

Unveiling the volatility connectedness and hedging effectiveness between green ETFs and cryptocurrencies: evidence from dynamic short-term perspective

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Abstract

Purpose – This study aims to analyze the behavior of volatility connectedness among green exchange-traded funds (ETFs) and cryptocurrency markets. The study also examines the hedging effectiveness between green ETFs and cryptocurrencies.

Design/methodology/approach – This study uses a Time-Varying Parameter Vector Autoregression (TVP-VAR) model to highlight the salient facts of volatility connectedness between green ETFs and cryptocurrencies during the period 22 / 10 / 2021–05 / 01 / 2024.

Findings – The empirical findings reveal that cryptocurrencies (particularly, Bitcoin and Ethereum) consistently act as net transmitters of shocks, amplifying systemic risk during crisis periods. However, green ETFs primarily behave as net receivers, providing a conditional and modest hedging or safe-haven role. Portfolio-level analyses indicate that green ETFs (especially ICLN) help reduce overall portfolio risk within Minimum Variance Portfolios (MVP) under turbulent market conditions, enhancing risk-adjusted returns when included alongside cryptocurrencies. Conversely, cryptocurrencies contribute to substantial diversification benefits in terms of Minimum Correlation (MCP) and Minimum Connectedness Portfolios (MCoP) but exhibit higher volatility and tail-risk exposure. Dynamic Sharpe ratio analysis further demonstrates that no single allocation dominates across market regimes; instead, adaptive strategies – switching between MVP during calm periods and risk-parity portfolios (RPP) during crises – yield superior performance. These findings underscore the conditional stabilizing role of green ETFs and the dominant diversification and risk-transmission role of cryptocurrencies, highlighting important implications for portfolio management, sustainable investment and regulatory oversight in integrated digital and green finance markets.

Practical implications – The empirical findings offer insightful implications for policymakers, regulatory authorities and investors to promote sustainable and strategic allocation, as well as support and expand sustainable investment markets.

Originality/value – This study explores if and to what extent cryptocurrencies could be linked to green ETFs. It also examines the diversification and hedging features of green ETFs for portfolio including Bitcoin and Ethereum given the ongoing debate regarding the effective hedging instruments for cryptocurrency portfolios.

Keywords Sustainable assets, portfolio strategies, Dynamic perspectives, Risk management, Cryptocurrencies

Paper type Research paper



1. Introduction

The recent surge in global financial markets has been marked by two important transformations, namely, the digital transition and the sustainability transition. The increasing emphasis on sustainability has nudged to the development of green finance, where investors largely channel capital flows toward environmentally responsible assets that support the low-carbon transition. In this respect, green exchange-traded funds (ETFs) have appeared as crucial tools of environmental finance, allowing transparent and diversified exposure to companies with great ESG profiles. Therefore, green finance and sustainable economy have increasingly attracted different stakeholders as countries endeavor to balance economic growth and environmental considerations. On the other side, the emergence of digital finance has created cryptocurrencies which are considered as new and alternative asset class which provides innovative yet volatile opportunities for portfolio managers and investors. Cryptocurrencies are based on financial and technological innovation driven by decentralized market mechanisms and blockchain technology. Together, such developments illustrate a convergence of sustainability-oriented finance and technological innovation in modern capital markets.

In spite of their distinguishable foundation, digital and green asset classes can share common characteristics that may lead to structural and theoretical linkages. Indeed, they can lure a similar segment of risk-tolerant and forward-looking investors which search for exposure to transformative trends outside conventional markets. Afterwards, liquidity and capital flow channels could interlink the two markets, as investors rebalance portfolios to react to shifts in macroeconomic uncertainty, risk appetite or regulatory environments. Policy and macroeconomic shocks could also affect both sustainable and digital asset valuations. The aforementioned factors suggest that digital and green assets could show information spillovers and dynamic connectedness, offering a conceptual basis for analyzing their interdependence within a unified analytical structure. Apprehending such interactions is increasingly substantial for policymakers and investors, especially as sustainable finance and digital assets gain significance in global portfolios.

