	2.44	2.8	75.31
BAT	10.97	11.69	11.32	25.01	7.19	6.43	8.3	6.72	7.08	0.66	2.24	2.39	74.99
MKR	7.51	9.07	8.5	9.03	34.43	7.36	6.33	5.29	6.1	1.35	2.28	2.75	65.57
LINK	5.24	8.65	6.27	6.57	6.16	43.68	6.34	5.43	5.65	1.25	2.23	2.53	56.32
OCEAN	8.28	9.03	9.67	9.24	5.63	6.48	28.96	7.93	9.86	1.01	2.19	1.72	71.04
AGIX	8.07	8.81	8.47	8.34	4.73	6.25	8.53	31.1	10.2	0.59	2.35	2.57	68.9
FET	8.97	8.59	9.2	8.09	5.3	6.16	10.55	9.72	28.48	0.62	2.21	2.1	71.52
SNRY	2.07	1.91	2.43	1.65	1.66	1.85	2.5	1.66	1.84	77.65	1.83	2.95	22.35
WNDY	3.83	3.91	4.81	4.13	3.61	3	3.22	3.14	2.46	1.22	51.91	14.74	48.09
Biofuel	3.66	3.81	4.64	3.69	3.93	3.3	2.44	3.55	2.99	1.11	13.35	53.53	46.47
TO	80.57	85.44	88.9	85.61	58.16	59.54	73.13	64.22	69.27	10.25	35.28	39.14	749.53
Inc.Own	107	110.03	113.59	110.62	92.59	103.22	102.1	95.32	97.76	87.9	87.2	92.67	TCI
Net	7	10.03	13.59	10.62	−7.41	3.22	2.1	−4.68	−2.24	−12.1	−12.8	−7.33	62.46
Panel B: Pre-War													
MANA	31.28	7.4	11.72	9.71	6.57	6.7	7.46	5.76	7.16	1.32	2.16	2.75	68.72
XTZ	7.16	28.24	7.99	9.5	8.04	12.31	7.73	6.67	6.44	0.87	2.37	2.68	71.76
ENJ	10.43	8.11	29.31	10.02	6.63	7.47	8.04	5.77	6.78	1	2.79	3.65	70.69
BAT	9.19	9.88	9.27	29.01	7.31	9.26	7.25	5.61	6.39	1.02	2.78	3.02	70.99
MKR	6.22	9.3	7.48	7.87	32.92	10.9	6.48	5.1	5.92	1.83	2.62	3.36	67.08
LINK	6.47	12.11	7.32	8.43	8.33	28.06	8.04	7.27	7.4	1.21	2	3.35	71.94
OCEAN	7.31	7.74	9.15	7.79	6.15	9.01	33.37	5.69	7.69	1.32	2.66	2.13	66.63
AGIX	7.27	8.32	7.51	7.18	5.03	9.1	6.38	34.35	7.92	0.66	2.86	3.42	65.65
FET	8.31	7.46	8.02	7.07	5.63	8.63	8.63	7.35	32.51	0.75	2.81	2.82	67.49
SNRY	1.92	1.88	2.05	1.75	1.65	1.78	2.56	1.62	2.24	76.23	2.02	4.29	23.77
WNDY	3.48	3.59	4.78	4.12	3.27	3.42	3.57	3.82	2.64	1.45	50.47	15.4	49.53
Biofuel	3.59	4.09	5.14	3.85	4.3	4.51	2.84	4.34	3.7	1.44	12.94	49.27	50.73
TO	71.35	79.88	80.42	77.29	62.9	83.09	69	59.02	64.27	12.87	38.01	46.87	744.97
Inc.Own	102.64	108.12	109.73	106.3	95.83	111.15	102.37	93.37	96.78	89.1	88.48	96.14	TCI
Net	2.64	8.12	9.73	6.3	−4.17	11.15	2.37	−6.63	−3.22	−10.9	−11.52	−3.86	62.08
Panel C: War													
MANA	19.81	12.89	14.51	13.66	5.97	3.38	8.52	7.71	8.65	1.05	1.93	1.92	80.19
XTZ	12.71	19.89	12.91	14.37	5.37	3.53	9.36	8.04	7.64	0.98	2.76	2.42	80.11
ENJ	14.27	13.1	19.18	13.62	5.52	3.32	9.01	8.33	8.05	1.15	2.56	1.89	80.82
BAT	12.78	13.95	13.22	20.28	6.62	3.35	9.26	7.88	7.63	1.09	1.99	1.97	79.72
MKR	9.03	8.14	8.52	10.38	35.54	3.74	6.54	4.59	6.62	2.87	1.57	2.46	64.46
LINK	4.59	5.35	4.82	5.97	4.57	55.73	5.04	3.04	3.6	2.18	2.64	2.48	44.27
OCEAN	9.61	10.56	10.12	10.78	4.95	3.72	23.28	9.81	11.57	1.78	2.07	1.76	76.72
AGIX	9.69	9.75	10.3	9.65	3.45	2.43	10.6	25.84	11.43	1.13	3.83	1.91	74.16
FET	10.2	9.22	9.49	9.45	6.35	2.99	12	11.48	22.08	2.35	2.57	1.83	77.92
SNRY	3.34	2.9	3.95	3.79	2.21	2.47	3.62	2.37	2.01	69.82	2.07	1.45	30.18
WNDY	5.47	4.77	4.87	4.99	3.57	2.95	2.9	3.03	2.3	2.13	50.96	12.06	49.04
Biofuel	3.99	3.97	3.54	4.14	4.54	3.74	2.88	2.15	2.21	1.87	11.86	55.11	44.89
TO	95.7	94.59	96.23	100.81	53.11	35.62	79.73	68.42	71.7	18.58	35.85	32.15	782.49
Inc.Own	115.5	114.49	115.41	121.08	88.65	91.34	103.01	94.25	93.78	88.41	86.81	87.27	TCI
Net	15.5	14.49	15.41	21.08	−11.35	−8.66	3.01	−5.75	−6.22	−11.59	−13.19	−12.73	65.21
Mean difference									3.13	*t*-value	2.59	*p*-value	<0.01

Notes: This table reports the static return spillovers between digital assets and energy markets during three sample periods. Full sample (September 24, 2019, to April 23, 2024), pre-war (September 24, 2019, to February 24, 2022), and war-period (February 25, 2022, to April 23, 2024). The *t*-value indicates the mean difference between the dynamic spillover index for the pre-war and war periods.

cryptocurrencies, and away from speculative assets like AI tokens and NFTs, resulting in weaker overall volatility linkages (Eichengreen, Nguyen, and Viswanath-Natraj 2025). This aligns with Baruník and Křehlík (2018), who argue that extreme shocks can sometimes lower systemic connectedness due to flight-to-safety behaviour and market segmentation. When a conflict starts, two mechanisms may explain the lower volatility TCI: (i) market segmentation, where different asset classes are driven by distinct factors, such as, supply shocks in energy

Table 3. Static volatility spillovers.

	MANA	XTZ	ENJ	BAT	MKR	LINK	OCEAN	AGIX	FET	SNRY	WNDY	Biofuel	FROM
Panel A: Full Sample													
MANA	31.5	7.72	10.27	8.92	4.55	4.09	7.97	7.62	6.38	5.37	2.44	3.18	68.5
XTZ	8.33	25.95	9.71	9.93	6.47	7.14	6.94	7.51	5.56	6.23	2.79	3.45	74.05
ENJ	9.45	8.99	25.21	9.99	6.27	5.53	7.5	7.26	6.34	6.13	3.39	3.93	74.79
BAT	9.22	10.62	11.29	27.22	6.49	5.3	6.46	7.15	5.4	4.6	2.63	3.61	72.78
MKR	6.83	7.86	9.36	7.77	30.28	5.97	5.67	6.93	5.08	5.78	4.77	3.7	69.72
LINK	5.2	9.2	7.32	5.66	6.24	36.77	6.31	5.87	4.99	6.38	2.82	3.24	63.23
OCEAN	9.37	7.16	8.55	7.33	4.9	5.26	31.68	6.37	9.28	4.79	2.2	3.12	68.32
AGIX	7.19	5.25	6.28	5.14	3.54	3.26	5.53	44.13	7.23	6.65	2.4	3.4	55.87
FET	8.94	6.51	8.42	6.28	4.92	4.95	8.95	8.78	31	4.56	3.04	3.65	69
SNRY	4.75	5.38	5.38	4.68	4.07	4.21	4.63	7.72	4.21	48.11	2.75	4.1	51.89
WNDY	4.56	4.23	6.08	4.07	6.66	3.39	3.41	6.4	3.79	4.6	40.7	12.13	59.3
Biofuel	6.4	4.65	5.82	4.8	4.47	3.25	3.63	6.34	3.73	5.28	8.83	42.78	57.22
TO	80.23	77.56	88.47	74.58	58.58	52.33	66.99	77.96	61.99	60.37	38.07	47.53	784.67
Inc.Own	111.73	103.51	113.68	101.8	88.86	89.1	98.67	122.1	92.99	108.48	78.78	90.31	TCI
NET	11.73	3.51	13.68	1.8	−11.14	−10.9	−1.33	22.1	−7.01	8.48	−21.22	−9.69	65.39
Panel B: Pre-War													
MANA	28.43	6.13	10.51	7.53	6.4	4.87	8.75	10.21	5.7	3.36	3.86	4.26	71.57
XTZ	8.89	21.87	8.17	7.61	7.1	10.28	5.86	12	5.82	2.57	4.74	5.1	78.13
ENJ	9.7	6.33	26.42	7.41	6.49	6.12	6.99	10.82	6.16	3.42	5	5.14	73.58
BAT	9.56	8.22	9.56	24.38	7.26	6.67	5.35	10.51	5.65	3	4.55	5.29	75.62
MKR	8.57	7.39	9.35	7.12	23.4	7.55	5.4	12.23	5.49	3.57	5.11	4.83	76.6
LINK	7.08	12.36	7.76	6.47	7.67	23.77	5.24	10.22	6.67	2.31	5.23	5.23	76.23
OCEAN	10.95	4.91	10.09	6.42	5.83	4.97	28.57	6.53	9.34	4.02	3.56	4.8	71.43
AGIX	9.52	4.52	9.1	4.64	4.07	3.67	5.04	44.34	4.68	2.94	3.53	3.96	55.66
FET	10.54	6.06	8.15	6.87	6.53	6.52	8.38	7.58	24.66	3.24	5.04	6.43	75.34
SNRY	8.41	4.87	7.18	5.72	7.33	4.14	6.29	7.16	5.48	36.31	3.01	4.12	63.69
WNDY	8.18	4.79	9.72	4.92	6.14	4.64	4.94	11.45	5.34	2.8	23.11	13.98	76.89
Biofuel	10.47	5.35	9.68	5.8	5.8	4.7	5.36	10.62	6.26	3.06	10.47	22.43	77.57
TO	101.87	70.93	99.27	70.5	70.61	64.12	67.6	109.31	66.56	34.29	54.09	63.15	872.3
Inc.Own	130.3	92.8	125.69	94.89	94.01	87.9	96.17	153.65	91.22	70.6	77.2	85.58	TCI
NET	30.3	−7.2	25.69	−5.11	−5.99	−12.1	−3.83	53.65	−8.78	−29.4	−22.8	−14.42	72.69
Panel C: War													
MANA	28.1	9.91	14.3	12.36	4.39	3.15	6.85	7.93	5.5	4.2	1.31	2	71.9
XTZ	10.05	27.1	12.75	14.68	5.35	4.44	8.36	6.1	4.18	2.85	1.67	2.47	72.9
ENJ	13.04	11.41	24.47	14.3	5.87	3.31	8.17	7.03	5.58	3.39	1.08	2.35	75.53
BAT	11.1	12.87	14	25.69	5.92	3.51	7.82	5.39	4.4	5.53	1.75	2.02	74.31
MKR	8.09	8.29	10.38	10.33	35.76	4.89	6.12	4.87	4.26	2.35	2.31	2.35	64.24
LINK	4.56	6.39	5.88	5.67	5.26	51.97	4.96	3.48	2.56	5.84	1.41	2.02	48.03
OCEAN	7.15	8.64	9.26	9.17	4.01	3.46	32.23	10.33	8.69	3.42	1.47	2.18	67.77
AGIX	9.13	6.8	8.57	6.33	3.87	2.48	10.03	35.14	10.44	3	1.02	3.19	64.86
FET	6.8	6.94	7.83	5.03	3.43	2.3	11.14	13.98	31.43	3.21	4.48	3.44	68.57
SNRY	4.78	3.8	7.17	3.98	2.46	3.77	4.29	4.09	3.61	58.17	1.78	2.1	41.83
WNDY	2.93	2.83	2.7	3.57	3.66	2.84	1.9	3.3	5.47	3.55	58.33	8.92	41.67
Biofuel	3.49	3.7	3.79	3.37	4.17	1.99	2.76	5.73	3.25	4.81	9.76	53.18	46.82
TO	81.12	81.58	96.63	88.77	48.39	36.13	72.39	72.23	57.94	42.15	28.05	33.04	738.43
Inc.Own	109.22	108.68	121.1	114.46	84.15	88.1	104.62	107.37	89.38	100.32	86.38	86.22	TCI
NET	9.22	8.68	21.1	14.46	−15.85	−11.9	4.62	7.37	−10.62	0.32	−13.62	−13.78	61.54
Mean difference									−11.15	*t*-value	9.48	*p*-value	<0.01

Notes: This table reports static volatility spillovers between digital assets and energy markets across three sample periods. Full sample (September 24, 2019, to April 23, 2024), pre-war (September 24, 2019, to February 24, 2022), and war-period (February 25, 2022, to April 23, 2024). The *t*-value indicates the mean difference between the dynamic spillover index for the pre-war and war periods.

assets and liquidity shocks in digital assets, and (ii) shock concentration, where volatility intensifies in certain sectors (e.g. energy or commodities) while others decouple or serve as safe havens. As a result, even if individual asset volatilities increase, the overall system-wide volatility connectedness may decrease. Similar evidence from Hamill et al. (2021) confirms that during crises, connectedness patterns can change direction or weaken as transmission channels adapt to new market conditions.

