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Portfolio Diversification with Non-Conventional Assets: A Comparative Analysis of Bitcoin, FinTech, and Green Bonds Across Global Markets

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Abstract

This study examines the diversification and hedging potential of non-conventional assets like cryptocurrency (Bitcoin), FinTech equities (FINXs), and green bonds (QGREENs) against traditional equity benchmarks, namely the MSCI World and MSCI Emerging Markets indices using daily data from 2016 to 2021. Employing Time-Varying Parameter Vector Autoregression (TVP-VAR), network connectedness analysis, and the Minimum Connectedness Portfolio (MCoP) approach, the study uncovers dynamic interdependencies among these markets. The results reveal that Bitcoin consistently acts as a net receiver of shocks, providing strong diversification benefits during crisis periods, such as the COVID-19 pandemic. FinTech assets show moderate resilience, while green bonds primarily serve as shock transmitters with limited hedging ability. Optimal portfolio weights indicate the highest allocation to Bitcoin, followed by FinTech and green assets, supporting their inclusion in diversified portfolios. Overall, the findings underscore Bitcoin's superior risk-mitigating role and highlight the strategic importance of digital assets in achieving portfolio stability and sustainability in volatile global markets.

Keywords: bitcoin; fintech; green bonds; TVP-VAR; network connectedness; MCoP; Portfolio diversification; sustainable finance

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1. Introduction

The global financial landscape has undergone rapid transformation, driven by technological innovation, financial digitalization, and increasing sustainability awareness. The growing convergence of digital finance and green finance has redefined portfolio construction, investment risk management, and market efficiency. Emerging instruments such as cryptocurrencies, FinTech equities, and green bonds have gained prominence as alternative investment avenues capable of enhancing diversification and contributing to sustainable development goals (Letho et al., 2022; Xu et al., 2018; Oche, 2020). However, despite the attention these assets have received individually, there remains limited understanding of their interconnected behavior and joint role in portfolio diversification under dynamic market conditions.

The recent series of crises, notably the COVID-19 pandemic, has highlighted the fragility of traditional portfolios dominated by conventional equities and bonds. It has simultaneously accelerated digital transformation and the transition toward sustainability-focused investment strategies. As a result, investors and policymakers are seeking asset combinations that can ensure resilience and stability in turbulent environments (Hasan et al., 2021; Meo et al., 2025). This study responds to this need by examining how Bitcoin (BTC), FinTech equities (FINXs), and green bonds (QGREENs) interact dynamically with global equity benchmarks, such as the MSCI World and MSCI Emerging Markets indices.

While several studies have examined the diversification benefits of cryptocurrencies (Bouri et al., 2017; Mensi et al., 2020; Khaki et al., 2022), FinTech equities (Pham, 2025; Agarwal et al., 2024; S. Wang, 2023), and green bonds (Yadav et al., 2023) independently, very few have integrated these three asset classes into a unified framework. Existing research largely focuses on static or pairwise relationships and therefore fails to capture the time-varying connectedness that characterizes modern financial systems (Antonakakis et al., 2020; L. Huang, 2024). Moreover, the interaction between innovation-driven assets and sustainable instruments—two critical components of Industry 5.0 and the sustainable digital economy—remains underexplored.

Accordingly, this study aims to bridge this gap by investigating the dynamic connectedness and diversification potential among Bitcoin, FinTech equities, and green bonds relative to global equity markets. Using daily data from January 2016 to December 2021, the study applies a combination of Time-Varying Parameter Vector Autoregression (TVP-VAR), network connectedness analysis, and Minimum Connectedness Portfolio (MCoP) optimization. This tri-method framework enables a comprehensive assessment of return spillovers, directional connectedness, and optimal portfolio allocation strategies under evolving market regimes.

To achieve these objectives, the study addresses the following research questions: (1) How do Bitcoin, FinTech equities, and green bonds interact dynamically with global and emerging equity markets? (2) Do these assets provide meaningful diversification and hedging benefits during market stress periods, such as the COVID-19 crisis? (3) How can investors minimize systemic risk using Minimum Connectedness Portfolios based on dynamic interdependencies? Based on these questions, the following hypotheses are formulated:

H1: *The connectedness between Bitcoin, FinTech equities, and green bonds is time-varying and regime-dependent.*

H2: *Bitcoin offers superior diversification and hedging potential during crisis periods compared to FinTech and green assets.*

H3: *Minimum Connectedness Portfolios derived from connectedness indices enhance risk-adjusted returns and portfolio resilience.*

The selection of Bitcoin, FINX, and QGREEN reflects the intersection of digital and sustainable finance. Bitcoin represents decentralized digital assets that exhibit hedging and speculative characteristics (Goodell & Goutte, 2021; Milka, 2020). FinTech equities embody technology-driven innovation that enhances market accessibility and financial inclusion (Chopra et al., 2024; Zen & Saputra, 2023), while green bonds reflect the sustainability transition through environment-focused financing instruments. Analyzing their dynamic interlinkages contributes to a deeper understanding of how innovation and sustainability can jointly shape financial stability.

This research makes three key contributions. First, it extends the literature by jointly analyzing cryptocurrency, FinTech, and green assets, thus integrating digitalization and sustainability perspectives within a single empirical framework. Second, it applies the TVP-VAR and MCoP models to assess time-varying spillovers and optimal portfolio configurations, improving upon conventional static connectedness approaches. Third, it offers actionable insights for investors and policymakers by identifying asset combinations that balance technological innovation with environmental responsibility to achieve resilient and sustainable portfolios. The remainder of this paper is structured as follows: Section 2 reviews the relevant literature, Section 3 details data and methodology, Section 4 discusses empirical results, and Section 5 concludes with implications and directions for future research.

2. Literature Review

The evolution of financial markets in the post-global crisis era has been characterized by the simultaneous rise in digital financial innovation and sustainability-driven investment. Within this landscape, three prominent asset classes—cryptocurrencies, FinTech equities, and green bonds—have emerged as transformative forces influencing diversification, risk management, and global capital flows. Existing literature provides rich insights into each of these domains, yet very few studies have integrated them within a single analytical framework to assess time-varying connectedness and portfolio resilience. The detailed literature reviews in tabular format has been encapsulated in Table 1.

Table 1. Summary of Literature on Time-Varying Diversification between Crypto, FinTech, and Green Assets and Identified Research Gaps.

Author(s) and Year	Asset Class/Theme	Objective/Focus	Methodology Used	Key Findings	Expanded Limitations/Gaps (Reviewer-Ready)
Letho et al. (2022)	Crypto	Diversification role	Portfolio analysis	BTC enhances diversification intermittently	Uses static diversification tests; ignores time-varying dynamics and does not consider interdependence with digital or green assets.
Milka (2020)	Crypto	Speculative nature	Behavioral and speculative review	Crypto markets driven by speculation	Lacks empirical spillover modeling; does not incorporate multi-asset interactions or dynamic regime shifts.
(Hasan et al., 2021)	Crypto	Hedging during COVID-19	Copula and hedging	BTC shows hedging ability in crisis	Limited to crisis-specific analysis; bilateral focus prevents understanding broader systemic linkages.
Goodell and Goutte (2021)	Crypto	Safe-haven properties	Wavelet coherence	BTC hedges equities during shocks	Wavelet produces correlations, not true directional spillovers; exclude FinTech and green instruments.
Mensi et al. (2020)	Crypto	Connectedness	Spillover index	Time-dependent hedging efficiency	Measure limited to crypto–crypto relationships; lacks cross-domain diversification analysis.

Table 1. *Cont.*

Author(s) and Year	Asset Class/Theme	Objective/Focus	Methodology Used	Key Findings	Expanded Limitations/Gaps (Reviewer-Ready)
Pham (2025)	FinTech	Shock buffering	Volatility models	FinTech reduces volatility in APAC	Regional restriction; does not explore global connectedness or interaction with crypto/green markets.
Agarwal et al. (2024)	FinTech	AI-based portfolio enhancement	Multi-factor	FinTech improves efficiency	Conceptual focus; lacks empirical spillover assessment across sectors.
Jain et al. (2023)	FinTech	Inclusion and innovation	Empirical/qualitative	FinTech broadens access but adds contagion risk	No modeling of volatility transmission or inter-market dynamics.
Ramadugu and Doddipatla (2022)	FinTech	Cybersecurity and regulation	Regulatory review	Volatility from digital risks	Theoretical; no multi-asset or dynamic connectedness analysis.
Chopra et al. (2024)	FinTech (NFTs/Stablecoins)	Portfolio effects	Portfolio models	New instruments reshape diversification	Narrow focus on niche assets; no broader ecosystem analysis.
Bhutta et al. (2022)	Green bonds	Sustainability and risk	Spillover tests	GBs moderately hedge volatility	Green bonds treated in isolation, ignoring emerging digital finance interactions.
Oche (2020)	Green bonds	Crisis behavior	Wavelet/GARCH	Regime-dependent spillovers	No cross-market integration with crypto or FinTech equities.
Meo et al. (2025)	Green bonds	Safe-haven tests	Connectedness	Mixed safe-haven evidence	Lacks broader financial ecosystem analysis; narrow asset coverage.

2.1. Cryptocurrencies and Diversification

The academic discourse on cryptocurrencies has evolved from understanding their speculative behavior to evaluating their portfolio diversification potential. Ehlers and Gauer (2019) examined the role of cryptocurrencies in enhancing diversification opportunities, while Juškaitė and Gudelytė-Žilinskienė (2022) reviewed their speculative characteristics and behavioral biases. In the context of financial crises, Elu and Williams (2022) and Goodell and Goutte (2021) found that cryptocurrencies, particularly Bitcoin, exhibit safe-haven or hedging attributes during turbulent market conditions, such as the COVID-19 pandemic.

Extending this strand, Khaki et al. (2022) explored the diversification benefits of cryptocurrencies in emerging markets and their co-movement with MENA stock markets, while Esparcia and López (2023) investigated dynamic relationships among cryptocurrency returns, revealing that their hedging efficiency is time-dependent. Koutmos et al. (2021) emphasized conditional hedging strategies using dynamic approaches, underscoring that cryptocurrencies may switch between hedging and speculative roles depending on market regimes.

A growing stream of studies integrates cryptocurrencies with other financial instruments. Zhang et al. (2023) examined their behavior during market turbulence and found evidence of asymmetric connectedness, whereas Abakah et al. (2023) established dynamic linkages among cryptocurrencies, FinTech, and green finance assets. Collectively, these studies highlight that Bitcoin and similar assets can serve as diversification tools under specific conditions, though their performance is largely regime-dependent.

While prior research has established cryptocurrencies as potential hedging or diversification instruments, it often relies on static frameworks or bilateral relationships. The joint connectedness of cryptocurrencies with FinTech and green assets remains largely unexplored, leaving a critical gap in understanding multi-asset integration within sustainable digital finance.

2.2. FinTech Equities and Financial Market Dynamics

The FinTech sector, representing the technological revolution in financial services, has emerged as a new class of innovation-driven equities. Kong and Lin (2021) documented that FinTech firms act as buffers against financial volatility in Asia–Pacific markets, while Martins and Ashofteh (2023) discussed the potential of AI-driven FinTech solutions to improve portfolio efficiency. Alam and Rahman (2019) emphasized the systemic innovation and inclusion facilitated by FinTech, though they warned of contagion risks associated with rapid digital integration.