Against this backdrop, this study examines the dynamic spillover and connectedness among ETFs and cryptocurrencies, an interaction has infrequently been explored in the ongoing literature. Previous studies have increasingly analyzed either digital assets or sustainable assets in isolation, or have focused on volatility and return linkages without translating such dynamics into portfolio-appropriate insights. However, this research adopts an investor-oriented perspective by bringing together dynamic connectedness analysis and portfolio performance metrics, comprising the Sharpe ratio and hedge effectiveness to evaluate diversification and risk-management advantages. We also provide interesting insights into cross-asset contagion and diversification potential by highlighting the transmission of information flows and shocks through such markets. To do so, this study fills an important gap in the apprehending of how sustainability-driven financial instruments such as green ETFs can interact with speculative digital assets, thus contributing to both the crypto-finance and sustainable finance research domains.

Accordingly, the current study attempts to address the following research questions: (i) How green ETFs and cryptocurrencies show dynamic connectedness over time?; (ii) Are spillover effects among markets vary according to market conditions?; and (iii) To what extent the interaction between cryptocurrencies and green ETFs can be used by investors and portfolio managers from portfolio diversification and risk management strategies?

Based on the aforementioned questions, the following hypotheses can be formulated:

- H1.* There exists a substantial spillover effects between cryptocurrencies and green ETFs.

H2. The degree of connectedness between cryptocurrencies and green ETFs increases during turbulent times.

H3. Combining green ETFs with cryptocurrencies influences their potential as hedging and diversification instruments to set up sustainable investment portfolios.

From a theoretical perspective, this study is anchored in the Modern Portfolio Theory which argues that diversification across assets with negative or low correlations can reduce portfolio risk for a given level (Markowitz, 1952) and hedging theory which highlights the specific role in compensating exposure to negative market movements by determining, for instance, the appropriate hedge ratio (Ying and Huishuo, 2009). Both theoretical frameworks offer the foundation for examining spillover dynamics, risk transmission and connectedness between green ETFs and cryptocurrencies. This could offer interesting insights into their potential roles in sustainable investment strategies.

From a methodological standpoint, this study combines time-varying parameter vector autoregression (TVP-VAR) modeling with portfolio optimization techniques to comprehensively assess asset behavior under dynamic market conditions. The TVP-VAR framework offers a robust approach to capture the evolving interdependence and shock transmission among assets over time, particularly during periods of heightened uncertainty. By quantifying time-varying connectedness measures, it provides valuable inputs such as dynamic variance-covariance matrices and directional spillovers, which are essential for constructing adaptive portfolios. Portfolio optimization methods, in turn, leverage these dynamic relationships to allocate assets efficiently, minimize risk and enhance performance. The integration of these two approaches allows us not only to understand systemic risk and interconnectedness but also to translate these insights into practical investment strategies that are responsive to changing market dynamics.

Overall, our study extends the literature on sustainable and digital finance by examining the dynamic interactions within a multivariate portfolio composed of the iShares Global Clean Energy ETF (ICLN), the SPDR S&P Kensho Clean Power ETF (CNRG), Bitcoin (BTC) and Ethereum (ETH) over the period from October 22, 2021 to January 5, 2024. This period is particularly significant as it encompasses multiple phases of heightened market uncertainty, including the post-pandemic recovery, the 2022 global inflationary surge, tightening monetary policies by major central banks and the heightened volatility in both cryptocurrency and clean energy markets. Such conditions provide a robust testing ground for understanding the resilience and adaptability of cross-asset portfolios under shifting macroeconomic and policy regimes. While previous research has often considered clean energy assets and cryptocurrencies in isolation (e.g. Yang *et al.*, 2024; Zeng *et al.*, 2020), our approach provides deeper insights into how these distinct asset classes can be jointly integrated to enhance portfolio diversification and resilience. By using a dynamic Sharpe ratio analysis, we capture time-varying risk-adjusted performance, enabling a more nuanced understanding of optimal allocation strategies under changing market conditions. Building on these findings, portfolio managers and investors are encouraged to explore adaptive, cross-asset strategies that harness the growth potential of both clean energy equities and cryptocurrencies while managing volatility in a sustainable investment framework.