The FROM column shows that ENJ (74.79%), XTZ (74.05%), and BAT (72.78%) absorb the most spillovers, meaning NFT-related assets are vulnerable to changes in investor sentiment and speculative trading. This reflects their speculative nature and sensitivity to investor sentiment: they function as shock absorbers, meaning that when volatility originates elsewhere (e.g. in energy or broader crypto markets), NFTs amplify and internalise it. From a financial stability perspective, this underlines their vulnerability to risk contagion. On the other hand, SNRY (51.89%), WNDY (59.3%), and Biofuel (57.22%) receive minimal spillovers, as Hanif et al. (2021) find that energy assets are relatively decoupled from speculative shocks and follow energy market fundamentals. On the TO side, ENJ (88.47%), XTZ (77.56%), and BAT (88.47%) are the strongest transmitters, as Kyriazis (2026) argues that NFTs often show high volatility, speculative demand, and sensitivity to investor hype. Economically, this means that investors holding NFTs are not only exposed to external volatility but also risk contaminating other assets in their portfolios with NFT-driven shocks.

On the other hand, WNDY (38.07%), Biofuel (47.53%), and SNRY (60.37%) transmit relatively lesser volatility because they have limited liquidity, lower investor speculation, and depend on energy policy rather than short-term sentiment. The NET values show that energy assets like WNDY (-21.22%) and Biofuel (-9.69%), and AI tokens FET (-7.01%) and OCEAN (-1.33%) are net recipients of spillovers, meaning they are more prone to absorbing shocks from speculative sectors than exporting them. NFTs like ENJ, XTZ, and MANA are net exporters, meaning they are shock transmitters due to their high sensitivity to technological hype cycles and investor risk appetite. For investors, this makes NFTs high-risk assets that can destabilise a diversified portfolio rather than mitigate risk. Sub-period evidence confirms this asymmetry: during the war, NFTs and AI tokens intensified their transmission roles while energy assets remained net receivers. This aligns with Liu, Liu, and Lee (2024), who find that NFTs absorb return shocks but transmit volatility shocks, making them risky diversifiers in mixed portfolios. Wang (2022) also linked NFTs' behaviour to gold, meaning they are partially detached from traditional finance but highly responsive to sentiment-driven volatility.

Figure 2 shows network graphs that provide an overview of the static directional return and volatility connections among energy assets and digital tokens. This figure is drawn from the steps outlined in the literature and other studies (Corbet et al. 2023). Blue (yellow) nodes represent net senders (receivers) of shocks, while net pairwise directional values scale vertex sizes. Node size reflects the net total directional connectivity, which provides insight into systemic importance. The results show that NFTs (ENJ, MANA, XTZ) and DeFi tokens (BAT, LINK) emerge as the primary transmitters of return shocks. In contrast, NFTs (ENJ, MANA, XTZ) and DeFi tokens (BAT) also transmit volatility shocks. This behaviour can be explained by their high speculative demand and sensitivity to investor sentiment, which amplifies spillovers to other tokens. NFTs like ENJ and MANA exhibit bubble-like dynamics, as noted by Corbet, Goodell, and Günay (2022), which explains their role as transmitters.

While earlier literature often attributes receiver status to low liquidity or niche adoption, the study period (2022–2024) suggests a more nuanced driver of narrative-driven speculation. The period coincides with the launch of ChatGPT, and Nvidia's rapid valuation growth could transform AI tokens from niche assets into primary vehicles for speculative retail and institutional sentiment. Despite this AI boom, these tokens remain net receivers because they function as sentiment-beta assets, i.e. they are popular but still move in response to the big players (see Appendix Table A1). Also, they react intensely to broader market shifts and technological optimism, which are transmitted from established benchmarks like Bitcoin. Interestingly, LINK plays another role in sub-periods: it is a transmitter during the pre-war period and a receiver during the war period. This dynamic behaviour suggests that AI tokens gain speculative importance during crisis episodes, when technological narratives and uncertainty-driven trading increase their connectedness. This would mean that portfolio managers would gain diversification benefits from investing in AI and renewable tokens, since they are the recipients. However, they should also be aware that these investments remain highly sensitive to systemic shocks transmitted by speculative markets.

4.2. Time-varying returns and volatility spillover analyses

Figure 3 illustrates the dynamic total return spillovers (left panel) and total volatility spillovers (right panel) across the network of twelve markets under study. The grey-shaded area represents the war period. The results

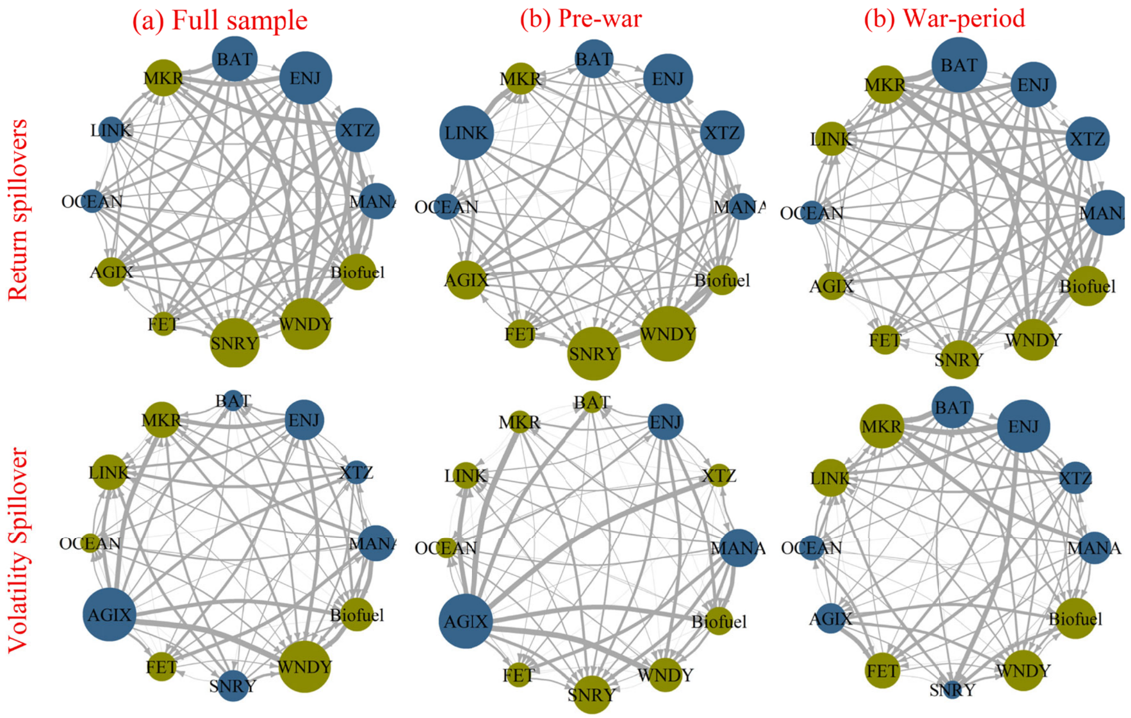
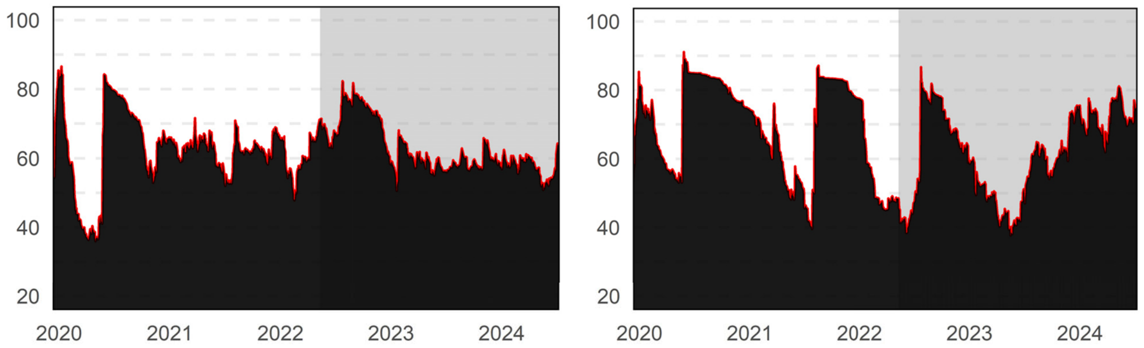


Figure 2. Network plots.

Note: This figure shows network diagrams of directional return (upper pane) and volatility (lower pane) for 12 markets under study during the full sample period, the pre-war period, and the war period, as shown in parts 2a, 2b, and 2c, respectively.

indicate that both the return and volatility spillovers increased substantially during the war, which suggests heightened systemic risk and stronger market interdependence in this period. From the graphs above, it can be inferred that spillover is not constant, underscoring the need for investors to rebalance their portfolios dynamically. These values reached their highest level in 2022, corresponding to the Russia-Ukraine crisis (Goodell and Goutte 2021; Gunay et al. 2023). The spillover value significantly declined in Q3 of 2023, which can be attributed to partial stabilisation in global energy prices, gradual investor adjustment to prolonged geopolitical risk, and central bank coordinated monetary interventions aimed at containing financial volatility. As uncertainty eased, markets showed lower cross-asset shock transmission. This trend aligns with the work of Cui and Maghyereh (2023), who note that connectedness typically weakens once crisis conditions are absorbed into market expectations.

Figure 4(a) and (b) present the dynamic net spillovers of returns and volatility, respectively, highlighting how the interconnections of assets shift over time and across different market regimes. The net connectedness index fluctuates between positive (net transmitters) and negative (net receivers), demonstrating changing asset roles depending on market conditions. Figure 4(b) shows that during the war period, MKR, AGIX, and Biofuel act as shock absorbers of returns, while BAT, ENJ, XTZ, and MANA are significant transmitters of systemic risk. SNRY generally receives shocks, except during the Russia-Ukraine conflict, which aligns with the prior results of Karkowska and Urjasz (2023). This increase in volatility can be explained by heightened attention toward renewable energy. Supply chain disruptions in energy commodities and surging fossil fuel prices have increased investment flows into clean energy markets, thereby intensifying their connectedness. The figure further shows that the Russia-Ukraine war magnifies volatility spillovers across most markets, highlighting how geopolitical shocks accelerate the transmission of systemic risk and reshape the roles of assets as either transmitters or receivers of volatility.



(a) Total returns spillover (b) Total volatility spillovers

Figure 3. Returns and volatility spillovers.

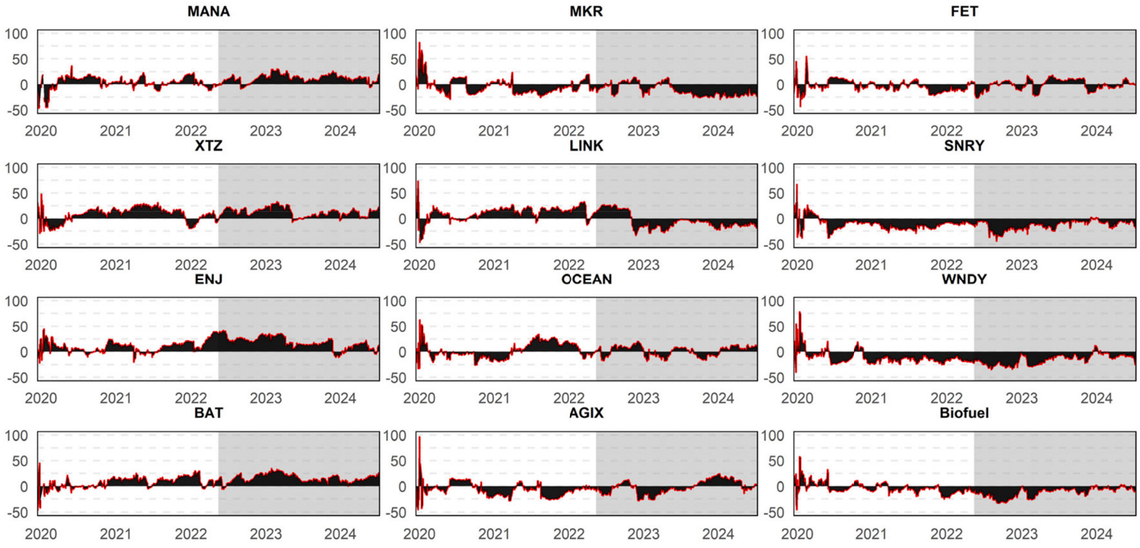
Note: This figure shows static total return (3a) and volatility (3b) spillovers in the system of twelve markets during the full sample period, with a grey area showing the war period.