Regulatory perspectives have also been examined. Ramadugu and Doddipatla (2022) and Oladinn and Odumuwagun (2025) highlighted the significance of cybersecurity and global regulatory frameworks, noting that volatility in FinTech markets often stems from digital infrastructure vulnerabilities. Empirical studies by Zhang et al. (2023) and Z. Wang et al. (2023) revealed strong volatility spillovers and global liquidity transmission effects within FinTech equities, particularly during systemic shocks.

From an innovation–risk trade-off standpoint, Ante and Kauffman (2023) examined the diversification impact of stablecoins and NFTs, showing how emerging FinTech-linked instruments influence multi-asset portfolios. Sharma et al. (2024) and Zhou (2025) extended this discussion by demonstrating how blockchain, AI, and digital tokens reshape asset allocation paradigms.

The FinTech literature confirms the sector's dual nature: enhancing innovation and inclusion while increasing sensitivity to global shocks. However, comparative evidence on how FinTech interacts with other non-traditional assets, such as Bitcoin and green bonds, is still limited. This highlights the need for an integrated empirical framework to assess cross-sector spillovers and their implications for portfolio resilience.

2.3. Green Bonds and Sustainable Investment Linkages

In parallel, green bonds have evolved as an essential mechanism linking finance and sustainability. Bhutta et al. (2022) identified green bonds as key instruments promoting environmentally responsible investments. Empirical findings of Oche (2020) demonstrated that green bonds exhibit moderate hedging capability against traditional market volatility. During crisis periods, Meo et al. (2025) and Guo et al. (2021) observed that green bonds act as partial safe havens, though their effectiveness depends on market regimes.

Recent research increasingly connects green finance with energy and digital assets. Wu et al. (2025) and Yadav et al. (2023) found time-varying correlations between green bonds, clean energy indices, and cryptocurrencies, whereas Liu (2024) explored their integration with ESG and FinTech markets. Similarly, Wu et al. (2024) emphasized asymmetric connectedness patterns and volatility transmission mechanisms across green and conventional bonds.

Despite growing interest, most studies continue to analyze green bonds in isolation from the broader digital transformation of finance. The potential synergy between sustainability-linked assets and digital innovation (FinTech and crypto) remains underexplored, particularly through dynamic connectedness models.

The green bond literature validates their hedging and ESG alignment potential but provides limited evidence of how they integrate with rapidly evolving digital financial instruments. This gap underscores the need to study cross-market linkages between sustainable and digital assets using time-varying econometric frameworks.

2.4. Research Gap

Across these three domains—cryptocurrencies, FinTech, and green bonds—existing research provides valuable but siloed insights into diversification and contagion dynamics. The majority of studies adopt static connectedness frameworks (VAR, DCC-GARCH, or wavelet models) and analyze pairwise interactions, thereby overlooking the evolving tri-sector relationships shaping today's financial ecosystem.

This study addresses these limitations by jointly analyzing Bitcoin (BTC), FinTech equities (FINXs), and green bonds (QGREENs) alongside MSCI World and MSCI Emerging Markets indices. By applying Time-Varying Parameter Vector Autoregression (TVP-VAR) and Minimum Connectedness Portfolio (MCoP) models, the research captures dynamic spillovers and derives optimal portfolio allocations under shifting market regimes.

The study thus contributes to the literature by bridging digital and sustainable finance, integrating technological and environmental dimensions of modern investments, and offering empirical evidence for resilient, low-connectedness portfolio strategies relevant to both investors and policymakers.

3. Methodology and Data

3.1. Methodological Roadmap

This study adopts a comprehensive approach by utilizing a multi-stage methodological framework that integrates time-varying connectedness with portfolio optimization. The process unfolds in the following four distinct steps:

(1) Data Collection: We start by gathering raw financial data from various sources. This foundational step ensures that we have accurate and relevant information to work with.
(2) Model Estimation (TVP-VAR): Next, we apply a Time-Varying Parameter Vector Autoregression (TVP-VAR) model. This sophisticated statistical technique helps us estimate the dynamic relationships and connections between different financial assets over time, allowing us to see how they interact with one another.
(3) Network Construction: After estimating the model, we construct a network that visually represents these interconnections. This network helps us understand the complex relationships among the assets, highlighting how they influence each other.
(4) Portfolio Optimization (MCP): Finally, we leverage the insights gained from the previous steps to optimize our investment portfolios using the Minimum Connectedness Portfolio (MCP) approach. This step focuses on minimizing systemic risk, ensuring that our portfolios are not only well-diversified but also resilient to market shocks.

By following this structured workflow, we transform raw financial data into meaningful measures of time-varying connectedness, which ultimately guide us in creating optimized portfolios that effectively reduce risk. This methodical approach enhances our understanding of asset relationships and supports informed investment decisions. The methods and models are discussed sequentially in this section.

3.1.1. Data Profile

The empirical analysis of this study focuses on three important asset classes aligned with technology, digital finance, and sustainability: Bitcoin (BTC), the Global X FinTech ETF (FINX), and the Nasdaq Green Economy Benchmark (QGREEN).

(1) Bitcoin (BTC) acts as a stand-in for the digital asset market, showcasing innovations in decentralized finance. It is a key player that reflects how digital currencies are reshaping the financial landscape.
(2) FINX, on the other hand, represents the performance of companies within the FinTech ecosystem. This includes firms involved in digital payments, blockchain applications, and various online financial services. Essentially, it gives us a glimpse into how these tech-driven companies are performing in the market.
(3) QGREEN tracks businesses that are committed to the green economy and renewable technologies. It embodies the shift towards sustainability, focusing on equities that are driving the transition to a more environmentally friendly future.

For this analysis, we gathered data from Bloomberg, covering daily information from January 2016 to December 2021, which captures both the pre-pandemic and COVID-19 crisis phases, a period of heightened volatility and structural shifts across global financial markets.

3.1.2. Time-Varying Parameter Vector Autoregression (TVP-VAR)

To explore the dynamic interdependence among Bitcoin (BTC), the Global X FinTech ETF (FINX), and the Nasdaq Green Economy Benchmark (QGREEN), this study utilizes the Time-Varying Parameter Vector Autoregression (TVP-VAR) framework, which was developed by (Antonakakis & Gabauer, 2017). This model is particularly effective because it captures the changing relationships between these assets without relying on fixed rolling-windows. This adaptability is crucial, especially during periods of market upheaval, like the COVID-19 pandemic.

Unlike traditional methods such as GARCH, DCC-GARCH, or Wavelet coherence, which often assume that relationships between assets remain static, TVP-VAR offers much more flexibility. It allows the coefficients and variance–covariance matrices to evolve smoothly over time, making it ideal for identifying real-time connections and structural changes in volatile markets.

Henceforth, TVP-VAR captures dynamic relationships among variables over time. Constant parameters, as assumed in traditional VAR models, do not hold well in this approach. TVP-VAR allows parameters as well as variances to evolve, making it particularly useful for analyzing structural changes in financial and macroeconomic data. This model integrates stochastic volatility using a Kalman Filter-based estimation procedure along with factors as developed by Koop and Korobilis (2014), enabling more responsive adjustments to recent information. By avoiding the need for a fixed rolling-window size—often selected arbitrarily in conventional time-varying models—TVP-VAR reduces the risk of producing volatile or overly smoothed parameter estimates. Furthermore, it preserves the integrity of the dataset by incorporating all available observations, thereby enhancing the reliability of the model's insights, particularly in periods of market turbulence or regime shifts.

$$Y_t = \beta_t Y_{t-1} + \epsilon_t \quad \epsilon_t | F_{t-1} \sim N(0, S_t) \tag{1}$$

$$\beta_t = \beta_{t-1} + \nu_t \quad \nu_t | F_{t-1} \sim N(0, R_t) \tag{2}$$

where Y_t represents an $N \times 1$ conditional volatilities vector, Y_{t-1} is an $N_p \times 1$ lagged conditional vector, β_t is an $N \times N_p$ dimensional time-varying coefficient matrix, and ϵ_t is an $N \times 1$ dimensional error disturbance vector with an $N \times N$ time-varying variance–covariance matrix S_t. The parameters β_t depend on their own values β_{t-1} and on an $N \times N_p$ dimensional error matrix with an $N_p \times N_p$ variance–covariance matrix.

The dynamic structure of time-varying coefficients and error covariances facilitates the application of generalized connectedness, as given by (Diebold & Yılmaz, 2014). This approach relies on GIRF and GFEVD, conceptualized by Koop et al. (1996) and further refined by Pesaran and Shin (1998). These tools enable the assessment of directional spillovers with interconnectedness among multiple time-series variables without requiring orthogonalization of shocks. To compute the GIRF and GFEVD, the VAR model is altered into its VMA (Vector Moving Average) form, as prescribed by the Wold representation theorem. The altered variation allows for obtaining shock movements over time and stands critical for computing forecast error variances. Thus, it identifies each variable's individual contribution to the total variance. The integration of these advanced tools allows researchers to quantify and visualize how shocks to one variable affect others, thereby uncovering the evolving structure of interconnectedness within financial or macroeconomic systems. We convert the VAR to its VMA representation as given below:

$$Y_t = \beta_t Y_{t-1} + \epsilon_t \tag{3}$$

$$Y_t = A_t \, \epsilon_t \tag{4}$$

$$A_{o,t} = I \tag{5}$$

$$A_{i,t} = \beta_{1,t} A_{i-1,t} + \cdots + \beta_{p,t} A_{i-p,t} \tag{6}$$

where $\beta_t = [\beta_{1,t}, \beta_{2,t}, \ldots, \beta_{p,t}]'$ and $A_t = [A_{1,t}, A_{2,t}, \ldots, A_{p,t}]'$, and hence $\beta_{i,t}$ and $A_{i,t}$ are $N \times N$ dimensional parameter matrices. Generalized Impulse Response Functions (GIRFs) capture the reaction of all variables towards shock originating in variable (i). GIRFs are derived by comparing the outcomes of a J-step-ahead forecast under two scenarios, where structural identification is absent: (1) the variable (i) experiences a shock, and (2) it does not. The resulting difference between these two forecasts isolates the outcome of the shock on variable (i) and quantifies its impact on the system. The difference can be accounted to the shock in variable i, which can be calculated as follows:

$$GIR_t(J, \delta_{j,t}, F_{t-1}) = E(Y_{t+J} | \epsilon_{j,t} = \delta_{j,t}, F_{t-1}) - E(Y_{t+J} | F_{t-1}) \tag{7}$$

$$\Psi^g_{j,t}(J) = \frac{A_{J,t} S_t \epsilon_{j,t}}{\sqrt{S_{jj,t}}} \frac{\delta_{j,t}}{\sqrt{S_{jj,t}}} \tag{8}$$

$$\begin{gathered} \delta_{j,t} = \sqrt{S_{jj,t}} \\ \Psi^g_{j,t}(J) = S_{jj,t}^{-\frac{1}{2}} A_{J,t} S_t \epsilon_{j,t} \end{gathered} \tag{9}$$