Our empirical findings underscore the critical role of green ETFs, particularly ICLN, as effective hedging instruments within balanced portfolios, most notably during periods of heightened financial distress. In contrast, while Bitcoin and Ethereum contribute to portfolio diversification, especially within Minimum Correlation and Minimum Connectedness frameworks, they exhibit pronounced volatility and operate as net transmitters of systemic shocks during crisis episodes. These results emphasize the superior risk-mitigating capacity

of green ETFs and reinforce their potential as reliable safe-haven assets amid market turbulence.

The layout of this paper is given as follows. Section 2 presents the literature review. Section 3 is the methodology used in this study. Section 4 reports the data used and the descriptive statistics. Section 5 presents the empirical findings. Section 6 concludes.

2. Related review

Many studies have analyzed the role of digital currencies (in particular, Bitcoin and Ethereum) in portfolio diversification and hedging against classical financial assets. Previous studies focus on their weak or dynamic correlations with equity markets, revealing potential advantages. For instance, [Mensi et al. \(2020\)](#) evaluate how Bitcoin and Ethereum perform as diversifiers and hedging tools, particularly for US stock market sectors. They consider sector-specific variations to better understand the connectedness between cryptocurrencies and traditional financial assets. [Ji et al. \(2019\)](#) analyze the relationship between Bitcoin and various traditional financial assets, focusing on energy markets and stocks. The study highlights how shocks in one market can propagate to others, with a specific emphasis on Bitcoin's potential as a hedge in energy-intensive activities. Many studies use time-varying and nonlinear structures to capture the evolving dependence framework among digital currencies and financial assets. [Bouri et al. \(2020\)](#) examine Bitcoin's ability to hedge against global market risks. They use dynamic correlation analyses to assess Bitcoin's behavior as a hedge or safe-haven asset under different market conditions. This study evaluates Bitcoin's hedging potential against global uncertainty, represented by the first principal component of VIX indices from 14 equity markets. Using quantile and quantile-on-quantile regression, the findings show that Bitcoin acts as a hedge against uncertainty, particularly at higher quantiles and shorter investment horizons. Hedging effects are strongest at the extremes of Bitcoin returns and global uncertainty, highlighting its role for short-term investors during periods of heightened uncertainty. Using a multivariate GAS model, [Ivanovski and Abebe Hailemariam \(2023\)](#) find that Bitcoin and Ethereum provide hedging opportunities against stock market volatility, particularly with indices like the S&P500 and NASDAQ, due to persistent nonlinear correlations. [Tiwari et al. \(2019\)](#) investigate the time-varying dynamic conditional correlation (DCC) between stock markets and cryptocurrencies, specifically Bitcoin (BTC), Ethereum (ETH) and Litecoin (LTC), using the copula-ADCC-EGARCH model to capture nonlinear and asymmetric dependencies. The findings highlight significant fluctuations in correlations over time, with cryptocurrencies providing diversification opportunities for investors, especially during market downturns. [Urquhart and Zhang \(2019\)](#) explore Bitcoin's potential as a hedge, diversifier and safe haven against world currencies, using hourly data to account for its high intraday volatility. The ADCC model reveals that Bitcoin acts as an intraday hedge for CHF, EUR and GBP and a diversifier for AUD, CAD and JPY. In addition, the [Hansen \(2000\)](#) test confirms Bitcoin's safe-haven role during extreme market turmoil for CAD, CHF and GBP, offering valuable insights for currency, cryptocurrency and high-frequency investors. In spite of their growing evidence, empirical results remain mixed. While some studies reveal low or unstable correlations that show cryptocurrencies' hedging role (e.g. [Tiwari et al., 2019](#); [Ivanovski and Abebe Hailemariam \(2023\)](#)), others display that Bitcoin's speculative nature and extreme volatility undermine its reliability as safe haven during systemic crises (e.g. [Long et al., 2021a, 2021b](#)). Such conflicting findings indicate that hedging effectiveness (*HE*) is greatly sensitive to method, sample period and market conditions.