4.3. *Frequency domain dynamic spillover*

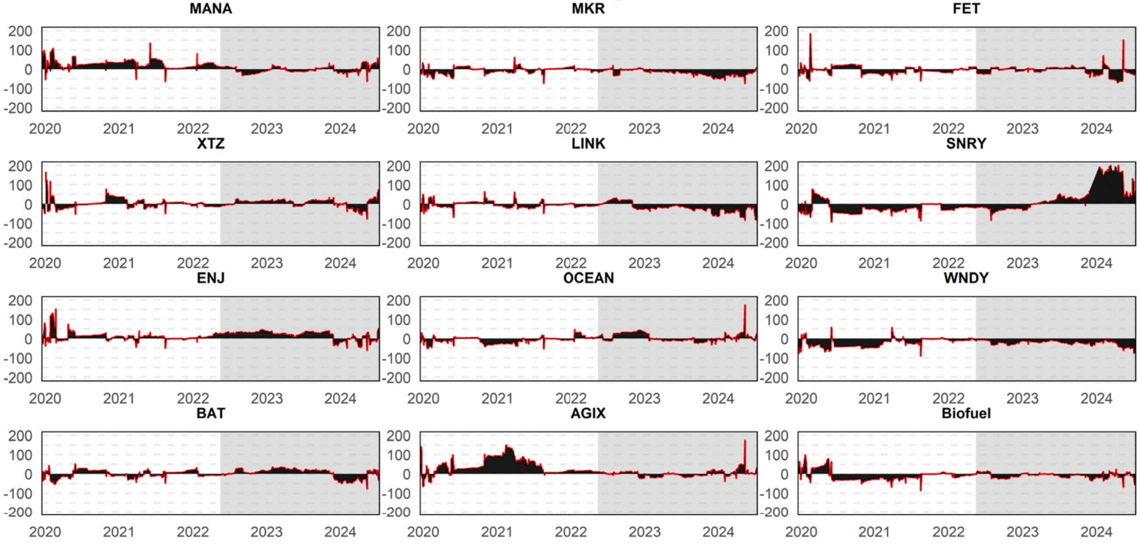
Table 4 reports the frequency-domain connectedness of returns across the twelve assets, classified into short-, medium-, and long-term horizons. The total connectedness index (TCI) values indicate the overall level of spillovers across assets at each horizon, while the net transmitter/receiver roles capture which assets send or absorb shocks in each frequency band. This allows us to disentangle short-lived speculative spillovers from more persistent, fundamental-driven interdependencies. In the short horizon (Panel A), the system exhibits high connectedness (TCI = 43.88), indicating that shocks are transmitted quickly and strongly across assets. Digital tokens such as ENJ, MANA, and XTZ emerge as strong net transmitters, suggesting that, despite relatively weak fundamentals, these tokens propagate short-lived shocks across the system. This aligns with their speculative nature, in which trading activity is driven by liquidity and investor sentiment rather than underlying adoption. Economically, this implies that while the volatility of speculative digital assets influences clean energy assets, they do not destabilise the system themselves. Instead, they play a stabilising role by absorbing short-term disturbances.

In the medium horizon (Panel B), connectedness intensity declines substantially (TCI = 12.30), which implies that interdependencies are less pronounced once the immediate speculative shocks dissipate. Interestingly, the leadership of spillovers shifts. BAT (3.05) and XTZ (1.67) remain notable transmitters, but their influence is more muted compared to the short term. On the receiver side, renewable energy assets such as WNDY (-4.01) and SNRY (-1.04) continue to absorb shocks, consistent with their fundamental-driven nature. This indicates that, while they are less volatile transmitters, they remain vulnerable to medium-term dynamics in digital tokens. This shows that digital tokens drive medium-horizon sentiment, while renewable energy assets act more as followers than leaders in the system. Over the long horizon (Panel C), connectedness further weakens (TCI = 6.27), suggesting limited persistence of speculative effects. Nevertheless, renewable energy assets still appear as mild receivers. Thus, the results demonstrate a clear dichotomy: digital tokens drive short-run volatility spillovers, while renewable and biofuel assets absorb them across all horizons. This distinction aligns with the literature, which shows that cryptocurrencies act as shock transmitters in high-frequency connectedness networks, whereas renewable markets remain fundamentally anchored and policy-driven (Yin et al. 2025).

Table 5 shows the frequency-domain connectedness of volatility among 12 assets, divided into short-, medium-, and long-term horizons. Results reveal significant time-frequency heterogeneity in volatility spillovers. In the short-term (Panel A), volatility connectedness is at its peak (TCI = 28.41%), with MANA (+3.01), XTZ (+1.41), and ENJ (+8.21) transmitting shocks, while MKR (−1.35) and BAT (−0.48) absorb them. This high short-term connectedness demonstrates that markets are highly synchronised in reacting to speculative news and investor sentiment. Tokens such as MANA, XTZ, and ENJ serve as short-term conduits of risk because speculative investors heavily trade them and are sensitive to liquidity flows and hype cycles. Economically, this implies that short-term volatility in these tokens can quickly spill over across the system,



(a) Net return spillovers



(b) Net volatility spillovers

Figure 4. Net spillovers.

Note: This figure shows net dynamic total return (4a) and volatility (4b) spillovers in each of the twelve markets under study during the full sample period, with the grey area showing the war period.

reducing the portfolio diversification benefits for short-horizon investors. Conversely, renewable and biofuel assets absorb rather than transmit shocks in the short run, reflecting their linkage to policy frameworks, physical infrastructure, and structural demand rather than to speculative trading. For investors, this suggests that green assets offer partial short-term hedging against turbulence driven by AI and blockchain tokens. Spillovers drop significantly in the medium term (TCI = 13.87%), where digital tokens (MANA, ENJ, BAT, XTZ) continue to act as transmitters but with less influence.

These findings suggest that technology-based tokens mainly drive medium-term volatility, while renewable assets maintain a stabilising, shock-absorbing role. From a risk management perspective, this suggests that

Table 4. Return spillovers for short, medium, and long horizons.

	MANA	XTZ	ENJ	BAT	MKR	LINK	OCEAN	AGIX	FET	SNRY	WNDY	Biofuel	FROM
Panel A: Short-Term													
MANA	17.27	6.9	9.02	7.65	4.38	3.39	5.33	4.56	5.22	0.57	1.22	1.46	49.7
XTZ	6.93	18.17	7.44	8.35	5.29	5.95	5.88	5.25	5.42	0.49	1.35	1.49	53.84
ENJ	8.47	7.2	17.51	7.98	4.55	3.88	5.87	4.72	5.41	0.58	1.61	1.89	52.17
BAT	7.74	8.6	8.49	17.82	5.33	4.6	5.97	4.87	5.09	0.4	1.52	1.62	54.24
MKR	5.62	6.94	6.48	6.74	25.43	5.1	4.82	3.97	4.58	1.03	1.53	1.9	48.71
LINK	3.67	6.17	4.63	4.66	4.56	31.12	4.51	3.87	4.05	0.94	1.53	1.55	40.13
OCEAN	5.86	6.38	6.75	6.5	4.08	4.48	20.64	5.76	7.11	0.74	1.38	1.11	50.15
AGIX	5.45	6.38	6.04	5.79	3.52	4.41	6.18	23.11	7.22	0.43	1.51	1.71	48.65
FET	5.91	6.14	6.31	5.64	3.64	4.11	7.39	6.72	20.02	0.43	1.24	1.2	48.72
SNRY	1.62	1.5	1.87	1.31	1.27	1.44	2.1	1.31	1.4	62.13	1.46	2.44	17.72
WNDY	2.41	2.35	3.18	2.63	2.19	1.99	1.96	2.02	1.62	0.78	33.86	8.78	29.9
Biofuel	2.6	2.74	3.35	2.74	2.68	2.39	1.75	2.54	2.07	0.82	8.99	37.79	32.67
TO	56.28	61.3	63.57	59.99	41.48	41.74	51.75	45.6	49.21	7.21	23.34	25.15	526.61
Inc.Own	73.55	79.47	81.08	77.81	66.91	72.85	72.39	68.71	69.22	69.34	57.21	62.93	TCI
Net	6.58	7.46	11.4	5.75	−7.23	1.6	1.6	−3.06	0.48	−10.51	−6.56	−7.52	43.88
Panel B: Medium-Term													
MANA	5.93	1.89	2.79	2.47	1.35	1.01	1.72	1.44	1.74	0.25	0.56	0.59	15.82
XTZ	1.82	4.21	1.93	2.26	1.23	1.48	1.7	1.37	1.38	0.11	0.49	0.5	14.27
ENJ	2.51	1.99	4.81	2.47	1.32	1.15	1.75	1.37	1.54	0.19	0.57	0.61	15.46
BAT	2.13	2.06	1.9	4.77	1.27	1.23	1.54	1.24	1.32	0.18	0.47	0.51	13.84
MKR	1.26	1.43	1.36	1.53	6.06	1.51	1	0.9	1.03	0.23	0.49	0.55	11.29
LINK	1.04	1.64	1.1	1.27	1.08	8.38	1.22	1.04	1.07	0.22	0.46	0.64	10.79
OCEAN	1.59	1.73	1.93	1.8	1.05	1.32	5.43	1.44	1.82	0.18	0.53	0.4	13.8
AGIX	1.71	1.6	1.62	1.68	0.81	1.21	1.56	5.33	1.97	0.11	0.55	0.56	13.38
FET	2	1.62	1.91	1.6	1.1	1.34	2.08	1.96	5.59	0.12	0.62	0.58	14.93
SNRY	0.3	0.27	0.38	0.22	0.27	0.28	0.28	0.24	0.29	10.47	0.25	0.34	3.12
WNDY	0.92	1.01	1.08	0.98	0.93	0.68	0.79	0.74	0.55	0.29	11.78	3.88	11.85
Biofuel	0.7	0.71	0.86	0.63	0.83	0.61	0.45	0.67	0.6	0.19	2.84	10.4	9.1
TO	15.99	15.94	16.85	16.89	11.23	11.82	14.11	12.4	13.33	2.08	7.84	9.17	147.65
Inc.Own	21.92	20.16	21.66	21.66	17.29	20.2	19.53	17.73	18.92	12.55	19.62	19.57	TCI
Net	0.17	1.67	1.39	3.05	−0.06	1.03	0.31	−0.98	−1.6	−1.04	−4.01	0.07	12.3
Panel C: Long-Term													
MANA	3.23	0.99	1.42	1.3	0.64	0.53	0.87	0.72	0.89	0.12	0.27	0.29	8.05
XTZ	0.95	2.21	0.98	1.15	0.59	0.74	0.92	0.68	0.69	0.05	0.27	0.26	7.3
ENJ	1.29	0.99	2.37	1.25	0.61	0.58	0.88	0.66	0.77	0.07	0.26	0.3	7.68
BAT	1.1	1.03	0.93	2.42	0.59	0.6	0.79	0.62	0.67	0.08	0.24	0.26	6.91
MKR	0.62	0.71	0.66	0.76	2.95	0.76	0.5	0.42	0.5	0.09	0.25	0.29	5.56
LINK	0.53	0.84	0.54	0.64	0.52	4.18	0.61	0.52	0.53	0.09	0.24	0.34	5.4
OCEAN	0.83	0.92	0.99	0.94	0.5	0.67	2.9	0.73	0.93	0.09	0.28	0.21	7.08
AGIX	0.9	0.82	0.81	0.87	0.39	0.63	0.79	2.66	1.01	0.05	0.29	0.3	6.87
FET	1.06	0.84	0.98	0.85	0.56	0.71	1.08	1.04	2.87	0.06	0.35	0.32	7.86
SNRY	0.15	0.13	0.19	0.11	0.13	0.13	0.13	0.11	0.15	5.05	0.12	0.17	1.51
WNDY	0.5	0.55	0.55	0.53	0.49	0.33	0.47	0.38	0.29	0.16	6.27	2.09	6.34
Biofuel	0.36	0.37	0.43	0.33	0.42	0.3	0.23	0.34	0.32	0.1	1.52	5.34	4.71
TO	8.31	8.2	8.48	8.73	5.44	5.98	7.28	6.22	6.74	0.96	4.1	4.83	75.27
Inc.Own	11.54	10.41	10.85	11.15	8.38	10.17	10.18	8.88	9.61	6.01	10.37	10.17	TCI
Net	0.26	0.9	0.8	1.82	−0.12	0.59	0.19	−0.65	−1.12	−0.55	−2.23	0.12	6.27

Note: This table provides frequency-based return spillovers for short-, medium-, and long-term frequency bands in 4a, 4b, and 4c, respectively.

holding renewable assets alongside speculative tokens may improve the portfolio resilience beyond the immediate shock. In Panel C, in the long term, the TCI value is 23.11%, with AI tokens dominating, while OCEAN (+3.36) and AGIX (+7.72) continue to act as volatility transmitters. This long-term contrast highlights a fundamental difference between asset classes: digital tokens, especially AI tokens, spread volatility due to their sensitivity to technological hype and liquidity cycles, whereas renewable energy assets absorb shocks, reflecting their dependence on policy stability and physical demand. Economically, this implies that renewable assets behave more like defensive or policy-driven assets, while AI tokens resemble high-beta growth stocks that carry

Table 5. Volatility spillovers for short, medium, and long horizons.