Here, J denotes the forecast horizon, δ_(j,t) is a selection vector containing a value of one at the j^{th} position and zeros elsewhere, and F_{t-1} represents the available information set up to time $t-1$. Using this set up, the Generalized Forecast Error Variance Decomposition (GFEVD) is calculated to evaluate the share of the forecast error variance in one variable credited to tremors in supplementary ones. Variance portions are then normalized so that the sum of each row equates to one. This normalization ensures that the total contribution from all variables accounts for 100% of the forecast error variance of variable i. The GFEVD is computed as follows:

$$\tilde{\phi}^g_{ij,t}(J) = \frac{\sum_{t=1}^{J-1} \Psi^{2g}_{ij,t}}{\sum_{j=1}^{N} \sum_{t=1}^{J-1} \Psi^{2g}_{ij,t}} \tag{10}$$

with $\sum_{j=1}^{N} \widetilde{\phi}_{ij,t}^{N}(J) = 1$ and $\sum_{i,j=1}^{N} \widetilde{\phi}_{ij,t}^{N}(J) = N$. Using the GFEVD, we construct the total connectedness index as follows

$$C_t^g(J) = \frac{\sum_{i,j=1,\ i\neq j}^{J-1} \widetilde{\phi}_{ij,t}^{g}(J)}{\sum_{i,j=1}^{N} \sum_{t=1}^{J-1} \widetilde{\phi}_{ij,t}^{g}(J)} * 100 \tag{11}$$

$$C_t^g(J) = \frac{\sum_{i,j=1,\ i\neq j}^{N} \widetilde{\phi}_{ij,t}^{g}(J)}{\sum_{i,j=1}^{N} \widetilde{\phi}_{ij,t}^{g}(J)} * 100 \tag{12}$$

$$= \frac{\sum_{i,j=1,\ i\neq j}^{N} \widetilde{\phi}_{ij,t}^{g}(J)}{N} * 100 \tag{13}$$

This connectedness framework demonstrates the extent to which a tremor originating in one variable can influence other variables. Specifically, it begins by examining the impact of shocks from variable *i* on all other variables *j*, referred to as the total directional connectedness from variable *i* to others, and is defined as follows:

$$C_{i\to j,t}^g(J) = \frac{\sum_{j=1,\ i\neq j}^{N} \widetilde{\phi}_{ij,t}^{g}(J)}{\sum_{j=1}^{N} \widetilde{\phi}_{ij,t}^{g}(J)} * 100 \tag{14}$$

Further, the directional connectedness from variable j to variable i can be defined as follows:

$$C_{i\leftarrow j,t}^g(J) = \frac{\sum_{j=1,\ i\neq j}^{N} \widetilde{\phi}_{ij,t}^{g}(J)}{\sum_{i=1}^{N} \widetilde{\phi}_{ij,t}^{g}(J)} * 100 \tag{15}$$

Thus, the net total directional connectedness is attained by subtracting the total directional connectedness received by variable *i* from the total directional connectedness transmitted. This measure reflects the relative dominance or influence of variable *i* within the entire network, effectively capturing its role as a net transmitter or receiver of shocks.

$$C_{i,t}^g = C_{i\to j,t}^g(J) - C_{i\leftarrow j,t}^g(J) \tag{16}$$

A positive value of the net total directional connectedness for variable *i* indicates that it exerts greater influence on the network than it receives, positioning it as a net transmitter of shocks. Conversely, a negative value suggests that variable *i* is more affected by the dynamics of other variables in the system, identifying it as a net receiver of shocks.

3.1.3. Network Analysis

Network analysis is a widely used technique for examining the interrelationships among multiple variables within a complex system. It visualizes these relationships through a structure composed of nodes and edges, where nodes represent the entities under study and edges denote the magnitude and direction of interactions between them. In the context of this study, nodes correspond to the three asset classes, i.e., Bitcoin (BTC), Global X FinTech ETF (FINX), and Nasdaq Green Economy Benchmark (QGREEN), while edges illustrate the dynamic spillovers and connectedness derived from the TVP-VAR model.

Conceptually, a network can be represented as a set of vertices and links, where the strength and direction of the links indicate how strongly one asset influences another. Directed edges represent one-way relationships (i.e., when shocks in one market transmit to another), while undirected edges capture mutual associations. Networks can also be weighted to reflect the intensity of these connections, or unweighted when only the presence or absence of linkages is considered.

To interpret the resulting structures, several network metrics are employed. Network density measures the ratio of existing edges to all possible edges, providing insight into how tightly the markets are interconnected. Degree centrality reflects the number of connections each node possesses, helping to identify dominant transmitters and receivers of risk, while strength centrality in weighted networks captures the total intensity of these relationships. Other measures, such as betweenness centrality and eigenvector centrality, evaluate the influence of specific nodes within the overall system by identifying those that act as bridges or key conduits in volatility transmission.

This study employs dynamic network analysis to capture the evolving structure of connectedness among BTC, FINX, and QGREEN across time. By translating the TVP-VAR-based spillover matrix into a visual and quantitative network, the analysis provides an intuitive understanding of how these assets interact, especially during periods of market stress such as the COVID-19 pandemic. Network visualization complements statistical measures by highlighting shifts in market interdependence, revealing whether diversification benefits persist or diminish as the system becomes more interconnected.

3.1.4. Portfolio Techniques: Minimum Connectedness Portfolio (MCoP)

In the final stage of our analysis, we take the insights gained from the connectedness assessment and apply them to portfolio optimization using the Minimum Connectedness Portfolio (MCoP) framework, as outlined by Diebold and Yılmaz (2014), Broadstock et al. (2022), and L. Huang (2024). What sets the MCoP apart from traditional mean–variance optimization is its focus on minimizing systemic connectedness rather than just reducing return variance. This means that the MCoP aims to lower the risk of contagion within the portfolio, making it a valuable strategy for investors.

To determine the optimal portfolio weights, we minimize the total connectedness index while adhering to full-investment and non-negativity constraints. This method results in portfolios that are not only well-diversified but also more resilient to spillovers from one asset to another. For investors looking to gain exposure to innovative and sustainable asset classes, the MCoP offers an effective alternative risk management tool, helping them navigate the complexities of modern financial markets while mitigating potential risks.

It may be expressed as follows:

$$w_{Rt} = \frac{PCI_t^{-1}I}{IPCI_t^{-1}I} \tag{17}$$

PCI_t shows pairwise connectedness index matrix and identity matrix is represented by I.

To measure the performance of the portfolio, the Sharpe ratio has been adopted and the hedging effectiveness scores advanced by Sharpe (1994). The Sharpe Ratio, also described as the reward-to-volatility ratio, is shown below

$$SR = \frac{\bar{r}_p}{\sqrt{Var(r_p)}} \tag{18}$$

where r_p = denotes portfolio returns, assuming risk-free rate (R_f) equals zero. Higher estimates of the SR implies more returns as compared to their risk level in the portfolio.

Finally, we use the hedging effectiveness (HE) index to measure the performance of the optimal hedge ratios (OHRs) obtained using versions of varied GARCH approaches, following Chang et al. (2011) and Ku et al. (2007).

$$HE = \frac{\text{var}_{unhedged} - \text{var}_{hedged}}{\text{var}_{unhedged}} \tag{19}$$

where var_{hedged} means variance of portfolio returns and $\text{var}_{unhedged}$ means unhedged asset variance. The HE index reflects the percentage (of reduction in the variance) of the unhedged position. A higher HE index implies greater risk reduction and, therefore, shows higher hedging effectiveness.

3.1.5. Robustness Analysis

To ensure the reliability and stability of the empirical findings, a robustness and sensitivity analysis was conducted. The estimations were re-examined using alternative lag structures (p = 2 and p = 3) within the TVP-VAR framework, and the overall connectedness patterns remained consistent across specifications. Furthermore, a rolling-window TVP-VAR was implemented to capture potential shifts in connectedness over shorter horizons, confirming the persistence of the main results. To validate structural stability, the analysis was also segmented into pre-COVID (January 2016–December 2019) and COVID (January 2020–December 2021) sub-periods. The observed spillover dynamics and net transmission behavior were broadly aligned across all checks, reinforcing the robustness of the study's core conclusions.

4. Empirical Findings

This section is dedicated to the discussion of average and dynamic linkages with reference to TVP-VAR results. The model has been able to capture return transmissions between conventional asset classes and the non-conventional asset class. Following this, we proceed to pairwise time-varying linkages, then followed by Network Analysis, and lastly, we examine portfolio diversification opportunities.

4.1. Preliminary Analysis

Table 2 presents the preliminary analysis in terms of descriptive statistics of our analysis, revealing some interesting insights about the performance of different asset classes. When it comes to average returns, Bitcoin (BTC) leads and has a maximum average return of 0.0026, followed by FinTech at 0.001, QGREEN at 0.0007, the MSCI World Index at 0.0005, and the MSCI Emerging Markets Index at 0.0004. This trend shows that the maximum returns align closely with the average returns, indicating a consistent performance pattern.

In terms of maximum yield, BTC again takes the top with an impressive value of 0.2372, followed by FinTech at 0.1056, the Green Equity Index at 0.0925, the MSCI World Index at 0.0841, and finally, the MSCI Emerging Markets Index at 0.0691. Notably, BTC also exhibits the highest unconditional deviation at 0.048, indicating significant volatility. FinTech follows closely at 0.0166. Both of these technology-driven assets show strong returns, reinforcing the idea that higher returns often come with higher risks.

When we look at the MSCI Emerging Markets Index, it shows a volatility of 0.0129, followed by QGREEN at 0.012, and the MSCI World Index at 0.0106. Interestingly, the skewness of all asset classes indicates negative returns, suggesting that the returns are not evenly distributed around the mean. This means there is a greater chance of experiencing negative yields, with skewness values ranging from −1.11 to −1.72, except for BTC, which has a skewness of −0.9628, indicating a moderately negative skew.

Table 2. Descriptive statistics of the returns of conventional and non-conventional assets.

	Rqgreen	Rfinx	Rmscid	Rmscie	Rspgsci	Rbitcoin
Nobs	1098	1098	1098	1098	1098	1098
Minimum	−0.1224	−0.1374	−0.1044	−0.1343	−0.1252	−0.4809
Maximum	0.0925	0.1056	0.0841	0.0691	0.0768	0.2372
Mean	0.0007	0.001	0.0005	0.0004	0.0002	0.0026
Stdev	0.012	0.0166	0.0106	0.0129	0.0142	0.048
Skewness	−1.5085	−1.1125	−1.7243	−1.6789	−1.359	−0.9628
Kurtosis	20.4159	12.1082	25.0212	17.8756	14.1281	11.9894
Jarque–Bera Test	19566 ***	6965 ***	29305 ***	15198 ***	9511.2 ***	6776.5 ***
ADF-Test	−9.229 ***	−9.345 ***	−9.3345 ***	−9.8139 ***	−9.5854 ***	−9.7308 ***

Note: *** 0.01% significance level.

Additionally, the kurtosis values for all assets and indices exceed the threshold of 3, which suggests that the return series have heavier tails than a normal distribution, characterizing them as leptokurtic. The Jarque–Bera Test (JB Test) indicates that the return series for all asset classes do not follow a normal distribution, as the significant coefficients lead us to reject the null hypothesis.