A related strand of literature tends to compare cryptocurrencies with classical hedging assets like gold and commodities. Studies by [Corbet et al. \(2018\)](#) and [Shahzad et al. \(2019\)](#) and [Cheah et al. \(2020\)](#) report that gold remains a more consistent hedge than digital currencies during turbulent times. [Baur et al. \(2018\)](#) and [Kliber and Będowska-Sójka \(2024\)](#)

show that Bitcoin often displays speculative behavior compared to gold's stability. While literature offers interesting benchmarks, its focus on commodities and gold is not central to the current study. Rather, such results show that cryptocurrencies' hedging features are neither universal nor stable, strengthening the need to assess them alongside alternative modern assets such as sustainable instruments, rather than classical safe havens.

More recent studies analyze sustainable assets (in particular, green bonds) as potential hedges and diversifiers. [Pham and Nguyen \(2021\)](#) analyze how green bonds can serve as hedging asset against implied volatility. The empirical results show significant time-varying connectedness between green bonds and implied volatilities of the stock, energy and commodity markets. [Tian et al. \(2022\)](#) show that green bond markets display heterogeneities facing uncertainty. [Xu et al. \(2024\)](#) examine the return connectedness of green bonds with different asset classes. They display that the connectedness of green bonds with other assets tends to be somewhat low and can be used as a receiver in the network. [Ferrer et al. \(2021\)](#) study the frequency-time connectedness between the green bond markets and several financial and energy markets. The empirical findings reveal that linkages among the green bond markets and energy and financial markets are well-documented, especially at shorter time horizons. This reveals that shocks seem to be fast transmitted between different markets with an effect lasting less than a week. A strong volatility and return connectedness among investment-grade corporate bonds and green bonds. [Pham and Nguyen \(2021\)](#) study the tail dependence among green bonds and other asset classes including conventional bonds, stock markets and energy markets. They show that the spillovers between such asset classes seem to change strongly among quantiles. [Sahoo and Singh \(2025\)](#) examine the dynamic connectedness between sustainable assets (green bond and clean energy index), cryptocurrency and classical assets (crude oil and traditional index). The empirical results show that median connectedness of 36.94% in the short-term and 4.81% in the long-term, with short-term dynamics dominating system transmission. [Mensi et al. \(2025\)](#) analyze tail contagion risks between green assets (ESG Leader Index, Global Clean Energy Index and the Green Bond Index), clean cryptocurrencies and some commodities (WTI and gold). The empirical findings show that clean cryptocurrencies are linked to greater tail risks, especially during market disruptions whereas ESG indices, gold and green bonds display higher resilience. They also report that market connectedness is stronger during extreme conditions, with spillovers more pronounced in the bull market phases. [Nasir et al. \(2026\)](#) analyze the spillover transmission and extreme connectedness among green bonds, traditional and green energy markets and digital assets against uncertainties. The study shows that spillover magnitude under bullish market conditions is greater than bearish and normal market conditions. In particular, cryptocurrencies and green energy assets are net transmitters in only bearish market conditions. Spillover-based analyses report nonlinear and asymmetric transmission mechanisms, including green assets. [Duan et al. \(2023a, 2023b\)](#) analyze asymmetric spillovers from Bitcoin to traditional and green assets. They report that cross-market spillover features show nonlinearity and asymmetry from different standpoints implying different quantiles of the joint distribution of (in)dependent variables, data in volatility and return and before/after the health crisis. [Hanif et al. \(2023\)](#) analyze the time-frequency dependence and risk connectivity among green stocks and oil shocks. The study reports that the dependence relationships are tighter whereas lag-lead patterns are mixed and time-varying. Total risk spillovers among the oil and green stock markets could be mostly conveyed over time is also documented.