	MANA	XTZ	ENJ	BAT	MKR	LINK	OCEAN	AGIX	FET	SNRY	WNDY	Biofuel	FROM
Panel A: Short-Term													
MANA	16.23	3.46	4.53	4.32	1.97	1.88	4	2.04	3.15	0.82	1.11	1.14	28.42
XTZ	3.59	15.74	4.89	5.37	3.63	4.03	3.62	2.47	2.93	1.44	1.49	1.67	35.12
ENJ	3.94	4.26	13.23	5.08	3.32	2.95	3.71	1.84	3.2	1.11	1.63	1.51	32.55
BAT	4.37	5.67	6.04	17.08	3.65	2.92	3.5	2.59	2.97	1.28	1.51	1.78	36.28
MKR	2.54	3.87	4.45	3.88	18.89	3.28	2.71	1.92	2.51	1.47	2.72	1.68	31.03
LINK	2.33	4.81	4.02	3.11	3.48	23.23	3.61	1.91	2.87	1.47	1.51	1.59	30.72
OCEAN	4.58	4.1	4.54	4.21	2.86	3.21	20.09	3.19	5.39	1.13	1.27	1.61	36.09
AGIX	1.61	1.76	1.64	1.49	1.09	1.22	1.99	17.03	2.73	0.67	0.68	0.64	15.52
FET	3.94	3.31	4.32	3.23	2.53	2.85	4.87	3.75	19.45	1.12	1.54	1.64	33.1
SNRY	1.03	1.43	1.39	1.39	1.55	1.28	1.42	1.23	1.16	14.65	1.03	1.58	14.48
WNDY	1.56	1.95	2.79	1.8	3.73	1.72	1.73	1.51	2.03	1.39	26.89	6.07	26.29
Biofuel	1.92	1.9	2.13	1.89	1.89	1.56	1.53	1.28	1.55	1.09	4.63	26.11	21.38
TO	31.44	36.52	40.76	35.79	29.68	26.89	32.69	23.74	30.47	12.97	19.12	20.91	340.97
Inc.Own	47.67	52.27	53.98	52.87	48.57	50.12	52.78	40.77	49.93	27.61	46	47.02	TCI
Net	3.01	1.41	8.21	−0.48	−1.35	−3.82	−3.4	8.22	−2.63	−1.52	−7.17	−0.47	28.41
Panel B: Medium-Term													
MANA	7.65	1.6	2.19	1.96	0.99	0.84	1.83	1.47	1.4	0.69	0.57	0.58	14.13
XTZ	1.85	5.47	2.03	2.15	1.35	1.55	1.46	1.69	1.16	0.86	0.63	0.66	15.41
ENJ	2	1.82	5.63	2.13	1.24	1.08	1.68	1.43	1.35	0.88	0.76	0.81	15.19
BAT	1.9	2.28	2.37	5.6	1.4	1.13	1.34	1.41	1.13	0.64	0.55	0.67	14.82
MKR	1.61	1.78	2.2	1.78	6.68	1.34	1.36	1.64	1.21	0.84	1.07	0.87	15.7
LINK	1.1	2.12	1.5	1.14	1.32	7.98	1.24	1.4	0.98	1.06	0.63	0.65	13.15
OCEAN	2.61	1.55	2.08	1.73	1.13	1.25	6.77	1.37	2.16	0.66	0.53	0.72	15.78
AGIX	1.47	1.05	1.19	0.97	0.71	0.6	1.12	12.41	1.67	0.79	0.54	0.54	10.65
FET	2.32	1.45	1.9	1.46	1.18	1.06	1.97	1.94	6.85	0.63	0.76	0.89	15.56
SNRY	0.89	1.2	1.03	0.97	0.85	1	0.94	1.68	0.87	11.66	0.68	0.86	10.96
WNDY	1.11	0.9	1.39	0.91	1.43	0.75	0.78	1.48	0.83	0.73	8.21	2.73	13.03
Biofuel	1.56	0.93	1.23	1.04	1.02	0.62	0.77	1.31	0.85	0.69	2.04	8.9	12.04
TO	18.43	16.67	19.12	16.24	12.61	11.22	14.49	16.81	13.6	8.48	8.76	9.99	166.43
Inc.Own	26.09	22.14	24.75	21.84	19.29	19.2	21.26	29.22	20.45	20.13	16.97	18.89	TCI
Net	4.3	1.26	3.93	1.42	−3.09	−1.93	−1.29	6.16	−1.96	−2.48	−4.28	−2.05	13.87
Panel C: Long-Term													
MANA	7.61	2.65	3.55	2.63	1.59	1.36	2.14	4.11	1.83	3.86	0.77	1.46	25.95
XTZ	2.89	4.74	2.79	2.4	1.49	1.56	1.87	3.35	1.47	3.92	0.66	1.12	23.52
ENJ	3.51	2.91	6.35	2.77	1.71	1.5	2.12	3.99	1.8	4.14	1	1.61	27.05
BAT	2.95	2.67	2.88	4.54	1.45	1.25	1.62	3.16	1.3	2.68	0.57	1.15	21.68
MKR	2.68	2.21	2.7	2.1	4.72	1.35	1.6	3.37	1.37	3.48	0.98	1.15	22.99
LINK	1.76	2.27	1.79	1.41	1.44	5.57	1.45	2.55	1.14	3.85	0.68	1	19.36
OCEAN	2.17	1.51	1.93	1.39	0.91	0.8	4.81	1.8	1.73	3.01	0.41	0.79	16.46
AGIX	4.11	2.45	3.45	2.67	1.74	1.44	2.41	14.69	2.84	5.18	1.17	2.22	29.7
FET	2.67	1.76	2.19	1.59	1.21	1.04	2.11	3.09	4.7	2.81	0.74	1.13	20.34
SNRY	2.83	2.75	2.96	2.33	1.68	1.94	2.28	4.81	2.18	21.8	1.05	1.66	26.45
WNDY	1.89	1.38	1.9	1.36	1.5	0.91	0.89	3.41	0.93	2.47	5.6	3.33	19.98
Biofuel	2.91	1.82	2.46	1.87	1.57	1.07	1.33	3.76	1.33	3.51	2.17	7.77	23.8
TO	30.36	24.37	28.6	22.54	16.29	14.21	19.82	37.42	17.92	38.93	10.2	16.62	277.27
Inc.Own	37.98	29.11	34.95	27.08	21	19.78	24.63	52.11	22.61	60.73	15.8	24.4	TCI
Net	4.41	0.85	1.55	0.86	−6.7	−5.15	3.36	7.72	−2.42	12.47	−9.78	−7.18	23.11

Note: This table provides frequency-based volatility spillovers for short-, medium-, and long-term frequency bands in 5a, 5b, and 5c, respectively.

systemic volatility risk. For portfolio construction, this suggests that combining speculative digital assets with renewable tokens can create long-term diversification gains. However, the systemic risk posed by AI tokens as volatility hubs should not be underestimated.

The network plots in Figure 5 illustrate horizon-specific spillovers between return and volatility, highlighting how different assets play asymmetric roles. In the short term, the networks for returns and volatility are highly dense, with digital tokens such as ENJ, XTZ, and MANA acting as central transmitters. Their larger node

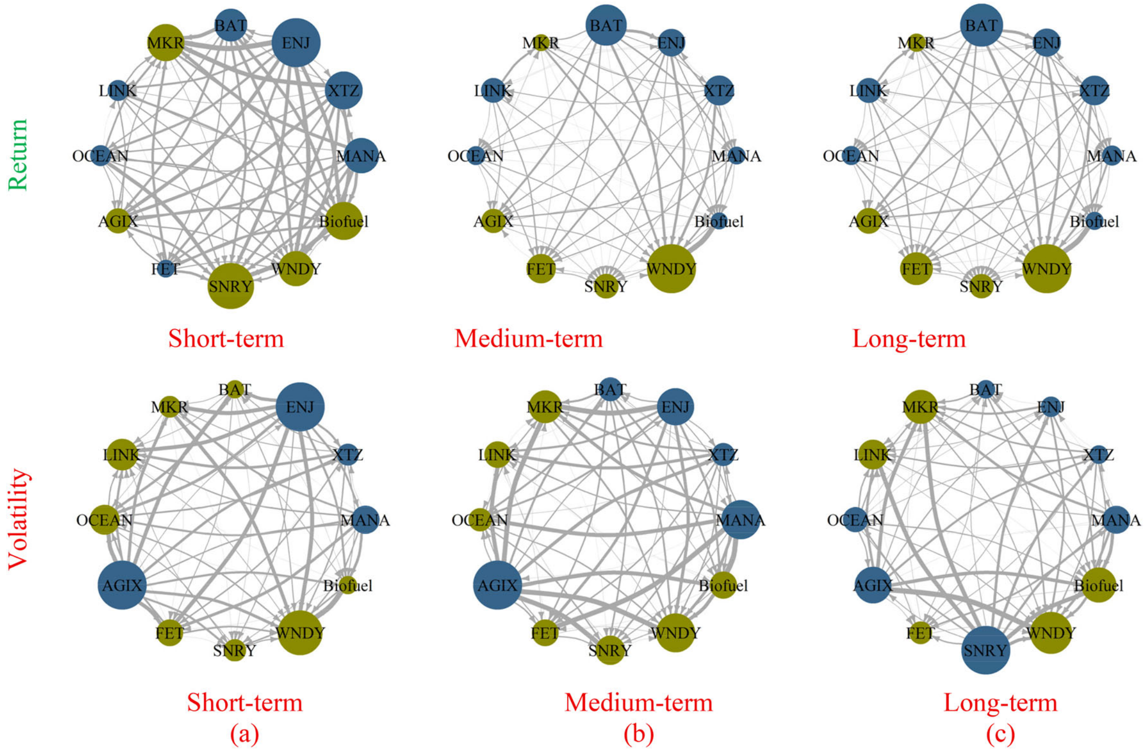


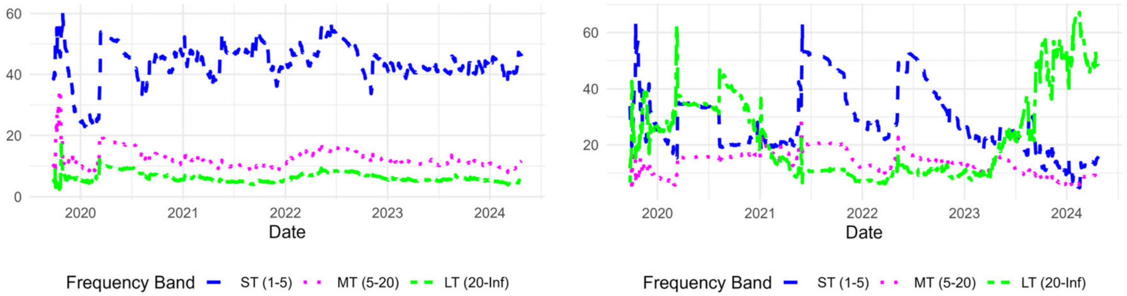
Figure 5. Network plots for three investment horizons.