For time-series analysis, having normally distributed data is not necessarily ideal; instead, we want the data to be stationary. To check for stationarity, we conducted the Augmented Dickey–Fuller Test (ADF-Test), and the results show that all return series are stationary at the 0.05 significance level. This is a positive outcome, as it meets the assumptions needed for effective time-series analysis.

4.2. Average Connectedness Measures

Table 3 provides the TVP-VAR findings. From the results, a wide range of asymmetries in the volatility transmissions across the assets has been captured. Volatility is observed in the results both on a standalone basis and within asset classes, as reflected in the cross-values (matrix). Values apart from the cross figures in matrices reveal transmission among asset classes. The term "*FROM*" refers to the volatility transmissions from other asset classes. The term "*TO*" refers to the volatility spillover contributed by the asset to the rest of the asset classes. The "NET" value shows the net effect, or the difference between "FROM" and "TO". For the entire sample, we find the BTC is the least contributor to the volatilities of other asset classes (2.38%), followed by the MSCI Emerging Markets Index (43.3%), FINX (57.27%), QGREEN (73.88%), and the highest contributor, the MSCI World Index (74.64%). The results of BTC as the least transmitter of shocks to rest of the asset classes is in consonance with the studies performed by Kliber et al. (2019), Stensas et al. (2019), Bouri et al. (2017), and Qin et al. (2021). However, the results are not consistent with the studies performed by Naeem et al. (2020). Among non-conventional assets, green bonds act as the maximum transmitter, the results are not in consonance with the studies performed by Arif et al. (2022) and Celik et al. (2025). It is noteworthy that the diagonal elements are showing own-variable/idiosyncratic shocks. We observe that BTC depends 97.06% on its own shock/behavior, making it resilient to external shocks. The low spillover from BTC to other assets can be attributed to its market isolation, limited institutional integration, and distinct investor base compared to equity markets. Unlike traditional assets, BTC's pricing is largely driven by speculative sentiment and blockchain network dynamics, rather than macroeconomic fundamentals (Goodell & Goutte, 2021; Nguyen, 2022). The remaining 2.94% is due to network connection, with FINX being the maximum contributor. The disconnected nature of BTC could be because of the peculiar nature of the crypto market, which is based on blockchain technology and not having any underlying assets, making it unique. BTC connection with FINX may stem from both being technology-based assets aimed at making financial services accessible to the general public. Bitcoin helps in transferring funds with the least intervention based on blockchain technology, while the same blockchain technology, in the form of smart contracts, has been used extensively in the financial system.

Table 3. Averaged dynamic connectedness (Antonakakis et al., 2020).

	QGREEN	FINX	Bitcoin	MSCID	MSCIE	FROM Others
QGREEN	34.26	20.26	0.53	30.1	14.84	65.74
FINX	23.13	39.88	0.84	23.39	12.77	60.12
Bitcoin	0.63	0.97	97.06	0.72	0.61	2.94
MSCID	30	20.41	0.48	34.04	15.08	65.96
MSCIE	20.12	15.64	0.53	20.23	43.49	56.51
TO Others	73.88	57.27	2.38	74.44	43.3	251.27
NET	8.15	−2.85	−0.56	8.48	−13.21	TCI = 50.25

Note: results are based on a TVP-VAR (0.99,0.99) model with lag length of order 1 (BIC) and a 10-step-ahead forecast.

In total, the MSCI World Index and MSCI Emerging Markets Index have emerged as interesting contributors to volatility in non-conventional assets. Both conventional assets contributed least to the shocks of BTC. However, the MSCI World Index contributes (0.72%) more than the MSCI Emerging Markets Index (0.61%) in the volatilities of BTC. The next, non-conventional asset, FINX, is more tightly connected with other asset classes by 60.12%, with the rest 39.88% attributable to its own shocks. For FINX, 60.12% of its volatility originates from other asset classes, with conventional assets contributing the most at 60.14%. Among conventional assets, maximum transmissions are from the MSCI World Index (23.39%), followed by the MSCI Emerging Markets Index (12.77%). QGREEN shows high vulnerability with other shocks, thus showing idiosyncratic volatility of 34.26%. The maximum volatility among non-conventional assets is contributed by the MSCI World Index (30.1%). Henceforth, we noticed that the MSCI World Index is a prominent transmitter in the volatilities of the innovative asset classes.

It has been observed that among non-conventional asset classes, BTC possesses the least contribution to the volatility of other asset classes (2.38%), followed by FINX (57.27%), while QGREEN is the highest contributor (73.88%). Among conventional assets, the MSCI World Index is the highest contributor (74.64%), followed by the MSCI Emerging Markets Index (43.3%). Among the non-conventional asset classes, QGREEN receives the highest volatility transmission from other asset classes (65.74%), followed by FINX (60.12%), and the least by BTC (2.94%). Among non-conventional assets, the MSCI World Index is receiving the maximum volatility (65.96%), followed by the MSCI Emerging Markets Index (56.51). Henceforth, it could be concluded that among non-conventional asset classes, BTC contributes to and receives the least volatilities, followed by FINX and, lastly, QGREEN. The most significant contributor is the MSCI World Index. Additionally, FINX and QGREEN are both connected with the conventional asset, specifically the MSCI World Index. The result of BTC not being connected with the stock market had a negative impact on relationship running from stock price movements to BTC (Zhao & Park, 2024). Further, technology-based assets are highly susceptible to external shocks (Le et al., 2021). QGREEN is connected with the stock market; this result is the consistent with Naeem et al. (2021), but not in line with the inferences drawn by Naqvi et al. (2021) and Celik et al. (2025).

From the results of net directional connectedness, we identified that among non-conventional assets, FINX (−2.85%) and BTC (−0.56%) are net receivers, meaning they achieve greater vulnerability from others rather than contributing to other's volatilities. In contrast, QGREEN is a net receiver, contributing more than receiving the volatility (8.15%). However, among conventional assets, the MSCI World Index is the net highest contributor (8.48%), and on the other hand, the MSCI Emerging Markets Index is the net receiver (−13.21%).

The average TCI value within the period is 50.25%, which signifies that co-movements within this sample network of variables indicate that, on average, only 50.25% of the shock in one asset can be connected to the shock in another asset class. The results of TCI shown in the table is an average of the full sample results, which may dilute meticulous time-varying linkages. Thus, we examine in-depth the time-varying dynamic total connectedness among asset classes, as given in Figure 1.

These results suggest that Bitcoin's limited role as a volatility transmitter indicates its independence from conventional financial markets, reflecting its decentralized and speculative characteristics. This behavior implies that BTC may provide hedging potential during global market turbulence, a finding consistent with Bouri et al. (2017) and Conlon et al. (2020).

4.3. Dynamic Total Connectedness

Figure 1 provides evidence of time-varying dynamic total connectedness by applying TVP-VAR. It captures higher levels of the total connectedness index (TCI), which indicate a higher level of connectedness among assets during the period under study. Lower TCI indicates lower connectedness and provides diversification opportunities during that time. Figure 1 shows substantial variation in the TCI, ranging from 75% to 50%, largely driven by the presence of the most resilient asset, BTC. This variation is captured because of the presence of the most resilient asset, BTC. From mid-2016 to 2018, the variation ranges from 63% to 50%, and from 2018 to the start of 2020, the magnitude of connectedness ranges from 68% (highest) to 57% (lowest). During this period, we noticed that the peaks of connectedness show three consecutive downwards movements, showing a downward trend of connectedness. Notably, during the outbreak of the COVID-19 pandemic in March 2020, overall connectedness surged sharply to its peak of 75%, before gradually declining. By the end of the period under study, the lowest connectedness is still on par with the previous highest magnitude, showing the impact of the crisis and the assets that are connected because of the pandemic. This dynamic co-movement implies that policy efforts promoting green and digital finance can shape cross-asset transmission pathways, especially in crises.

Cross-market linkages intensified sharply during the COVID-19 outbreak, echoing the global contagion effects observed by Ali (2022) and Huynh et al. (2020). However, Bitcoin's muted response reinforces its asymmetric role, acting as a diversification instrument when conventional and ESG-linked markets converge under stress. This finding highlights how digital assets can partially decouple from macro-financial shocks, offering investors a countercyclical hedge during systemic crises.

These findings are broadly consistent with prior evidence of increased connectedness during crises (Apergis & Apergis, 2022; Ali, 2022; Le et al., 2021), yet Bitcoin's independence aligns with the safe-haven characteristics reported by Conlon et al. (2020) and Guo et al. (2021). However, our results diverge from Chen et al. (2020), who found higher co-movement between BTC and equities in later market phases.

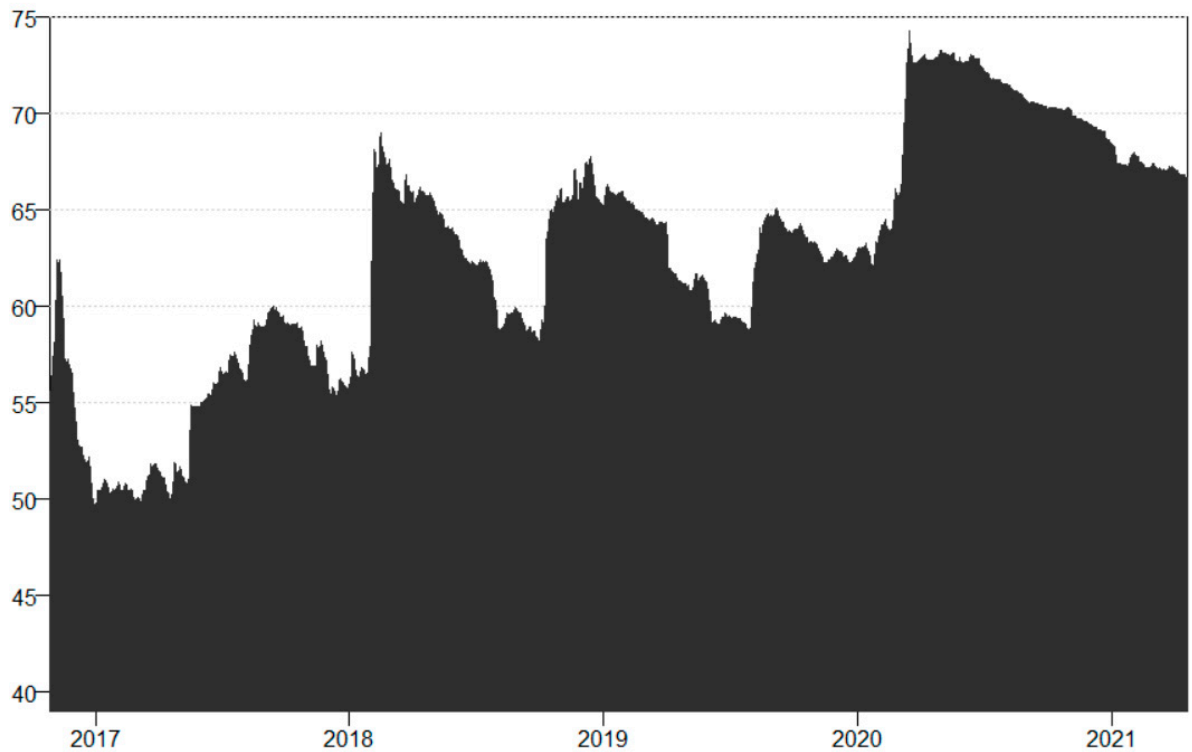

Figure 1. Dynamic total connectedness. Note: results are based on a TVP-VAR (0.99,0.99) model with lag length of order 1 (BIC) and a 10-step-ahead forecast.