Nevertheless, most studies focus on green bonds or green stock indices, while green ETFs still remain underexplored. This omission is non-trivial, given that ETFs seems to be insightful financial tool which offers many advantages such as flexibility and diversification

in trading, eventual hedging strategies and liquidity management (Alomari *et al.*, 2024). ETFs differ structurally given that they experience liquidity-driven price adjustments, are subject to redemption and creation mechanisms and track evolving indices. So, it seems to be interesting to what extent green ETFs behave in turbulent times and explore the potential existence of their hedging features in comparison to digital assets.

By leafing through literature on cryptocurrencies and sustainable assets, empirical evidence on spillover persistence and *HE* remains inconclusive. Mixed empirical results (such as Tiwari *et al.*, 2019 and Long *et al.*, 2021) could be attributed to differences in econometric methods, data frequency, time periods and assumptions about parameter stability. Several models impose constant or regime-specific parameters, which may not capture adequately the gradual evolution of cross-market linkages, particularly during prolonged periods of financial turbulence. The time-varying parameter VAR (TVP-VAR) structure addresses such limitations by allowing spillovers and connectedness metrics to evolve smoothly over time without imposing exogenous breakpoints. Such flexibility is adequate for examining green and digital assets, whose market structures, regulatory environments and investor bases seem to be changing. By jointly modeling green ETFs and cryptocurrencies within a TVP-VAR framework, this study offers a unified and dynamic evaluation of hedging potential and spillover transmission that existing static or regime-based models could not provide them.

To sum up, while previous studies largely analyzes digital currencies and to a lesser extent, green bonds as hedging assets, three gaps still remain. First, empirical results on *HE* and spillover strength, are inconsistent and greatly model-dependent. Second, in spite of their growing market relevance, green ETFs are greatly absent from the financial literature. Third, few studies compare sustainable and digital assets within a fully dynamic multivariate structure. Addressing such gaps, the current study analyzes the dynamic connectedness and *HE* of green ETFs and digital currencies based on a TVP-VAR method, providing new insights into their behavior during turbulent times.

3. Methodology

In this paper, we try to adopt a two-step methodology. First, we compute the different connectedness measures. Second, we attempt to assess and construct portfolios. The methodology to model dynamic connectedness in a system of variables implies many steps. All computations for both the TVP-VAR estimation and the portfolio analyses were conducted in R Studio.

We begin by estimating a multivariate TVP-VAR model using a state-space representation. The TVP-VAR is estimated via the Kalman filter, following Diebold and Yilmaz (2012, 2014). The Kalman filter allows model parameters and conditional error variances to evolve over time, thereby capturing structural changes and the dynamic nature of interdependencies among assets. At each time step, the filter recursively updates parameter estimates by optimally combining prior information with new observations, accounting for both transition and measurement uncertainty. The lag length of the VAR system is selected using the Bayesian Information Criterion (BIC). Specifically, TVP-VAR models are estimated under alternative lag specifications, and the optimal lag order is chosen as the one minimizing the BIC. This procedure ensures a parsimonious model structure while avoiding overfitting and is consistent with standard practice in the connectedness literature (Diebold and Yilmaz (2012, 2014)). Second, we convert the TVP-VAR to a TVP-Variance Moving Average (TVP-VMA). Such transformation allows the parameters and error variances to change over time. They serve as the foundation for the Generalized Impulse Response Functions (GIRF) and Generalized Forecast Error Variance Decompositions (GFEVD). Such econometric techniques help to determine the extent to which a variable “*i*” is affected by others and how