Note: This figure shows network diagrams of directional return (upper pane) and volatility (lower pane) for twelve markets under study during the full sample period, across short-, medium-, and long-term horizons, in parts 5a, 5b, and 5c, respectively.

sizes and multiple outgoing spillovers suggest that these assets amplify sentiment-driven turbulence and liquidity shocks, which is consistent with their speculative nature and high investor turnover. Over medium- and long-term horizons, the network structure becomes less dense, and the dominance of digital tokens gradually weakens. However, AI-linked assets such as AGIX and FET, as well as renewable energy assets (SNRY, WNDY, and Biofuel), remain subject to shocks. These results align with earlier findings in energy-finance research: digital assets drive short-term spillovers, while renewable energy assets anchor long-term stability.

Figure 6 illustrates the net spillovers for three investment horizons: short-term, medium-term, and long-term. For return spillovers, the short-term component (blue line) dominates, especially during crisis episodes such as the COVID-19 outbreak in early 2020 and the Russia-Ukraine conflict in early 2022. For instance, connectedness surges in early 2020 with the COVID-19 outbreak and again in early 2022 during the Russia-Ukraine war. In contrast, volatility connectedness exhibits different dynamics. Volatility spillovers are persistent across both short- and long-term horizons, which reflects amplification of systemic uncertainty by events such as the FTX collapse in 2022 and ongoing inflationary pressures in 2023. Over time, particularly in 2023–2024, long-term connectedness rises, as AI-linked tokens begin to influence more persistent risk structures. This highlights that while returns react smoothly to speculative events, volatility risks propagate more quickly but with greater impact, requiring investors and policymakers to adopt horizon-specific risk management strategies.

The results on net return and volatility connectedness in Figure 7 reveal that NFTs and AI tokens (e.g. OCEAN and FET) frequently act as net transmitters of shocks, especially during the 2021–2022 speculative episode. Their dominance implies they are the primary channel through which risks can spread across the ecosystem, reducing their diversification capacity for investors. On the other hand, DeFi tokens typically alternate between being transmitters and receivers e.g. MKR or LINK, which reflects their two-sided nature: when the markets are in a state of stress, it becomes more vulnerable to shocks because of collateralised lending risks, but when the markets



(a) Return spillover

(b) Volatility spillover

Figure 6. Return and volatility spillovers for three investment horizons.

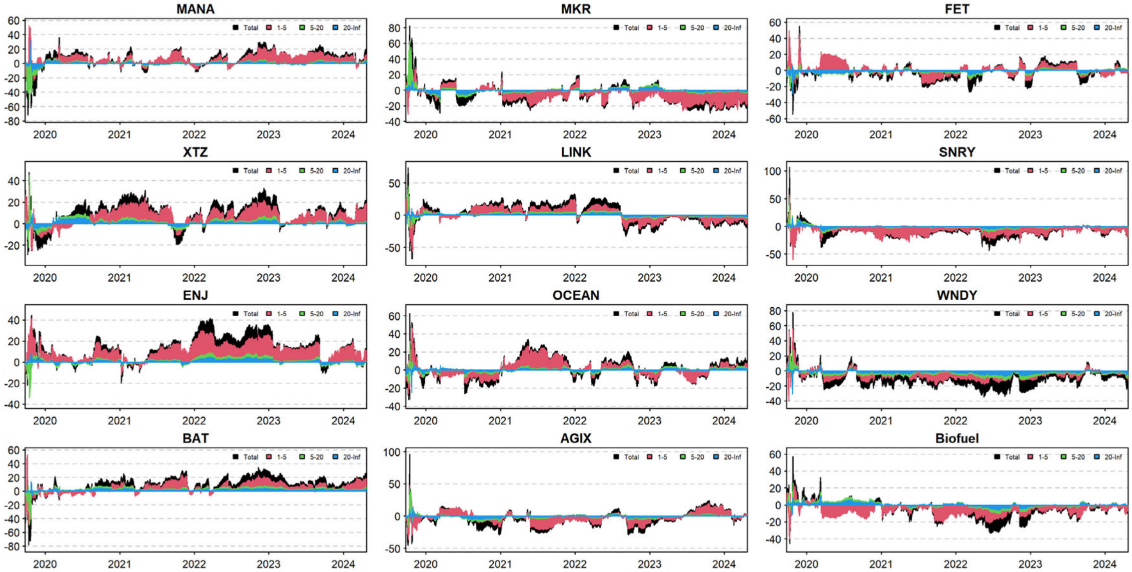
Note: This figure shows dynamic total return (6a) and volatility (6b) spillovers in the network of twelve markets during the full sample, with blue, pink, and green lines representing the short- (1-5 days), medium- (5-20 days), and Long- (above 20 days) horizons, respectively.

are calm, it becomes more resilient to shocks, which is as expected given that it is based on financial utility, not hyped speculation (Corbet et al. 2023; Yousaf, Nekhili, and Gubareva 2022). From a financial integration perspective, this highlights the limited diversification benefits of holding portfolios heavily exposed to these tokens, as their spillovers intensify contagion during stress episodes and they remain pulled into the same risk cycles. This is similar to concerns raised in earlier studies that the growing link between green assets and speculative digital markets may reduce the diversification benefits they are expected to provide (Corbet, Goodell, and Günay 2022).

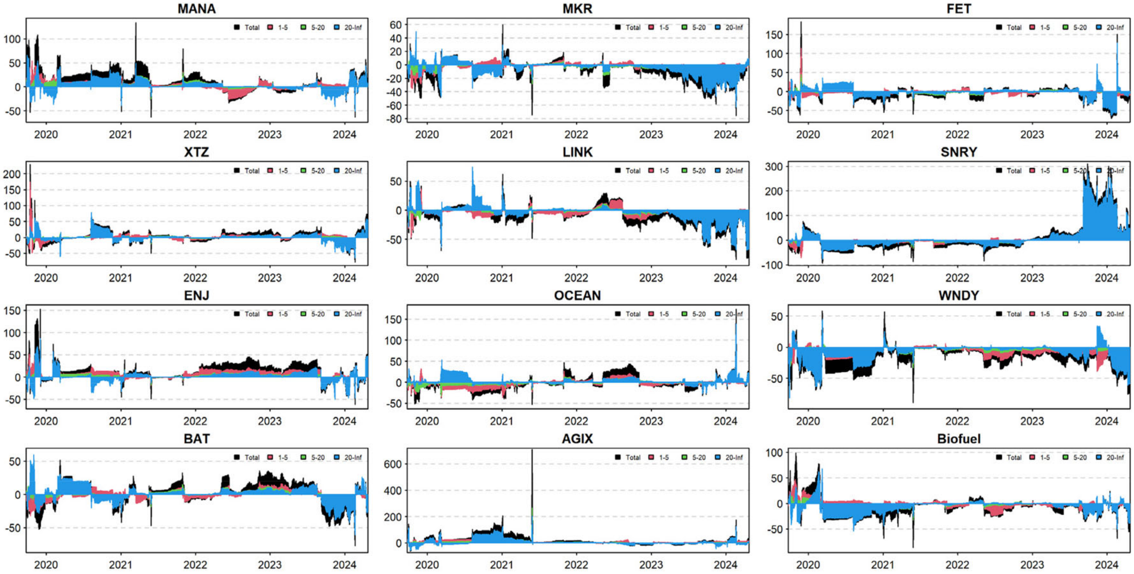
4.4. Additional analysis: higher-order moments spillover between markets

Following the spirit of previous work (e.g. Helmi et al. 2025), Table 6 presents the time-invariant connectedness among the 12 assets with respect to realised skewness and kurtosis. Panel A (skewness) provides additional insight into asymmetric risk transmission. The TCI is 54.69%, with MANA (11.66), AGIX (10.22), OCEAN (5.71), and BAT (9.04) as the main transmitters of skewness shocks. This demonstrates that DeFi-related tokens amplify downside risks and speculative asymmetry across the system. Renewable assets such as SNRY, WNDY, and Biofuel, along with AI tokens FET (-8.04), act as net receivers, indicating they are disproportionately exposed to negative asymmetries and tail risks. This finding resonates with the broader energy-finance literature, which shows that renewable energy investments often absorb shocks rather than lead markets, particularly during periods of financial turbulence (Li, Mo, and Nie 2023).

Panel B (kurtosis) highlights the propagation of extreme risk or tail events. With TCI at 55.88%, fat-tailed risk spillovers are systemic. Tokens such as XTZ (1.88), MANA (14.89), and MKR (18.78) are net transmitters of kurtosis shocks, while digital assets such as ENJ (-7.51) and LINK (-13.69) shift into the role of net receivers. As highlighted by Baruník and Křehlík (2018), extreme geopolitical shocks can trigger a flight-to-safety, in which investors reallocate their capital to established benchmarks. Thus, speculative assets become progressively more vulnerable to exogenous shocks. While their squared returns (our proxy for volatility) may affect the nature and intensity of volatility spillovers, they do not necessarily preserve proportionality in the fourth moment. These assets act as transmitters of kurtosis spillovers, transmitting extreme tail risk shocks. This moment-dependent shift signifies a change in the transmission of risk rather than a segmentation of the market. Their increased sensitivity to exogenous shocks, such as sudden regulatory interventions in AI or sudden supply disruptions of energy markets, generates fat-tailed return behaviour. In these extreme scenarios, the diversification benefits of energy equities may disappear. Instead of absorbing shocks, they become sources of systemic shocks, amplifying tail risk across the network (Foglia, Angelini, and Huynh 2024). For portfolio managers, this implies that these assets are diversifiers during calm periods but become a source of contagion during black-swan events, significantly reducing their effectiveness as long-term hedges.



(a) Net return spillovers for three investment horizons



(b) Net volatility spillovers for three investment horizons

Figure 7. Net spillovers for three investment horizons.

Note: This figure shows net dynamic return (7a) and volatility (7b) spillover in each of the twelve markets under study during the full sample period with blue, pink, and green lines representing the short- (1-5 days), medium- (5-20 days), and Long- (above 20 days) horizons, respectively.

4.5. Additional analysis: determinants of market linkages

After obtaining the return-volatility connectedness index, we move to the determinants of connectedness. Understanding the relationships among macroeconomic factors, AI token network connections, and the renewable energy market enables stakeholders to manage financial risks and improve portfolio performance across different time horizons. To address this issue, we use a linear regression model to predict the total return and the volatility connectedness index, drawing on previous studies (Bouri and Harb 2022; Ji et al. 2019). In line with the literature, we treat macroeconomic indicators as exogenous variables, meaning they influence the connectedness

Table 6. Higher-order moments spillovers for Skewness and Kurtosis.

	MANA	XTZ	ENJ	BAT	MKR	LINK	OCEAN	AGIX	FET	SNRY	WNDY	Biofuel	FROM
Panel A: Skewness													
MANA	37.12	8.47	9.41	10.42	4.84	4.41	5.42	6.74	6.02	1.95	2.07	3.12	62.88
XTZ	8.83	32.94	8.59	10.4	5.49	7.31	6.29	7.12	5.57	1.66	1.54	4.25	67.06
ENJ	11.67	9.83	33.77	9.51	5.27	4.67	6.59	6.26	5.58	2.56	2.35	1.94	66.23
BAT	9.1	10.44	9.8	36.72	6.36	3.73	6.09	7.81	4.28	2.72	1.7	1.25	63.28
MKR	6.29	4.77	4.57	6.55	51.37	4.41	6.03	4.98	2.82	2.81	3.57	1.83	48.63
LINK	4.78	5.94	4.5	5.48	5.22	49.56	5.93	6.46	5.06	1.78	1.72	3.58	50.44
OCEAN	7.22	5.99	6.75	6.4	4.22	5.09	41.1	7.11	7.77	4.38	1.98	1.99	58.9
AGIX	6.94	6.56	5.61	6.74	4.94	6.13	7.15	42.57	5.41	3.17	2.09	2.68	57.43
FET	6.82	4.59	6.46	5.3	4.72	7.75	9.48	8.01	40.29	2.32	2.8	1.47	59.71
SNRY	3.84	2.57	4.33	3.46	3.35	4.29	4.14	4.3	3.23	62.29	2.25	1.96	37.71
WNDY	5.25	2.76	4.12	3.7	5.31	4.25	4.2	3.06	3.45	2.78	56.17	4.95	43.83
Biofuel	3.81	4.6	2.97	4.35	3.24	3.01	3.28	5.8	2.47	2.57	4.05	59.86	40.14
TO	74.54	66.5	67.1	72.32	52.96	55.05	64.61	67.65	51.66	28.7	26.13	29.02	656.25
Inc.Own	111.66	99.45	100.87	109.04	104.33	104.6	105.71	110.22	91.96	90.99	82.29	88.88	TCI
NET	11.66	−0.55	0.87	9.04	4.33	4.6	5.71	10.22	−8.04	−9.01	−17.71	−11.12	54.69
Panel B: Kurtosis													
MANA	41.89	6.46	7.17	7.89	7.37	2.89	5.77	6.61	4.53	2.7	2.66	4.04	58.11
XTZ	6.87	35.61	9.2	10.11	4.99	6.03	7	6.89	5.26	1.92	3.1	3.02	64.39
ENJ	12.15	9.02	33.2	9.89	6.55	3.64	7.05	6.94	5.44	1.62	2.78	1.73	66.8
BAT	7.56	8.08	6.29	41.65	8.2	3.97	5.18	7.88	4.39	2.33	3.07	1.43	58.35
MKR	6.21	5.32	4.86	6.1	50.28	3.5	6.55	3.97	3.72	2.27	5.65	1.59	49.72
LINK	4.25	5.42	3.75	7.33	8.05	45.88	6.31	5.14	4.96	2.19	3.9	2.82	54.12
OCEAN	6.78	6.64	6.1	6.05	10.29	4.74	43.31	4.95	5.45	1.24	2.91	1.53	56.69
AGIX	9.02	6.28	6.35	8.86	5.04	3.22	6.55	41.82	5.62	2.13	2.48	2.61	58.18
FET	6.6	5.7	3.95	7.69	4.71	3.25	6.16	7.3	45.93	3.2	2.38	3.12	54.07
SNRY	4.85	3.22	2.8	2.53	4	2.1	3.89	2.25	4.76	65.56	2.64	1.4	34.44
WNDY	4.66	5.68	3.99	6.15	5.43	3.17	5.78	3.49	3	2.69	52.4	3.56	47.6
Biofuel	4.04	4.45	4.83	3.13	3.87	3.93	3.28	4.44	3.45	3.23	5.49	55.86	44.14
TO	72.99	66.26	59.29	75.72	68.5	40.44	63.51	59.85	50.59	25.52	37.07	26.86	646.61
Inc.Own	114.89	101.88	92.49	117.37	118.78	86.31	106.82	101.68	96.52	91.08	89.46	82.73	TCI
NET	14.89	1.88	−7.51	17.37	18.78	−13.69	6.82	1.68	−3.48	−8.92	−10.54	−17.27	53.88