4.4. Net Total Directional Connectedness

This section is very important for understanding the behavior of asset classes, whether the respective asset is a net transmitter or net receiver of shocks over the period under study. From Figure 2, we are able to capture the behavior of the assets considered in our study. The figure shows the net directional total connectivity index over time. A negative value of the index means that the asset is a net receiver of shocks, while a positive value of the index signifies that the asset class is the net transmitter. For the purpose of understanding and simplicity, in Figure 2, if the asset class showing shaded region lies at the positive side, it indicates that the asset is a net transmitter. On the other hand, if the shaded portion lies on the negative side, it indicates that the asset is a net receiver. In Figure 2, it is perceived that among the non-conventional asset classes, QGREEN is consistently a net transmitter, whereas the technology-based assets, FINX and BTC, are net receivers for the majority of the time. However, BTC shows some impressions of being a net transmitter up to 2017 and thereafter is mostly as a net receiver. The magnitude of BTC as a net receiver after 2017 is very low, and this is a peculiar pattern shown by the asset. These results are consistent with the studies performed by Zhao and Park (2024) and Le et al. (2021). However, among the conventional asset classes, the MSCI World Index is the net transmitter, whereas the MSCI Emerging Markets Index is a net receiver throughout the time period. During the COVID-19 period, all asset classes show a lower net Total Connectivity Index; but, the timing for BTC is different. During COVID-19, only the MSCI World Index and QGREEN are net transmitters. The asymmetry between transmitters and receivers highlights the need for policymakers to strengthen resilience in emerging market equities that are more exposed to global shocks.

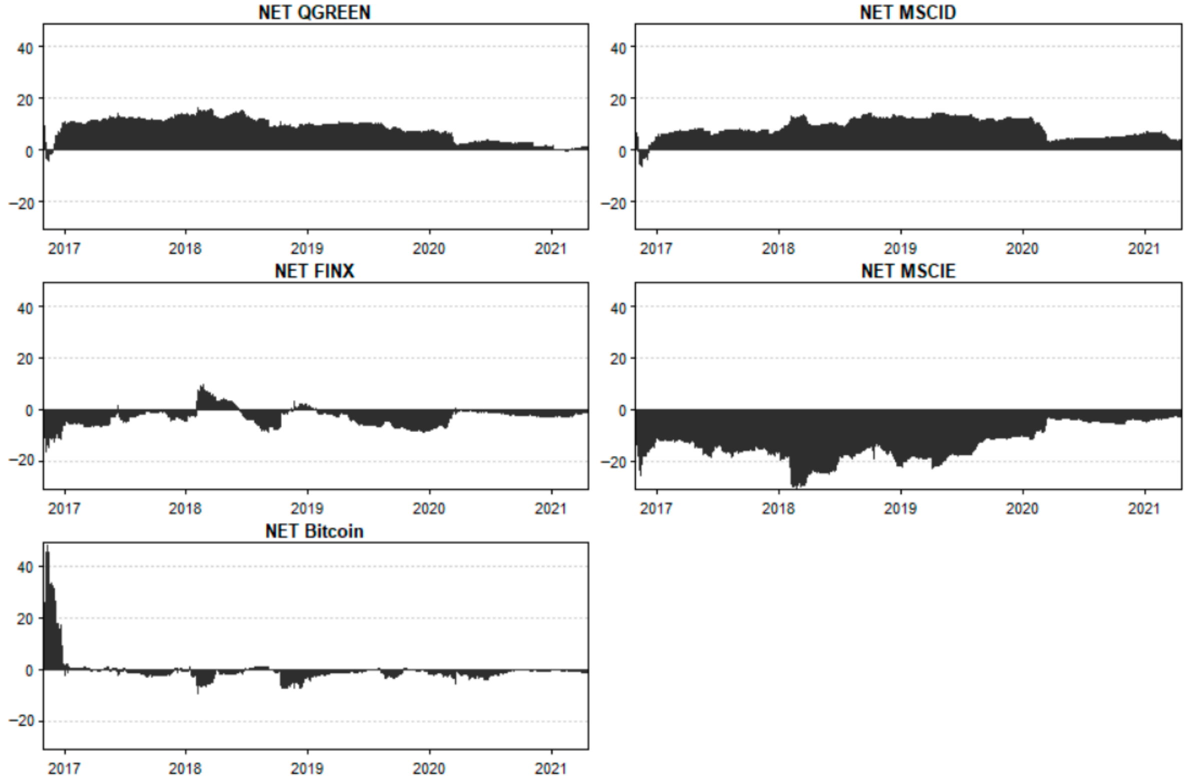

Figure 2. Net total directional connectedness. Note: positive values indicate net transmitters and negative values of net receivers of shocks. QGREEN and MSCIE act as consistent transmitters while BTC remains a net receiver, reflecting its diversification potential during crisis periods.

4.5. Net Pairwise Connectedness

The analysis now turns to a crucial component, i.e., pairwise net directional connectedness between conventional and non-conventional asset classes. While Figure 2 highlighted the overall role of each asset class as a net transmitter or receiver of shocks within the system, Figure 3 delves deeper by presenting a detailed view of how individual asset classes impact one another. This allows for a clearer understanding of the bilateral relationships and directional spillovers that exist among the assets under study.

The initial focus was on the pairwise directional connectedness from the MSCI World Index to the non-conventional assets, namely QGREEN, BTC, and FINX. The findings suggest that the MSCI World Index acts predominantly as a transmitter of shocks to QGREEN and, to a slightly lesser extent, to FINX throughout the majority of the sample period. However, during the latter part of 2016 through early 2017, the index appears to receive shocks from BTC and FINX. This phase is followed by a renewed period of shock transmission from the MSCI World Index between 2017 and 2021. Interestingly, the degree of net connectedness from the MSCI World Index to non-conventional assets increases during the COVID-19 period, with the notable exception of BTC. Bitcoin's resilience during this time is consistent with the findings of Bouri et al. (2017), Conlon et al. (2020), Chemka et al. (2021), Goodell and Goutte (2021), and Guo et al. (2021), but contrasts with the results reported by Chen et al. (2020) and Nguyen (2022).

Shifting attention to the MSCI Emerging Markets Index, the analysis reveals a strong inflow of shocks from QGREEN over the full sample period, although this impact diminishes somewhat during the COVID-19 phase. With regard to FINX, the Emerging Markets Index experiences relatively limited spillover effects, which further decrease during the pandemic period. In the case of BTC, only a mild and short-term shock transmission from the Emerging Markets Index is observed.

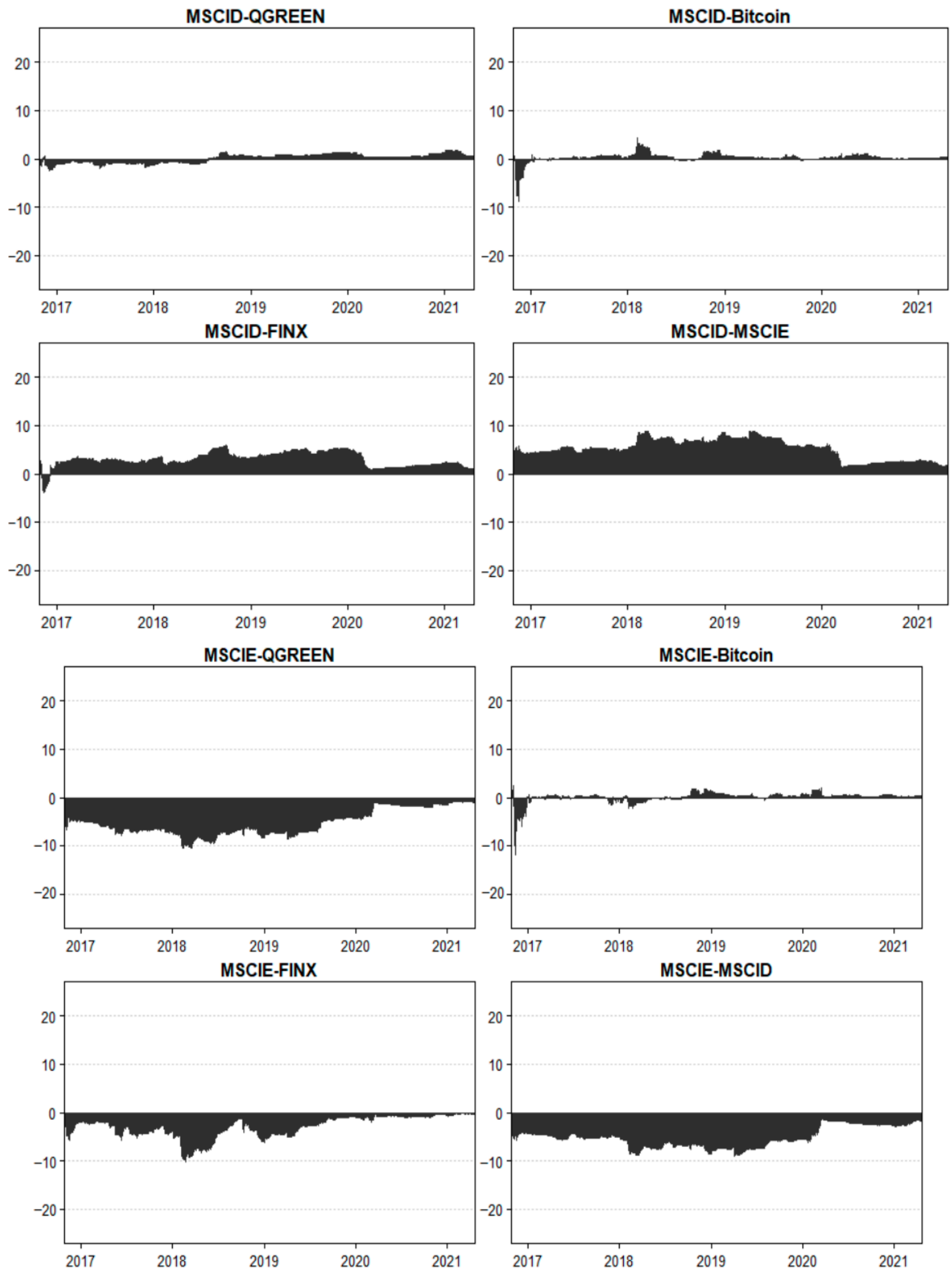

Figure 3. Net pairwise directional connectedness. Results are based on a TVP-VAR model (0.99,0.99) with one lag. Notes: the black areas represent the overlap of the dynamic total directional connectedness TO and FROM Others. A positive net total connectedness is marked in blue (TO > FROM), whereas a negative net total connectedness is marked in yellow (TO < FROM). Results are based on a TVP-VAR model (0.99,0.99) with one lag.

Figure 4 further supports the analysis by visually encapsulating the pairwise connectedness and addressing the following two key questions: which non-conventional asset offers superior diversification opportunities with the MSCI World and Emerging Markets indices, and which among them demonstrates greater resilience across the study period.