much it impacts all other variables. By summing the shares of the error variances for variable “i” due to all other variables “j,” the total directional connectedness “FROM all others” is established, implying the impact of all other variables on variable “i.” On the other hand, computing the effect of variable “i” on all other variables “j” offers the total directional connectedness “TO all others,” which is provided by accumulating the impacts (error variance) which variable “i” has on each variable’s forecast error variance. We then compute the net total directional connectedness by subtracting the FROM measure from TO measure (TO-FROM). The Net Total Directional Connectedness measures the extent to which an asset acts as a net transmitter or net receiver of shocks within a system. Following [Diebold and Yilmaz \(2012, 2014\)](#), a positive net connectedness indicates that the asset transmits more shocks to other assets than it receives, whereas a negative value implies that it receives more shocks than it transmits. This metric is particularly useful for identifying the systemic role of each asset in the propagation of risk, allowing researchers and practitioners to understand how shocks are distributed across the network. The Total Connectedness Index (TCI) is used as the average amount of network comovement. Following [Gabauer \(2021\)](#) and [Chatziantoniou and Gabauer \(2021\)](#), the own variance shares are larger than or equal to all cross-variance shares.

Afterwards, we analyze the historical investment performance by conducting back tests on portfolios, one might use the estimated time-varying variance-covariance matrix of the TVP-VAR model. This approach is adopted by [Antonakakis et al. \(2021\)](#) for constructing portfolios. For robustness checks, four approaches for portfolio management are used based on time-varying connectedness. Finally, we analyze the hedge effectiveness and daily Sharpe ratios to capture the strategic role and impact of green ETFs within a robustly diversified portfolio, delivering critical insights into their potential to enhance global investment strategies.

3.1 Modeling dynamic connectedness based on a TVP-VAR model

Unlike standard VAR models with fixed parameters, the TVP-VAR framework allows both coefficients and error variances to evolve over time, making it particularly suitable for financial markets characterized by structural breaks, regime shifts and crisis episodes.

The TVP-VAR model [\[1\]](#) is presented as follows:

$$y_t = \varphi_t y_{t-1} + \varepsilon_t \quad (\varepsilon_t | F_{t-1} \sim N(0, H_t)) \quad (1)$$

$$\text{vec}(\delta_t) = \text{vec}\varphi_{t-1} + \epsilon_t \quad (\epsilon_t | F_{t-1} \sim N(0, \omega_t)) \quad (2)$$

y_t is the return series, F_{t-1} refers to all information up to $t - 1$. ε_t corresponds to the error variance $m \times 1$ dimensional vectors, φ_t and H_t refer to $m \times m$ dimensional matrices with, handle the time-varying error variance and parameter variance, respectively, indirectly accounting for changes in volatility. ϵ_t and $\text{vec}(\varphi_t)$ are $m^2 \times 1$ and ω_t is a $m^2 \times m^2$ dimensional matrix with ϵ_t the error term captures which the random fluctuations in the evolution of the VAR model parameters over time.

The model is estimated using the Kalman filter, which recursively updates parameter estimates by optimally combining prior information with new observations while accounting for both transition and measurement uncertainty. This estimation strategy follows the connectedness framework proposed by [Diebold and Yilmaz \(2012, 2014\)](#) and later extended by [Gabauer \(2021\)](#). The optimal lag length of the VAR system is selected using the BIC to ensure model parsimony and to avoid overfitting. To compute the GFEVD and GIRF, the

TVP-VAR should be converted into its TVP-VMA framework based on the Wold representation, which reports that:

$$z_t = \sum_{i=1}^p \varphi_{it} z_{t-i} + \varepsilon_t = \sum_{j=1}^{\infty} A_{it} \varepsilon_{t-j} + \varepsilon_t \quad (3)$$

z_t corresponds to the vector of endogenous variables at time t , p corresponds to order of the VAR process. This indicates the number of lags considered in the model. φ_{it} seems to be the coefficient matrix linked to z_t . ε_t refers to the vector of errors for the VAR model. A_{it} corresponds to be the coefficient matrix associated with the error ε_t . GIRFs are not contingent on or affected by the framework or the order of the errors, where K is the forecast horizon. The GIRF approach captures effectively the dynamics among and between all variables j . This could be expressed by:

$$\begin{aligned} &GIRF(\varphi_{ij,t}(K)) \\ &GIRF(K, \sqrt{H_{jj}}, F_{t-1}) = H_{jj,t}^{-1/2} A_{K,t} H_t \varepsilon_t \end{aligned} \quad (4)$$