Note: This table provides time-based spillover analysis of higher-order moments across digital assets and energy markets.

dynamics but are not influenced by them within our model structure (Ji et al. 2019). These indicators are selected based on prior literature highlighting their explanatory power for asset market uncertainty and risk transmission. Specifically, we incorporate four major indicators: the Volatility Index (VIX), the CBOE Oil Volatility Index (OVX), the Euro Currency Volatility Index (ECV), and the Economic Policy Uncertainty Index (EPU). VIX measures the aggregate investor fear and general market-wide risk aversion. In terms of asset pricing theory, greater volatility increases risk premia and leads to greater co-movement among risky assets as investors rebalance their portfolios. In economic terms, VIX spikes usually lead to flight-to-safety or herding, increasing systemic spillovers across digital and renewable asset markets. This mechanism has been confirmed by Będowska-Sójka and Kliber (2022). OVX captures uncertainty in the oil market, a core aspect of energy economics, given its impact on production costs, inflation expectations, and the transition away from fossil fuels toward renewables. For renewable energy assets, oil volatility is particularly relevant as it directly shapes investor appetite for green alternatives. At the same time, for digital assets, the transmission occurs through inflationary pressures and macro-liquidity channels.

The ECV reflects volatility in the Euro exchange rate, which influences global capital flows, hedging costs, and international portfolio diversification. According to uncovered interest rate parity, higher exchange rate volatility increases uncertainty for global investors, discourages cross-border diversification, and amplifies co-movement in internationally traded assets such as NFTs, DeFi, and AI tokens. This is particularly relevant given the global trading nature of these markets. Reboredo, Ugolini, and Aiube (2020) provide empirical support for the claim that exchange rate uncertainty significantly transmits volatility into commodity and digital markets. Lastly, the EPU index indicates uncertainty about fiscal, monetary, and regulatory policies. According to the policy uncertainty theory (Pástor and Veronesi 2013), the greater the government policy uncertainty, the greater the systematic risk and the lower the investor confidence, which enhances the level of co-movement among assets. Policy uncertainty is particularly important in the context of digital and renewable tokens, where shifts in financial markets and climate policy directly affect investors' expectations. Moreover, Bouri and Harb (2022) demonstrate that EPU shocks are important predictors of systemic connectedness and spillovers in several asset classes.

To capture the impact of the Russia-Ukraine war, we add a war dummy variable to the model: 1 for the period from February 25, 2022, to April 23, 2024, and 0 otherwise. This allows us to explicitly test the changes in patterns of connectedness that may have been significantly altered during the war period.

$$TCI_t = \beta_0 + \beta_1 OVX_T + \beta_2 VIX_T + \beta_3 EPU_T + \beta_4 ECV_T + \beta_5 WAR_{0,1} + \mu_T \tag{23}$$

While the regression model identifies broad macroeconomic drivers of systemic connectedness, it is important to recognise that the impact of these variables may not be uniform across all asset classes. The regression results in Table 7 provide several insights. For example, OVX shows a strong positive effect on short- and medium-term return spillovers, suggesting that the oil market may rapidly transmit shocks to digital and renewable assets due to their sensitivity to energy costs and geopolitical instability (Broadstock, Chatziantoniou, and Gabauer 2022; Ji et al. 2019). This likely stems from two distinct channels: a cost-push channel for renewable energy equities (affecting valuation) and a speculative-substitution channel for AI tokens, where energy volatility triggers a shift in high-tech sentiment. However, in the volatility spillover regressions (Panel B), OVX turns negative and significant across time horizons, demonstrating that rising oil uncertainty dampens volatility connectedness, potentially because investors may treat digital assets as hedges against energy risk. VIX exhibits positive and highly significant effects in the medium and long term, in both return and volatility connectedness, underscoring the central role of equity market stress and global risk aversion in amplifying digital asset co-movements over time (Corbet et al. 2023). However, the transmission mechanism differs across the network: for NFTs and DeFi, VIX spikes represent a liquidity drain, whereas for renewable energy equities, they represent a shift in institutional risk-premia. This distinction explains why volatility connectedness (Panel B) sometimes turns negative; extreme macro-uncertainty can lead to a decoupling effect, in which traditional equities and speculative digital assets react to different risk priorities (e.g. inflation vs. liquidity). EPU is mostly irrelevant in the short term, but as the medium horizon approaches, it becomes more relevant. This is how regulatory uncertainty and fiscal policy changes slowly transform investor behaviour and the interdependence of digital and renewable markets (Reboredo, Ugolini, and Aiube 2020). The most persistent driver is ECV, with strong positive coefficients in the medium- and long- return connectedness regressions, indicating that currency instability increases the co-movement of returns. Finally, the WAR dummy is significant across specifications, highlighting the disruptive impact of geopolitical shocks like the Russia-Ukraine conflict, which strongly intensifies both return spillovers. This is consistent with earlier research indicating that geopolitical situations and wars are associated with increased market volatility and poor asset performance (Będowska-Sójka and Kliber 2022).

4.6. Robustness checks

To assess the reliability of the results, we perform a robustness test with a rolling window of 180 days and a forecast horizon of 24 days to examine both time-domain and frequency-domain connectedness, given their potential sensitivity to short-term fluctuations. Table 8 presents the robustness analysis of return connectedness. In the time domain (Panel A), NFTs such as MANA, XTZ, ENJ, and BAT emerge as the primary transmitters of spillovers, with net positive values ranging from 7.44 to 13.56, while renewable assets (SNRY, WNDY, and Biofuel) consistently act as receivers with strong negative net spillovers. The frequency decomposition (Panel B) shows that spillovers are most pronounced in the short term (TCI = 47.47), with NFTs and AI token (FET) serving as strong transmitters, whereas renewable assets absorb shocks. Medium- and long-term spillovers are comparatively weaker (TCI = 11.71 and 3.08), with DeFi and AI tokens playing stabilising roles. Importantly, short-term connectedness is significantly higher than long-term connectedness, consistent with the main results and supporting the argument that speculative tokens (NFTs and AI) drive rapid co-movement. At the same time, renewable assets remain largely insulated from the transmission of systemic risk (Reboredo, Ugolini, and

Table 7. Determinants of systemic linkages.

	Panel A: Returns				Panel B: Volatility				Panel C: HOMs	
Variable	TCI_{ST}	TCI_{MT}	TCI_{LT}	TCI_{TOTAL}	TCI_{ST}	TCI_{MT}	TCI_{LT}	TCI_{TOTAL}	Skewness	Kurtosis
OVX	.079***	.003	−.002	.067***	.099***	−.01	.066***	−.052**	.003	.01
	(.018)	(.004)	(.002)	(.025)	(.023)	(.006)	(.025)	(.025)	(.033)	(.02)
VIX	.167***	.155***	.08***	.433***	−.153*	.035	.012	.266***	.35***	.061
	(.054)	(.016)	(.008)	(.071)	(.085)	(.029)	(.119)	(.099)	(.085)	(.081)
EPU	.008***	.004***	.002***	.012***	.001	−.001	.02***	.025***	−.002	.005
	(.002)	(.001)	(0)	(.003)	(.004)	(.001)	(.005)	(.005)	(.003)	(.005)
ECV	−.838***	.121***	.162***	−.698***	.153	.093	−1***	−.847***	.214	.085
	(.157)	(.046)	(.028)	(.177)	(.343)	(.108)	(.371)	(.321)	(.293)	(.274)
WAR	3.574***	.952***	.276***	4.469***	−15.766***	−5.376***	−12.469***	2.134	−6.124***	−18.163***
	(.778)	(.162)	(.102)	(.766)	(1.464)	(.553)	(2.309)	(1.611)	(1.148)	(1.253)
Constant	33.419***	5.681***	2.589***	45.748***	37.5***	14.609***	70.759***	13.34***	39.973***	54.407***
	(1.01)	(.231)	(.175)	(.913)	(1.853)	(.53)	(1.927)	(1.792)	(1.279)	(1.37)
IC_controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	.468	.764	.772	.626	.583	.645	.391	.684	.685	.615
F-stat (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: This table reports the regression results for the determinants of spillovers for return spillover (Panel A) and volatility spillover (Panel B) for short-term (TCI_{ST}), medium-term (TCI_{MT}), long-term (TCI_{LT}), and total connectedness (TCI_{TOTAL}) and Higher Order Moments. The explanatory variables include the Oil Market Volatility Index (OVX), the Volatility Index (VIX), the Economic Policy Uncertainty Index (EPU), and the Euro Currency Volatility Index (ECV). IC_controls indicate twelve control variables measuring each asset's interconnections from spillover analysis of the respective dependent variable; t-statistics are reported in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 8. Robustness checks for return linkages.

	MANA	XTZ	ENJ	BAT	MKR	LINK	OCEAN	AGIX	FET	SNRY	WNDY	Biofuel	Total
Panel A: Time Domain													
FROM	73.69	75.79	74.91	75.37	65.33	55.94	71.12	69.44	71.46	20.88	47.14	46.05	747.14
TO	81.13	87.47	88.47	85.67	57.99	58.6	72.76	66	69.2	8.06	34.03	37.77	
Inc.Own	107.44	111.68	113.56	110.3	92.65	102.66	101.64	96.56	97.74	87.18	86.89	91.71	TCI
NET	7.44	11.68	13.56	10.3	−7.35	2.66	1.64	−3.44	−2.26	−12.82	−13.11	−8.29	62.26
Panel B: Frequency Domain													
Short-Term													
FROM	55.43	58.71	56.21	58.97	52.99	42.43	54.5	52.63	53.26	17.78	31.77	34.98	569.66
TO	61.6	68.37	67.76	65.65	44.86	44.77	56.1	50.5	53.31	6.36	24.05	26.35	
Inc.Own	81.16	87.65	86.36	84.86	72.29	78.39	78.52	74.62	75.28	73.97	61.51	67.62	TCI
Net	6.17	9.66	11.54	6.68	−8.13	2.34	1.59	−2.13	0.05	−11.43	−7.72	−8.62	47.47
Medium-Term													
FROM	14.52	13.6	14.82	13	9.89	10.58	13.17	13.26	14.3	2.48	12.17	8.78	140.57
TO	15.49	15.21	16.38	15.83	10.41	10.8	13.27	12.29	12.65	1.35	7.88	9.01	
Inc.Own	20.85	19.15	21.5	20.12	16.2	18.99	18.41	17.42	17.87	10.59	20.09	19.1	TCI
Net	0.97	1.62	1.57	2.82	0.52	0.23	0.1	−0.97	−1.65	−1.13	−4.3	0.23	11.71
Long-Term													
FROM	3.74	3.49	3.88	3.41	2.46	2.94	3.44	3.55	3.9	0.62	3.21	2.3	36.91
TO	4.04	3.89	4.33	4.2	2.72	3.03	3.39	3.21	3.23	0.36	2.1	2.41	
Inc.Own	5.43	4.89	5.7	5.32	4.17	5.28	4.71	4.53	4.58	2.63	5.29	4.99	TCI
Net	0.31	0.41	0.45	0.79	0.26	0.09	−0.05	−0.33	−0.66	−0.26	−1.1	0.11	3.08

Notes: This table provides time-frequency spillover analysis across digital and energy markets. The table is estimated using a Time Frequency TVP-VAR model with a 180-day rolling window, a lag length of 1 (based on BIC), and a 24-step-ahead forecast.