This level of analysis is valuable because it isolates the interactions between specific asset pairs rather than evaluating systemic relationships across the entire network.

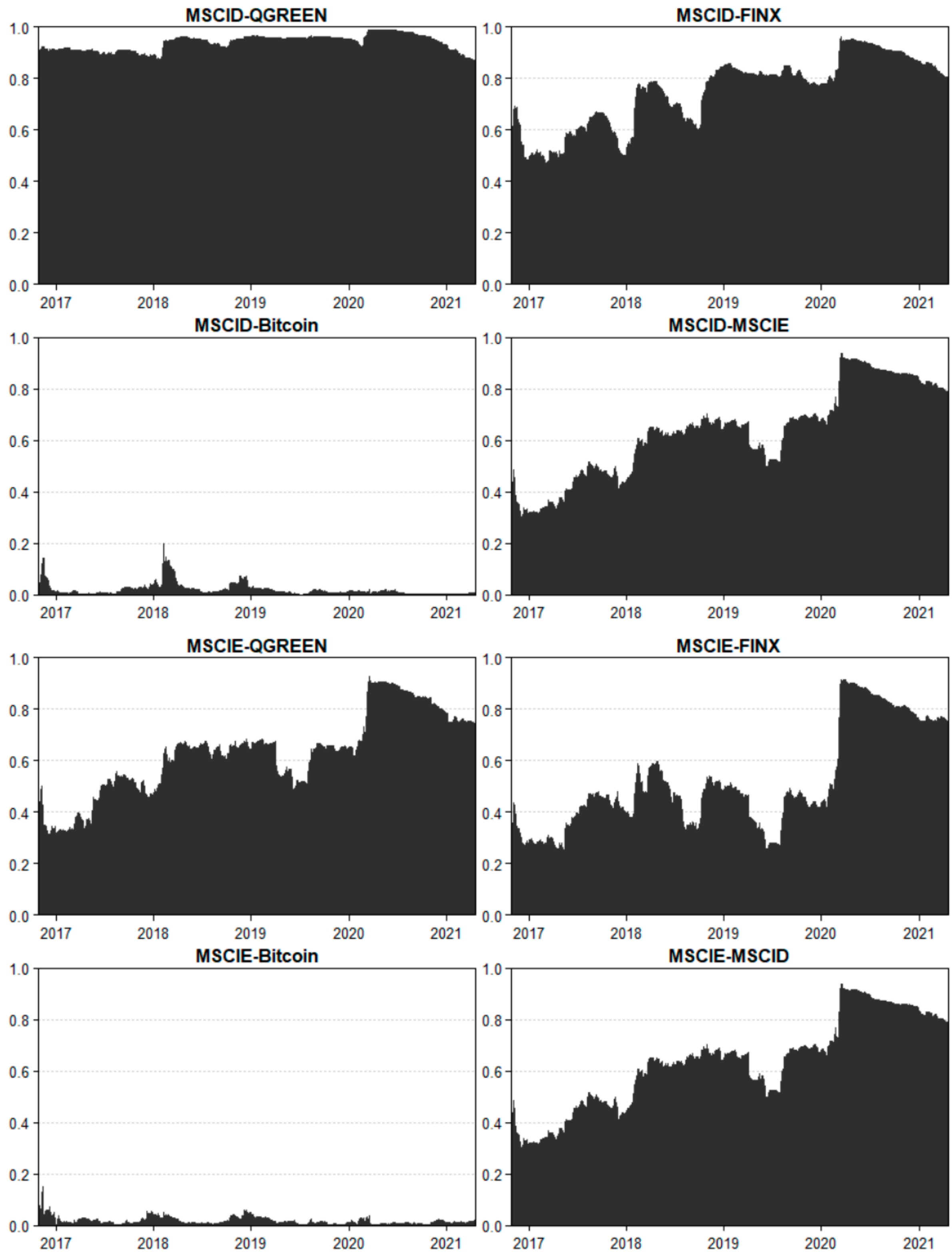

Figure 4. Dynamic pairwise connectedness index. Note: results are based on a TVP-VAR model (0.99,0.99) with one lag. The MSCI Developed Index shows strong co-movement with QGREEN, FINX, and the MSCI Emerging Markets Index—peaking during COVID-19 while maintaining minimal linkage with Bitcoin, underscoring BTC's decoupled and diversification role.

The MSCI World Index exhibits high levels of connectedness with QGREEN and FINX, ranging from 85% to 98% and 50% to 90%, respectively. In contrast, its connectedness with BTC remains consistently low, between 0% and 20%. Similarly, the MSCI Emerging Markets Index shows strong connectedness with QGREEN and FINX, with values ranging from 30% to 98% and 28% to 98%, respectively. Once again, BTC maintains a minimal degree of connectedness, fluctuating between 0% and 18%.

Several insights emerge from these findings. First, BTC's consistently low connectedness with both the MSCI World and Emerging Markets indices highlights its potential as an effective diversification tool. This aligns with earlier research by Conlon et al. (2020), Guesmi et al. (2019), Mariana et al. (2021), Y. Huang et al. (2021), and Goodell and Goutte (2021), although it contradicts findings by Chen et al. (2020). Second, the MSCI Emerging Markets Index, in comparison to the MSCI World Index, appears to offer better diversification when combined with non-conventional assets, confirming the observations made by Zhao and Park (2024). Moreover, the COVID-19 period witnessed a notable increase in spillovers between conventional and non-conventional assets in most pairwise combinations, except for BTC, which remained relatively unaffected. This again reinforces the findings of Bouri et al. (2017), Conlon et al. (2020), Chemka et al. (2021), Goodell and Goutte (2021), and Guo et al. (2021). These results position Bitcoin as a relatively independent and resilient asset during times of crisis. Its disconnection from stock market movements may be due to its pricing being driven more by transaction behavior among major users than by macro-financial trends, as suggested by Zhao and Park (2024). In contrast, technology-based assets such as QGREEN and FINX are shown to be more vulnerable to external shocks, a conclusion supported by Le et al. (2021).

4.6. Dynamic Transmissions of Spillovers

Additionally, we examined the behavior of assets as a transmitter and receiver from the rest of the system, captured in Figures 5 and 6, respectively. It has been perceived that over the time period, QGREEN and the MSCI World Index are the major transmitters, followed by FINX and the MSCI Emerging Markets Index. We captured a very mild behavior for BTC as a transmitter to the rest of the system. Similarly, the same patterns are perceived for BTC as a receiver of shocks from the rest of the market. Henceforth, the results further strengthen the previous inference that BTC is resilient and safe, as it neither acts as a significant transmitter or receiver over the period of study. Additionally, during the COVID-19 period, all assets showed high volatility as transmitters and receivers, with the exception of BTC. These results indicate that the financial market became volatile during the pandemic, and they are in consonance with Apergis and Apergis (2022), Gil-Alana and Monge (2020), and Huynh et al. (2020). Henceforth, this inference again strengthens our hypothesis that BTC is resilient and safe. This shows its diversification potential with conventional assets and its position as a superior diversifier among all non-conventional asset classes. For robustness, the results were further examined using network analysis. Robustness checks using alternative lag structures ($p = 2, 3$) and sub-period estimations (pre- and post-COVID) yielded qualitatively similar patterns of connectedness and spillover intensity, confirming the stability of the empirical results.

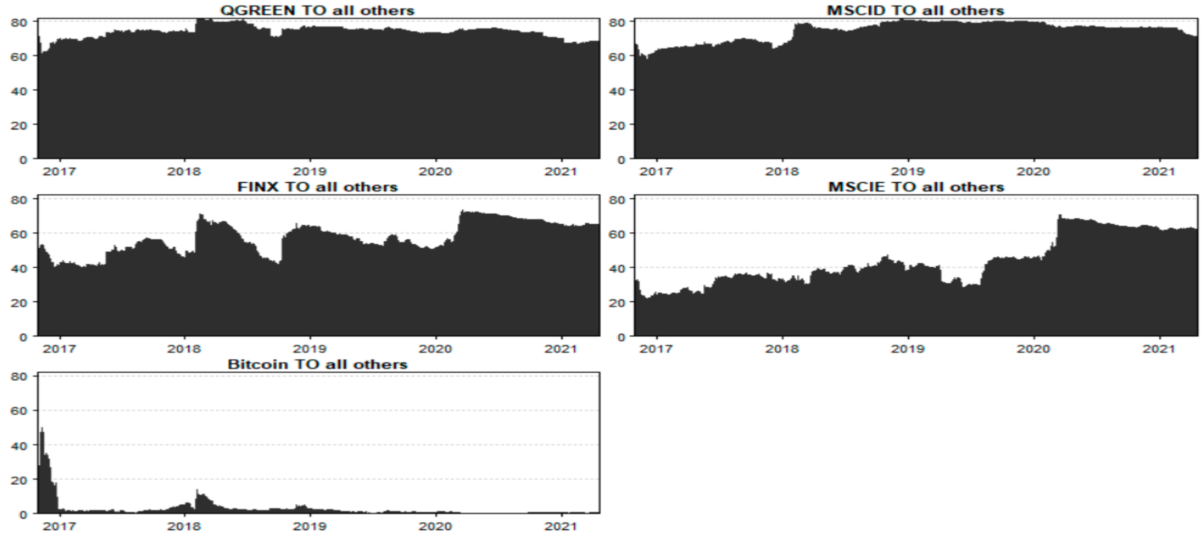

Figure 5. Dynamic spillover transmission to all other assets. Notes: this figure presents the dynamic transmission of shocks from each asset to all others, estimated using a Time-Varying Parameter VAR (TVP-VAR) model with a lag order of one, selected via the Bayesian Information Criterion (BIC), and a 20-step-ahead forecast horizon. The black-shaded region reflects the spillover estimates derived from the methodology of Antonakakis et al. (2020).