Then, the GFEVD shows each variable's distinct contribution to the forecast error variance of variable i . This implies how one variable (in percentage terms) affects the forecast error variance of another variable in the system. This could be presented as follows:

$$\begin{aligned} GFEVD_{ij,t}(K) &= \frac{\sum_{i=1}^{K-1} GIRF_{ij,t}^2}{\sum_j^m GIRF_{ij,t}^2}, \\ \sum_{j=1}^m GIRF_{ij,t}(K) &= 1, \quad \sum_{i,j=1}^m GIRF_{ij,t}(K) = m, \end{aligned} \quad (5)$$

One might compute the effect of variable iii by others, as well as the reciprocal impact of variable i on all others. We can also evaluate if variable iii strongly affects others than it is affected by them. To do so, the following three metrics could be used:

- The total directional connectedness FROM all others is computed as follows:

$$FROM_{i \leftarrow j,t} = \frac{\sum_{j=1, i \neq j}^m GFED}{\sum_{i=1}^m GFED} * 100 \quad (6)$$

The effect of all the others on variable i should be strictly below 100% as the effect of i itself has been excluded.

- The total directional connectedness TO all others is computed as follows:

$$TO_{i \rightarrow j,t} = \frac{\sum_{j=1, i \neq j}^m GFED}{\sum_{j=1}^m GFED} * 100 \quad (7)$$

From the foregoing, one might compute the TCI which indicates if the whole patterns of connectedness within the system are strong or weak. The TCI ranges in the interval of $[0, \frac{m-1}{m}]$. As we express the average level of network comovement (in percentage), it should ranges between 0 and 1. A slight adjustmnt of the TCI is required:

$$Net_{i,t}(K) = TO_{i \rightarrow j,t} - FROM_{i \leftarrow j,t} \quad (8)$$

Finally, TCI could be changed to obtain pairwise connectedness index (PCI) scores between variables i and j as follows:

$$TCI_i^e(K) = \frac{\sum_{j=1, i \neq j}^m Adj - GFED}{k} \quad \text{with } 0 < TCI_i^e(K) < 1 \quad (9)$$

$TCI_i^e(K)$ represents to the adjusted Total Connectivity Index for forecast horizon k . This index measures the average amount of network comovement between variables for this time horizon. Adj-GFED refers to the Adjusted-Generalized Forecast Error Variance Decomposition (Adj-GFEVD) among variables i and j for forecast horizon k . It computes the contribution of variable j to the forecast error variance of variable i , adjusted for the effect of other variables in the system.

3.2 Portfolio implications: dynamic allocation and risk assessment

In the second step of our methodology, we explicitly link dynamic connectedness to portfolio construction and performance evaluation. Using the time-varying variance–covariance matrix derived from the TVP-VAR model, we perform historical back testing of portfolios, following the approach of [Antonakakis et al. \(2021\)](#). To assess both robustness and economic relevance, we consider four portfolio strategies that capture different dimensions of risk and network effects. The Minimum Variance Portfolio (MVP) minimizes overall portfolio volatility by allocating weights to reduce total risk. The Minimum Correlation Portfolio (MCP), based on the conditional correlation matrix ([Christoffersen et al., 2014](#)), reduces exposure to highly correlated assets, mitigating systematic risk. The Minimum Connectedness Portfolio (MCoP) exploits pairwise connectedness indices to minimize exposure to network spillovers, explicitly accounting for the dynamic transmission of shocks across the asset network. Finally, the Risk Parity Portfolio (RPP) ([Maillard et al., 2010](#)) allocates weights such that each asset contributes equally to total portfolio risk, providing resilience during turbulent market conditions.