Aiube 2020). Overall, the empirical results using this alternative window length are consistent with the baseline findings, thereby confirming the stability of the observed spillover dynamics.

Table 9 presents the robustness analysis of volatility connectedness. In the time domain (Panel A), MANA (0.76), ENJ (5.85), XTZ (5.06), BAT (4.99), OCEAN (0.96), and AGIX (11.76) stand out as the dominant transmitters of volatility shocks, respectively. These roles are overall consistent with our earlier findings. The frequency decomposition further highlights this asymmetry. In the short term (Panel B), ENJ, XTZ, BAT, and MANA remain strong transmitters, followed by AGIX, while renewable assets, especially WNDY, are the

Table 9. Robustness checks for volatility linkages.

	MANA	XTZ	ENJ	BAT	MKR	LINK	OCEAN	AGIX	FET	SNRY	WNDY	Biofuel	Total
Panel A: Time Domain													
FROM	69.04	73.42	73.49	72.86	67.27	63.22	68.01	56.52	67.87	47.98	49.05	50.87	759.6
TO	69.8	78.48	79.35	77.84	58.38	53.2	68.97	68.28	61.76	60.39	39.85	43.31	
Inc.Own	100.76	105.06	105.85	104.99	91.11	89.98	100.96	111.76	93.89	112.41	90.79	92.44	TCI
NET	0.76	5.06	5.85	4.99	−8.89	−10.02	0.96	11.76	−6.11	12.41	−9.21	−7.56	63.30
Panel B: Frequency Domain													
Short-Term													
FROM	36.65	40.9	39.76	42.86	37.57	35.38	42.69	21.87	41.14	15.63	31.75	26.72	412.91
TO	37.99	45.06	44.07	47.24	35.92	32.22	40.78	31.37	37.88	14.62	21.91	23.83	
Inc.Own	57.52	63.03	60.93	66.05	58.71	57.82	63.77	51.66	60.69	35.14	58.56	58.61	TCI
Net	1.35	4.16	4.32	4.38	−1.65	−3.16	−1.91	9.5	−3.26	−1.01	−9.83	−2.89	34.41
Medium-Term													
FROM	18.44	18.35	19.18	17.95	17.04	15.85	15.13	18.07	15.9	16.42	10.67	13.76	196.77
TO	18.26	19.96	21.25	19.09	14.07	13.62	16.64	20.65	14.97	16.79	10.69	10.77	
Inc.Own	26.39	25.88	27.95	25.13	21.37	21.91	23.14	36.58	21.86	34.85	21.63	21.31	TCI
Net	−0.18	1.61	2.06	1.14	−2.97	−2.23	1.5	2.59	−0.94	0.37	0.02	−2.99	16.40
Long-Term													
FROM	13.95	14.16	14.55	12.04	12.67	11.99	10.19	16.59	10.82	15.94	6.64	10.38	149.93
TO	13.54	13.45	14.02	11.51	8.39	7.36	11.55	16.25	8.92	28.98	7.24	8.7	
Inc.Own	16.85	16.15	16.98	13.81	11.03	10.26	14.05	23.52	11.34	42.42	10.6	12.52	TCI
Net	−0.4	−0.71	−0.53	−0.53	−4.27	−4.63	1.36	−0.33	−1.91	13.04	0.6	−1.68	12.49

Note: See above Table 7 notes.

largest receivers. Over the long term, the pattern shifts notably, with renewables (SNRY and WNDY) becoming dominant transmitters, while most NFTs and DeFi tokens act as receivers. These results align with our main findings.

4.7. *Portfolio implications*

Table 10 shows the optimal portfolio weights (W), hedge ratios (HR), and hedge effectiveness (HE) for AI tokens, NFTs/DeFi assets, and renewable energy assets for the full sample, pre-war, and war periods. Several interesting observations can be made from these results. Firstly, the weights (W) indicate that AI tokens (especially OCEAN and AGIX) receive greater allocation when paired with NFTs and DeFi assets such as ENJ, MANA, and LINK. This is because they are more diversified (Goetzmann and Kumar 2008), and investors allocate more to assets that reduce the overall portfolio variance. On the other hand, renewable assets like SNRY receive very low weights (often 0.24-0.33), which limits diversification gains. This is consistent with earlier findings by Ali et al. (2024), who find that renewable assets track energy fundamentals rather than digital asset dynamics, thereby limiting their hedging appeal in mixed portfolios. Secondly, the hedge effectiveness (HE) values show important cross-asset complementarities. AI-NFT pairs, such as AGIX/BAT (0.75) and AGIX/ENJ (0.69), exhibit the highest hedging effectiveness, indicating that NFTs are effective risk-sharing instruments when combined with AI tokens. This aligns with the findings of BenMabrouk et al. (2024), who argue that NFTs enhance diversification benefits during volatile periods because they are sensitive to investor sentiment cycles, which often move differently from AI-driven financial assets. On the other hand, renewable assets like WNDY and Biofuel have lower HE values, indicating that although they provide stability, they do not significantly reduce overall risk because their price dynamics are more tied to physical energy markets (Bina, Schroeder, and Tonsor 2022).

Third, hedge ratios (HR) show that hedging costs vary across asset classes. Low HR values (e.g. OCEAN/MKR = 0.56; FET/MANA = 0.68) indicate that hedging is cost-efficient, requiring smaller offsetting positions to achieve the same level of risk reduction. More importantly, negative or near-zero HR values for solar energy pairs (SNRY/AGIX = 0.01; SNRY/FET = −0.01; SNRY/MANA = 0.07) mean SNRY is a natural hedge. The negative sign indicates inverse co-movement: when AI tokens decline, solar-linked assets (SNRY)

Table 10. Bivariate portfolio analyses.

	Panel A: Full-sample			Panel B: Pre-War			Panel B: War-period		
	W	HE	HR	W	HE	HR	W	HE	HR
Digital Assets (NFTs/Defi)									
MANA/BAT	0.21	0.4	0.84	0.24	0.44	0.74	0.21	0.29	0.93
MANA/MKR	0.39	0.45	0.55	0.41	0.48	0.49	0.44	0.35	0.57
MANA/LINK	0.41	0.44	0.44	0.42	0.43	0.55	0.43	0.47	0.29
XTZ/BAT	0.46	0.26	0.75	0.31	0.31	0.72	0.63	0.1	0.8
XTZ/MKR	0.52	0.3	0.56	0.46	0.34	0.6	0.64	0.17	0.47
XTZ/LINK	0.55	0.24	0.5	0.53	0.21	0.69	0.6	0.3	0.26
ENJ/BAT	0.25	0.39	0.82	0.27	0.44	0.73	0.23	0.22	0.91
ENJ/MKR	0.41	0.43	0.55	0.4	0.47	0.49	0.49	0.28	0.54
ENJ/LINK	0.43	0.42	0.46	0.42	0.43	0.56	0.46	0.4	0.3
AI/Digital Assets									
OCEAN/MANA	0.42	0.37	0.61	0.43	0.38	0.54	0.37	0.37	0.7
OCEAN/XTZ	0.24	0.46	0.75	0.32	0.43	0.63	0.14	0.52	0.9
OCEAN/ENJ	0.37	0.38	0.68	0.44	0.37	0.59	0.29	0.39	0.77
OCEAN/BAT	0.19	0.5	0.79	0.2	0.51	0.71	0.16	0.48	0.87
OCEAN/MKR	0.3	0.48	0.56	0.29	0.47	0.56	0.35	0.48	0.52
OCEAN/LINK	0.32	0.47	0.5	0.3	0.43	0.64	0.35	0.55	0.33
AGIX/MANA	0.31	0.68	0.66	0.38	0.71	0.56	0.17	0.6	0.84
AGIX/XTZ	0.21	0.72	0.87	0.28	0.72	0.78	0.08	0.71	1.03
AGIX/ENJ	0.29	0.69	0.75	0.36	0.71	0.62	0.16	0.63	0.93
AGIX/BAT	0.17	0.75	0.91	0.2	0.77	0.84	0.09	0.68	1.01
AGIX/MKR	0.28	0.75	0.59	0.32	0.78	0.59	0.25	0.68	0.55
AGIX/LINK	0.29	0.74	0.54	0.27	0.74	0.8	0.29	0.73	0.26
FET/MANA	0.29	0.42	0.68	0.35	0.39	0.56	0.17	0.47	0.84
FET/XTZ	0.15	0.5	0.83	0.22	0.44	0.71	0.06	0.62	0.98
FET/ENJ	0.24	0.43	0.73	0.34	0.38	0.58	0.12	0.51	0.9
FET/BAT	0.14	0.55	0.83	0.18	0.53	0.74	0.09	0.59	0.93
FET/MKR	0.23	0.52	0.6	0.25	0.49	0.57	0.24	0.58	0.62
FET/LINK	0.25	0.52	0.52	0.22	0.45	0.69	0.28	0.63	0.3
Energy/Other assets									
SNRY/MANA	0.32	0.83	0.07	0.27	0.86	0.1	0.37	0.68	0.02
SNRY/XTZ	0.25	0.85	0.06	0.21	0.87	0.14	0.28	0.76	−0.04
SNRY/ENJ	0.3	0.82	0.03	0.25	0.85	0.09	0.34	0.7	−0.05
SNRY/BAT	0.24	0.87	0.04	0.19	0.89	0.06	0.3	0.74	0.02
SNRY/MKR	0.25	0.86	0.07	0.2	0.89	0.07	0.33	0.72	0.04
SNRY/LINK	0.26	0.86	0.07	0.2	0.88	0.09	0.31	0.72	0.06
SNRY/OCEAN	0.33	0.79	0.1	0.26	0.81	0.21	0.42	0.63	−0.04
SNRY/AGIX	0.42	0.79	0.01	0.33	0.83	0.04	0.52	0.57	−0.02
SNRY/FET	0.39	0.79	−0.01	0.3	0.82	0.01	0.49	0.58	−0.04
WNDY/MANA	1	0.01	0.06	1	0	0.05	0.98	0	0.06
WNDY/XTZ	0.99	0.01	0.06	0.99	0.01	0.05	0.98	0.02	0.08
WNDY/ENJ	0.99	0.01	0.06	1	0	0.06	0.99	0.01	0.07
WNDY/BAT	0.99	0.01	0.06	0.99	0.01	0.06	0.98	0.01	0.07
WNDY/MKR	0.98	0.03	0.05	0.99	0.01	0.05	0.96	0.01	0.03
WNDY/LINK	0.97	0.03	0.03	0.99	0.01	0.05	0.93	0.06	0
WNDY/OCEAN	0.99	0.01	0.04	0.99	0.01	0.04	0.98	−0.01	0.04
WNDY/AGIX	0.99	0.01	0.04	1	0	0.05	0.99	0.01	0.04
WNDY/FET	0.99	0.01	0.03	0.99	0	0.04	0.98	−0.01	0.03
Biofuel/MANA	0.95	0.04	0.08	0.97	0.02	0.09	0.93	0.07	0.09
Biofuel/XTZ	0.94	0.05	0.1	0.97	0.02	0.11	0.89	0.1	0.1
Biofuel/ENJ	0.96	0.03	0.1	0.98	0.02	0.11	0.92	0.07	0.1
Biofuel/BAT	0.92	0.06	0.1	0.94	0.05	0.11	0.9	0.08	0.09
Biofuel/MKR	0.93	0.07	0.09	0.96	0.05	0.1	0.9	0.1	0.06
Biofuel/LINK	0.93	0.07	0.07	0.96	0.04	0.08	0.88	0.13	0.05
Biofuel/OCEAN	0.96	0.03	0.06	0.98	0.02	0.07	0.92	0.06	0.04
Biofuel/AGIX	0.96	0.03	0.06	0.98	0.01	0.08	0.95	0.06	0.04
Biofuel/FET	0.96	0.03	0.05	0.98	0.01	0.07	0.94	0.06	0.03

Note: This table reports the optimal weights (W), hedge effectiveness (HE), and hedge ratio (HR) for the bi-variate portfolios for the Full Sample, pre-war, and war-period of AI tokens with unconventional digital assets and renewable energy assets.

tend to rise, making them effective natural hedges. This makes SNRY not only cost-efficient but also self-hedging in some periods, as Zadeh and Romagnoli (2024) show that assets with opposite co-movements are cheaper and more efficient hedges. However, the high HRs for AGIX/BAT (0.91) and AGIX/XTZ (0.87) indicate that hedging is expensive, requiring nearly full exposure to offset risk, which makes them less attractive. Comparing the pre-war and war sub-periods provides further economic insights.