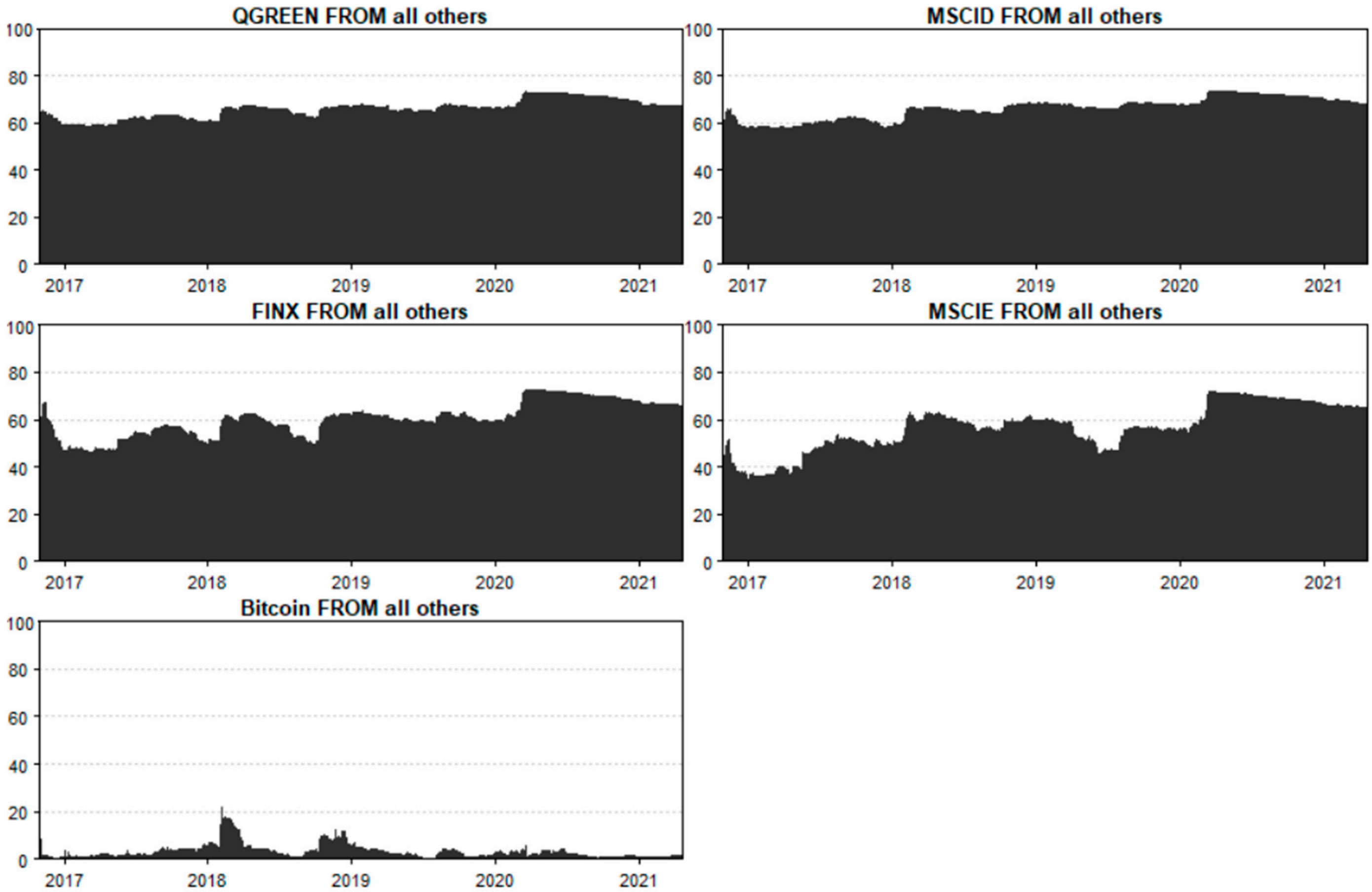

Figure 6. Dynamic spillover transmission from all other assets. Notes: the results are derived from a Time-Varying Parameter VAR (TVP-VAR) model with a lag order of one, selected based on the Bayesian Information Criterion (BIC), and a 20-step-ahead forecast horizon. The black-shaded area indicates the spillover estimates obtained using the methodology proposed by Antonakakis et al. (2020).

From an investment standpoint, a lower total connectedness index (TCI) implies greater diversification potential. During periods of heightened TCI, such as the COVID-19 shock, correlations rise, reducing the effectiveness of diversification. Investors should therefore view assets like BTC as countercyclical buffers, while QGREEN and FINX appear more synchronized with global equity cycles, diminishing their hedging power during crises.

4.7. Evidence of Network Analysis

This study applies a comprehensive network analysis framework, including network topology, centrality measures, and edge-weight validation, to explore the return interdependencies among the following five asset classes: the MSCI Emerging Markets Index, the MSCI World Index, QGREEN, FINX, and Bitcoin (BTC). As shown in Figure 7a, the network consists of five nodes, each representing one of the asset return series. Connections between these nodes are illustrated through edges, with edge thickness indicating the strength of association. A key observation is the isolation of BTC, which lacks any connecting edges to the other assets, emphasizing its independence within the network.

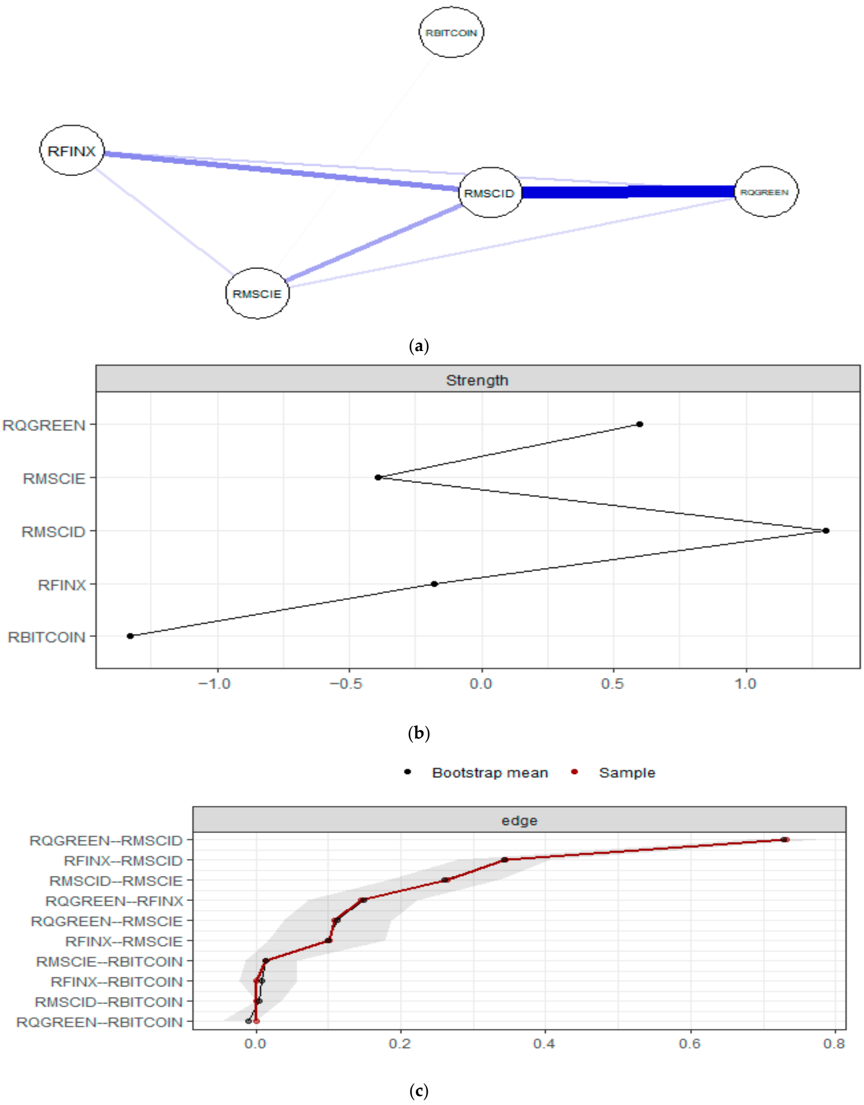

Figure 7. (**a**) Network structure among constituent variables. (**b**) Centrality indices among constituent series. (**c**) Accuracy of the edge-weight estimates. Note: Figure 7 illustrates the network dynamics among the studied assets. (**a**) shows the interconnected structure among constituent variables, (**b**) presents the centrality indices highlighting the most influential nodes in the network, and (**c**) displays the accuracy of the edge-weight estimates validating the robustness of the network relationships.

Among the connected assets, the strongest linkage is observed between the MSCI World Index and QGREEN, denoted by the relatively thicker edge. This suggests a high correlation between the two, implying limited diversification potential if both are held in the same portfolio. The absence of any direct connections between BTC and the remaining asset classes, namely the MSCI Emerging Markets Index, the MSCI World Index, QGREEN, and FINX, positions BTC as a potentially valuable diversification instrument.

Figure 7b presents the centrality indices, which measure the relative importance and connectivity strength of each node within the network (Hevey, 2018; Borgatti, 2005). The horizontal axis represents association strength, while the vertical axis lists the asset classes. Results indicate that the MSCI World Index holds the highest centrality score, followed by QGREEN, mirroring the strong correlation identified in the network structure and aligning with previous findings from the Time-Varying Parameter VAR (TVP-VAR) analysis.

To ensure the reliability of the network's edge estimates, a bootstrap-based confidence interval analysis is conducted and visualized in Figure 7c. Red lines denote the estimated edge weights, while gray bars reflect the bootstrapped confidence intervals around these estimates. The analysis reveals that several edge connections, including those between BTC and the MSCI Emerging Markets Index, FINX, the MSCI World Index, and QGREEN, are effectively zero, reinforcing BTC's detachment from the broader asset network. In contrast, the edge between the MSCI World Index and QGREEN stands out as significantly strong, confirming their persistent co-movement and lack of diversification advantage.

4.8. Portfolio Implications

In the concluding part of the study, we present key implications for constructing a multivariate portfolio comprising both conventional and non-conventional asset classes, using the Minimum Connected Portfolio (MCP) approach. This analysis explores optimal portfolio allocation alongside its hedging effectiveness. Figure 8 illustrates the time-varying dynamic portfolio weights across the study period. A closer examination reveals that Bitcoin (BTC) consistently holds the highest portfolio weight, followed by FINX, QGREEN, the MSCI Emerging Markets Index, and finally, the MSCI World Index. During the COVID-19 period, BTC saw a notable increase in allocation, whereas the weights assigned to QGREEN, FINX, and the MSCI Emerging Markets Index declined. The MSCI World Index, in particular, consistently held negligible weight throughout.

These weight distributions align with earlier findings indicating BTC as the most resilient asset, followed by FINX. In contrast, the MSCI World Index emerged as both a major transmitter and receiver of shocks, highlighting its vulnerability. The exact portfolio weights are detailed in Table 4. To interpret the investment implications of the MCP approach, we first consider the average portfolio allocation. When investing across conventional and non-conventional assets, the MCP recommends the highest allocation to BTC (39%), followed by the MSCI Emerging Markets Index (23%), FINX (21%), QGREEN (14%), and the lowest to the MSCI World Index (3%), as summarized in Table 3.

Table 4. Results of multivariate portfolio analysis.

	Mean	Std. Dev.	5%	95%	HE	*p*-Value
QGREEN	0.14	0.08	0	0.24	−2.05	0.000
FINX	0.21	0.04	0.16	0.27	−0.6	0.000
Bitcoin	0.39	0.05	0.29	0.46	0.81	0.000
MSCID	0.03	0.05	0	0.17	−2.93	0.000

Table 4. *Cont.*

	Mean	Std. Dev.	5%	95%	HE	*p*-Value
MSCIE	0.23	0.03	0.18	0.27	−1.66	0.000

Notes: Results of MVP are Christoffersen et al. (2014). Table reports the summary statistics of optimal portfolio weights and hedging effectiveness (HE) for each asset. Bitcoin holds the highest mean weight (0.39) and exhibits strong positive hedging effectiveness (0.81), confirming its diversification role. In contrast, QGREEN, FINX, MSCID, and MSCIE show negative HE values, indicating limited hedging capacity, particularly during turbulent periods.

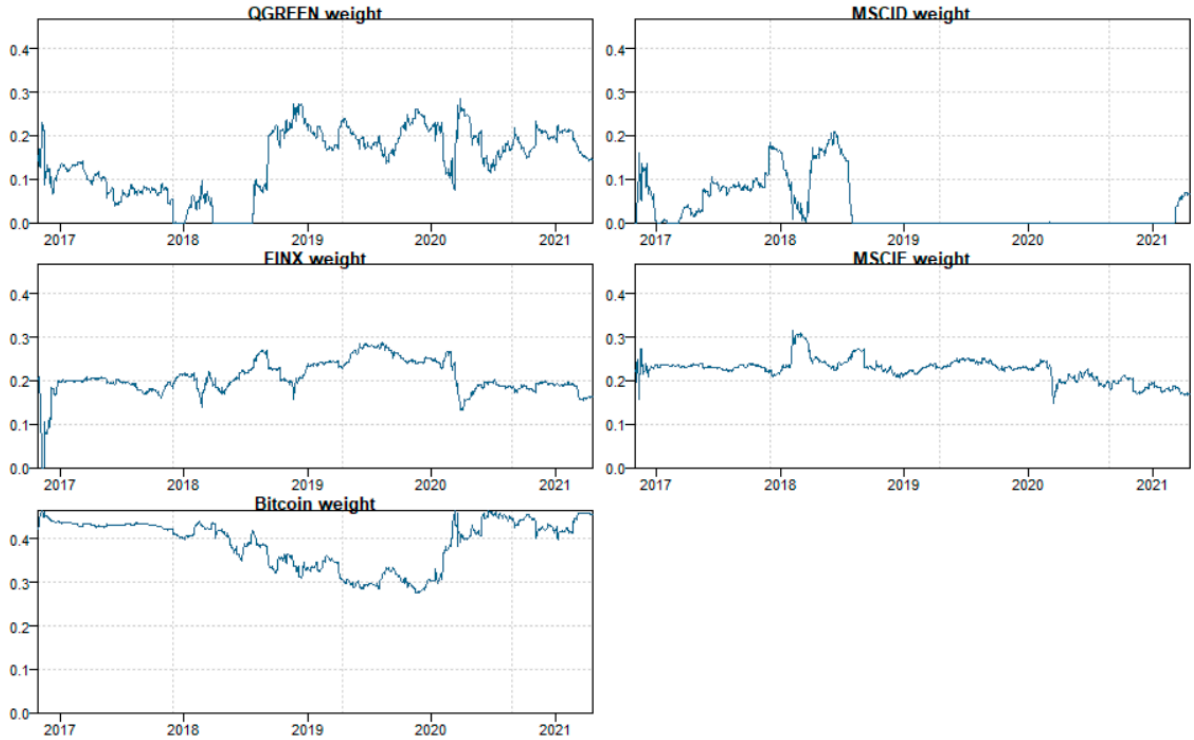

Figure 8. Minimum Connected Portfolio weights. Note: Figure 8 presents the time-varying portfolio weights of the Minimum Connected Portfolio (MCP). Bitcoin consistently holds the highest allocation, followed by FINX, QGREEN, the MSCI Emerging Markets Index (MSCID), and the MSCI World Index (MSCIF). During the COVID-19 period, Bitcoin's weight increases notably, underscoring its role as a resilient asset within a diversified portfolio.

Moreover, the constructed portfolio demonstrates superior performance (see Table 5), with an overall Sharpe ratio of 0.076, higher than the Sharpe ratios of the individual assets, indicating improved risk-adjusted returns through diversification. The impact of the portfolio construction on asset-specific volatility is also noteworthy: BTC's volatility reduced by 81%, while changes in volatility for QGREEN, FINX, the MSCI World Index, and the MSCI Emerging Markets Index were −2.05%, −60%, −2.93%, and −1.66%, respectively. Importantly, these changes in volatility are statistically significant at the 1% level, reinforcing the robustness of the results.

Table 5. Results of Sharpe Ratio.

QGREEN	FINX	Bitcoin	MSCID	MSCIE
0.061	0.062	0.055	0.046	0.033
Overall Sharpe ratio	0.076			

Note: table presents the Sharpe ratios for individual assets and the overall portfolio. The Minimum Connected Portfolio achieves a superior overall Sharpe ratio of 0.076, outperforming all individual assets (ranging from 0.033 to 0.062), highlighting the benefits of cross-asset diversification, especially with Bitcoin and FinTech exposure.

Finally, Figure 9 visualizes the portfolio's cumulative performance over time. A notable increase in portfolio value is observed from 2017 to 2018. However, a sharp decline occurred due to COVID-19, followed by a subsequent recovery. This pattern reflects broad market dynamics, where most asset classes initially experienced a steep downturn due to the pandemic but later rebounded, contributing to the post-COVID outperformance of the portfolio. For portfolio managers, the MCP findings reinforce the utility of integrating BTC and FinTech exposures for higher risk-adjusted returns in sustainability-driven portfolios.

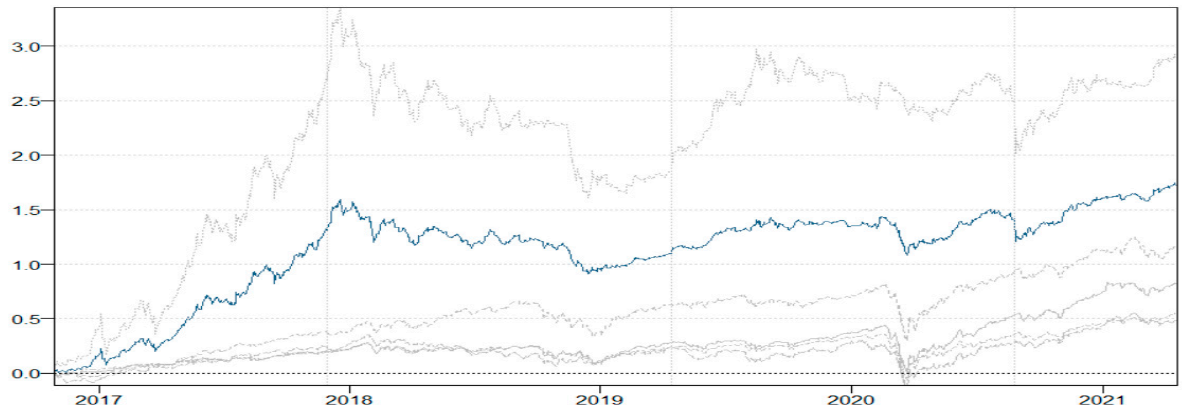

Figure 9. Equity line. Note: cumulative returns of the portfolio using the MCP strategy highlighted performance over time.

Consistent with the dynamic connectedness results, the MCP outcomes reveal that cross-market linkages intensified during the COVID-19 period, reflecting the temporary contagion among green, FinTech, and equity assets observed globally (Ali, 2022; Huynh et al., 2020). Bitcoin's consistently high weight, even under crisis conditions, underscores its countercyclical and relatively insulated nature, making it an effective hedge when sustainable and FinTech assets move more closely with global markets. For investors, this suggests that maintaining exposure to digital assets within a sustainability-oriented portfolio can mitigate systemic shocks and preserve diversification benefits during periods of financial stress. From a policy perspective, these findings reinforce the need to strengthen the institutional integration of digital and sustainable finance ecosystems to enhance market resilience and ensure stability across interconnected asset classes.

Overall, the results reveal a hierarchical spillover structure, where global equity indices dominate transmission, green assets act as intermediaries, and Bitcoin remains largely insulated. This hierarchy underscores distinct investment roles: green and FinTech assets enhance performance during stable periods, while Bitcoin safeguards portfolios during shocks. Such differentiation provides investors and policymakers with a clearer roadmap for strategic allocation and systemic risk management.

5. Conclusions and Implications

This study provides critical insights into the diversification potential of emerging non-conventional assets—Bitcoin (cryptocurrency), FINX (FinTech equities), and QGREEN (green bonds)—in relation to conventional markets represented by the MSCI World and MSCI Emerging Indices. By employing advanced econometric techniques such as the Time-Varying Parameter Vector Autoregression (TVP-VAR) and the Minimum Connectedness Portfolio (MCoP) frameworks, the research captures evolving interlinkages and reveals optimal asset allocations in an era characterized by digital transformation and sustainable finance (Antonakakis et al., 2020; Broadstock et al., 2022).

The findings highlight that Bitcoin consistently demonstrates independence from equity markets, confirming its countercyclical and resilient behavior, particularly during systemic crises such as the COVID-19 pandemic (Bouri et al., 2017; Conlon et al., 2020; Goodell & Goutte, 2021). In contrast, FinTech and green assets exhibit closer connections with conventional markets, offering conditional diversification during stable phases but showing contagion effects under stress (Le et al., 2021; Huynh et al., 2020). This asymmetry underscores a new diversification hierarchy where Bitcoin acts as a reliable safeguard during turbulence, while FinTech and green assets enhance returns and support portfolio performance in stable conditions (Sharif et al., 2023).

From a practical standpoint, the study carries meaningful implications for both investors and policymakers. For portfolio managers, the results demonstrate that combining technology-driven and sustainability-focused assets can lead to superior risk-adjusted returns and improved resilience to systemic shocks (Yousfi & Bouzgarrou, 2024; Urom, 2023). The MCP approach provides an evidence-based strategy for minimizing interconnected risks by balancing exposures between FinTech and green assets while retaining Bitcoin as a countercyclical hedge. For policymakers, the study underscores the importance of creating regulatory frameworks that promote responsible integration of digital assets and FinTech innovation into sustainable finance ecosystems. Strengthening these linkages can enhance market transparency, stability, and long-term financial resilience (Alharbi et al., 2025; Magableh et al., 2025).

Despite its contributions, the study acknowledges several limitations. First, it focuses on a limited sample of non-traditional assets, excluding other potential instruments such as DeFi tokens, ESG indices, or sustainable ETFs (Syed et al., 2022). Second, the data period (2018–2021) captures primarily the COVID-19 phase, which may not fully reflect structural transformations in post-pandemic markets. Third, the analysis relies on global indices that may obscure regional variations or policy-specific effects across developed and emerging economies (Zhao & Park, 2024; Celik et al., 2025).

These limitations offer fruitful directions for future research. Subsequent studies could incorporate broader datasets, including decentralized finance tokens, ESG-focused ETFs, and carbon credit-based instruments, to capture emerging intersections between digital and sustainable assets. Applying hybrid econometric and machine learning approaches could further enrich the understanding of nonlinear spillovers and dynamic structural breaks (Wu et al., 2025; Flavin & Sheenan, 2025). Additionally, examining cross-country differences in financial connectedness and resilience could reveal how institutional, technological, and policy environments influence the evolution of sustainable digital finance (Ediagbonya & Tioluwani, 2023).

This study makes both theoretical and practical contributions to the literature on sustainable digital finance. By uniting cryptocurrency, FinTech, and green assets within a single dynamic connectedness framework, it bridges a critical gap in understanding how these emerging asset classes interact and influence systemic stability. The integration of the TVP-VAR and MCoP methodologies provides a robust empirical lens for evaluating time-varying spillovers and portfolio optimization (Antonakakis et al., 2019; Gabauer, 2021). The evidence collectively reinforces that the convergence of technological innovation and sustainability is reshaping global asset allocation strategies, guiding investors and regulators toward more adaptive, inclusive, and future-ready financial systems (Huynh et al., 2020; Singh et al., 2025).

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