Before the war, the system showed stronger overall hedge effectiveness across AI-NFT pairs. During the war, however, HE values declined for several NFT-linked pairs, and weights shifted more heavily toward OCEAN, suggesting a flight to AI assets, a trend likely accelerated by the global AI boom and the launch of transformative technologies like ChatGPT in late 2022. This is consistent with Manahov and Li (2026), who document that during crises, investors reallocate portfolios toward technologically grounded assets with clearer value propositions (such as OCEAN), while sentiment-driven assets (NFTs) become less reliable. Meanwhile, renewable energy assets such as SNRY maintain stable hedging benefits across both sub-periods, highlighting the defensive nature of green equity assets during geopolitical uncertainty (Wang 2022).

Taken together, the results indicate that AI tokens (OCEAN, AGIX, FET) are the cornerstone of portfolio diversification, NFTs (ENJ, BAT, XTZ) provide complementary but costly hedging benefits, and renewable assets (especially SNRY) act as efficient, low-cost natural hedges. However, WNDY and Biofuel remain weak contributors to portfolio efficiency, which highlights the need for selective allocation. These findings emphasise that portfolio strategies involving AI and digital assets must be actively rebalanced across different market regimes to capture their hedging and diversification potential.

The results in Table 11 reveal distinct time- and regime-dependent portfolio dynamics, emphasising the complementary roles of AI tokens and renewable energy assets. Across all horizons, SNRY consistently leads in portfolio weightings (0.14–0.21), highlighting its stabilising and hedging capabilities, driven by low correlation with crypto-assets and strong long-term fundamentals in the renewable sector. AI tokens (OCEAN, AGIX, FET) maintain moderate yet persistent allocations (7–9%), reaffirming their function as diversifiers that improve portfolio efficiency without adding significant volatility. The pre-war period exhibits superior performance, with Sharpe ratios exceeding one (0.077 in the short term), indicating highly efficient risk-adjusted returns. Mean returns increase with the investment horizon, indicating a long-term strategic synergy between AI and renewable energy assets. The dominance of SNRY (22%) and Biofuel (12%) further indicates the resilience of green assets, aligning with literature on hedging properties of clean energy.

During the war period, portfolio efficiency declines sharply, as shown by negative Sharpe ratios (−0.004 to −0.0170) and decreasing average returns. The emergence of negative Sharpe ratios indicates that while these portfolios are optimised for risk reduction, they are unable to generate positive excess returns amidst the global market downturn triggered by the Russia-Ukraine conflict. Investors pivot slightly toward LINK and MKR (DeFi assets) and away from Biofuel and WNDY, reflecting a flight to safety and a preference for liquidity amid high uncertainty. Despite the negative performance, SNRY continues to provide moderate stability, suggesting that renewable equities serve as low-cost stabilisers, reducing total portfolio variance. However, they do not serve as absolute safe havens during systemic crises.

5. Conclusion

Amid the changing landscape of financial markets in the twenty-first century, the intersection of AI, energy markets, and digital assets like NFTs and DeFi is reshaping the future of innovation and sustainability. Energy markets are constantly seeking solutions for environmental issues. AI is transforming every facet of human life, and NFTs and DeFi are revolutionising financial systems by providing new means of ownership, trading, and investment in digital assets. Thus, the study analyses how NFTs, DeFi assets, AI tokens, and renewable energy markets constitute transmission networks using a time-frequency framework.

Our findings indicate that systemic connectedness between AI tokens, NFTs, DeFi, and renewable energy assets is regime-dependent, intensifying sharply during the Russia-Ukraine war. NFTs consistently transmit both return and volatility shocks, driven by their speculative nature. At the same time, AI and renewable assets primarily serve as receivers, absorbing risks given their niche adoption and lower liquidity. DeFi assets switch roles between transmission and reception in response to the crisis. Volatility connectedness is generally stronger than

Table 11. Multivariate portfolio weights and performance analyses.

	Short-term	Medium-term	Long-term
Panel A: Full-sample			
MANA	0.1	0.06	0.06
XTZ	0.05	0.07	0.07
ENJ	0.03	0.03	0.04
BAT	0.05	0.05	0.05
MKR	0.09	0.11	0.11
LINK	0.09	0.07	0.07
OCEAN	0.07	0.08	0.08
AGIX	0.08	0.09	0.09
FET	0.09	0.07	0.08
SNRY	0.14	0.2	0.21
WNDY	0.13	0.07	0.06
Biofuel	0.09	0.1	0.1
Mean Return	0.0023	0.0027	0.0029
Standard Deviation	0.0485	0.0573	0.0602
Sharpe Ratio	0.0469	0.0467	0.0476
Maximum Drawdown	82.834	85.903	86.159
Value-at-Risk (95%)	−6.795	−8.327	−8.402
Panel B: Pre-war			
MANA	0.1	0.04	0.04
XTZ	0.04	0.08	0.08
ENJ	0.05	0.05	0.04
BAT	0.06	0.06	0.06
MKR	0.09	0.11	0.12
LINK	0.06	0.03	0.03
OCEAN	0.07	0.06	0.06
AGIX	0.07	0.1	0.1
FET	0.11	0.07	0.06
SNRY	0.15	0.22	0.22
WNDY	0.14	0.07	0.07
Biofuel	0.07	0.12	0.12
Mean Return	0.0044	0.0053	0.0057
Standard Deviation	0.0570	0.0695	0.0738
Sharpe Ratio	0.0772	0.0769	0.0770
Maximum Drawdown	71.223	60.096	73.064
Value-at-Risk (95%)	−7.899	−10.451	−10.907
Panel C: War-period			
MANA	0.07	0.07	0.06
XTZ	0.06	0.07	0.07
ENJ	0.03	0.05	0.05
BAT	0.04	0.02	0.03
MKR	0.09	0.13	0.13
LINK	0.11	0.13	0.12
OCEAN	0.06	0.06	0.08
AGIX	0.09	0.07	0.07
FET	0.07	0.08	0.08
SNRY	0.12	0.18	0.17
WNDY	0.12	0.08	0.08
Biofuel	0.14	0.06	0.05
Mean Return	−0.0002	−0.0006	−0.0007
Standard Deviation	0.0358	0.0397	0.0402
Sharpe Ratio	−0.0042	−0.0144	−0.0170
Maximum Drawdown	75.043	78.820	77.895
Value-at-Risk (95%)	−5.623	−6.016	−6.079

Note: This table reports the multi-variate portfolio weights for the full-sample, pre-war, and war-period for sample markets. It also reports portfolio performance measures.

return connectedness. Furthermore, frequency-domain results show that digital tokens dominate short-term spillovers, while renewable assets continue to serve as absorbers across horizons. Likewise, higher-order moment analysis reveals that extreme risks (skewness and kurtosis) can shift transmission channels. The dominance of skewness spillovers reinforces that systemic connectedness is driven primarily by asymmetries. NFT assets like (ENJ, MANA, XTZ) and DeFi tokens (BAT, LINK) emerge as the primary transmitters of return shocks and volatility, while AI tokens (AGIX, FET), and renewable energy assets (SNRY, WNDY, Biofuel) function mainly as receivers, which demonstrates their potential for short-term diversification but continued exposure to systemic risk.

The regression analysis indicates that the market interconnections among AI tokens, digital assets, and renewable energy markets are highly vulnerable to macro-financial and volatility factors. The results reveal that oil market (OVX) shocks are the strongest short-term driver of return connectedness, while ECV volatility dominates in the medium- and long-term. EPU becomes more relevant at all horizons, reflecting policy-driven risks, while currency volatility continues to amplify return spillovers. Finally, geopolitical shocks, particularly wars, emerge as a consistent and powerful force that intensifies spillovers in return and volatility across markets.

The portfolio results show that AI tokens and renewable energy assets form a complementary mix, boosting diversification and stability across market conditions. WNDY consistently leads in portfolio weights, confirming its role as a hedge. Meanwhile, AI tokens maintain moderate allocations, providing steady diversification benefits across varying circumstances. The pre-war period shows efficient performance, with higher Sharpe ratios and lower tail risks, indicating strong investor confidence and a balance between digital innovation and green growth. However, during the war period, returns declined, as risk-adjusted performance weakened. Investors shift toward AI and DeFi, and policy-supported renewables. The results suggest that these portfolios perform efficiently in stable markets but have limited safe-haven property, highlighting the need for active rebalancing and flexible allocation strategies to maintain performance under uncertainty.

The findings of this study offer important practical implications for policymakers, regulators, and investors as digital assets such as NFTs, DeFi, and AI tokens become increasingly interconnected with renewable energy markets. Regulators should adopt cross-market monitoring systems to track how extreme shocks in crypto, AI, and DeFi markets can spill over into renewable equity markets, potentially affecting decarbonisation funding and financial stability. Clear regulatory frameworks are needed to mitigate fraud, enhance transparency, and safeguard financial stability. Regulators should prioritise systemic risk oversight mechanisms, particularly given the heightened asset spillovers during periods of economic and policy uncertainty. Encouraging diversification strategies that combine digital tokens with renewable energy could help stabilise portfolios and promote sustainable investment practices. Moreover, introducing incentives for responsible investment in AI and renewable energy markets can support broader sustainability transitions. For investors, the evidence highlights the importance of monitoring short-term oil shocks and longer-term equity and policy uncertainties when designing hedging and risk management strategies.

These results hold actionable guidance for navigating the ongoing Green-4IR transition. Environmental policymakers could provide targeted liquidity support or fiscal incentives for green assets during periods of geopolitical or market stress, shielding the renewable sector from speculative capital flight. Additionally, both investors and regulators should recognise the growing co-movement between digital assets and green investments: integrating ESG-focused digital finance metrics into investment and policy decision-making, which can strengthen the resilience of sustainable portfolios and ensure that the financial digitalisation supports long-term environmental goals. For investors, the evidence highlights the importance of monitoring short-term oil shocks and longer-term equity and policy uncertainties when designing hedging and risk management strategies. While investing in a specific token, investors in the token markets must consider asset-specific idiosyncrasies. Beyond practice, the study also contributes to the literature by enriching the understanding of market connectedness and systemic risk transmission by integrating time- and frequency-domain approaches with higher-order moments (skewness and kurtosis) across digital tokens and renewable energy markets. These insights enrich theories of financial contagion, particularly in the contexts where non-traditional digital assets interact with energy-linked markets.

Despite its contributions, this study uses a relatively shorter time window due to data limitations on new assets, which may limit the generalizability of the results. Secondly, though robust, connectedness estimates may be sensitive to major changes in model input parameters and rolling window lengths. Building on these limitations, future research could extend the analysis using higher-frequency intraday data to capture more granular spillover dynamics. Future studies can incorporate alternative econometric methods, such as machine learning models, which could explore the robustness of non-linear spillover structures. Future work may also broaden the asset set to include a wider range of cryptocurrencies and renewable technologies as additional data becomes available, thereby deepening our understanding of digital-technology-energy asset interdependencies. Future papers could also disaggregate the overall systemic linkages to examine how macro volatility shocks distinctly influence the connectivity of specific asset pairs or subsectors, such as digital assets versus renewable energy equities.

Note

1. $Variance_{hedged} = h_{x,t} + \beta_{xy,t}^2 \cdot h_{y,t} - 2\beta_{xy,t} \cdot h_{xy,t}$.

Author contributions

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Data sharing policy

Data available on request from the authors.

Disclosure statement

No potential conflict of interest was reported by the authors .

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Appendix A. Parameters of the connectedness approaches

We use RStudio version 2025.9.0.387 (Windows). We use the following versions of RStudio libraries for our analysis: Connectedness Approach (1.0.4), knitr (1.50), zoo (1.8.14), haven (2.5.4), ggplot2 (4.0.0), and tseries (0.10.58). We use the TVP-VAR frequency model (with nlag $= 1$, nfore $= 12$, and a window size of 36) in a specific configuration (with kappa1 $= 0.99$, kappa2 $= 0.96$, and prior $=$ BayesPrior). For the robustness check, we set the parameters to nfore $= 24$ and window size $= 180$. Identical results with only marginal differences may appear when using different operating systems, software, or package versions.

Table A1. Appendix Table A1. Trading volume of top AI assets and sample AI tokens

Date	31/12/2020	31/12/2021	31/12/2022	31/12/2023	31/12/2024
AI Assets					
Microsoft	20.94M	18.00M	21.94M	18.73M	13.25M
Alphabet	21.07M	18.14M	23.99M	18.73M	17.47M
NVIDIA	192.42M	266.53M	310.49M	389.29M	155.66M
Amazon	59.14M	47.83M	310.49M	389.29M	24.82M
AGIX	0.20M	3.38M	1.7M	22.2M	0.08M
FET	2.76M	47.6M	5.65M	56.6M	202M
OCEAN	3.21M	47.66M	5.65M	56.66M	202.6M