These portfolio strategies enable a comprehensive comparison between traditional risk-based allocation and network-informed optimization, integrating both volatility control and systemic risk considerations. The dynamic connectedness measures derived from the TVP-VAR, including the TCI and net directional connectedness, directly inform the MCoP and support adaptive allocation decisions in the presence of evolving interdependencies among assets. Portfolio performance is evaluated using two complementary metrics: the Sharpe ratio, capturing risk-adjusted returns by reflecting the tradeoff between expected returns and volatility, and *HE* ([Ederington, 1979](#)), which quantifies the percentage reduction in portfolio variance achieved through hedging strategies. By combining dynamic connectedness analysis with these portfolio metrics, our methodology provides a detailed and time-sensitive assessment of risk, return and systemic vulnerability, allowing investors to identify periods of heightened risk transmission and to implement agile, regime-sensitive portfolio strategies.

The Minimum Variance Portfolio (MPV) is largely used for portfolio construction. It serves to establish a portfolio with lowest possible volatility by including various assets. One might determine the portfolio weights by using the following formula:

$$OW^* = \frac{[Var - Cov]_t^{-1} I}{I [Var - Cov]_t^{-1} I} \quad (10)$$

where: OW^* is portfolio weight vector, I is a m -dimensional vector of ones, and $[Var - Cov]_t^{-1}$ represents the $m \times m$ conditional variance-covariance matrix for period t .

Christoffersen *et al.* (2014) develop a new recent approach for constructing portfolio based on the conditional correlation matrix to determine portfolio weights. The matrix $[Corr]$ is a $m \times m$ dimensional matrix. One might compute the weights for the MCP as follows:

$$OW^* = \frac{[Corr]_t^{-1} I}{I [Corr]_t^{-1} I} \quad (11)$$

One might develop the MCoP using the previous indicators. Instead of using the variance/correlation matrix, such approach uses pairwise connectedness indices. The portfolio tends to be less susceptible to network shocks by reducing the interconnectedness among variables and diminishing their spillovers. Therefore, investment tools affect nor are impacted by others are assigned higher weights. This could be written as follows:

$$OW^* = \frac{[PWConnect]_t^{-1} I}{I [PWConnectCorr]_t^{-1} I} \quad (12)$$

where $[PWConnect]_t^{-1}$ is the pairwise connectedness index matrix, and I is the identity matrix.

Following Maillard *et al.* (2010), one might use the risk-parity portfolio (RPP) approach. Such method allows us to allocate portfolio weights. Therefore, each asset could contribute to the overall portfolio in equal manner. The idea behind such approach is that a portfolio with equal risk contributions is expected to perform better and tend to be more resilient during bearish phases. One might write the minimization problem:

$$\min \sum_{i,j=1}^N (OW_{it}^* (Var - Cov) OW_t^*) i - OW_{jt}^* (Var - Cov) t OW_j^* 2 \quad (13)$$

To assess the portfolio performance, one might use the Sharpe ratio and hedge effectiveness score. The Shape ratio (or the reward-to-volatility ratio) proposed by Sharpe (1966) is calculated as follows:

$$SR_t = \frac{E(r_{p(t)})}{\sqrt{Var_t}} \quad (14)$$

where $\sqrt{Var_t}$ refers to daily portfolio's standard deviation and $E(r_{p(t)})$ is the daily expected portfolio return.

HE quantifies the extent to which a hedging instrument or strategy reduces the total risk (typically measured by variance) of a portfolio. It is commonly expressed as the percentage reduction in portfolio variance achieved through hedging, relative to an unhedged position. Mathematically, following Ederington (1979), HE is measured as follows:

$$HE = 1 - \frac{Var(Hedg)}{Var(Unhedg)} \quad (15)$$

where $Var(Unhedg)$ is the variance of the unhedged asset and $Var(Hedg)$ is the variance of the portfolio returns. HE refers to the percent reduction in the variance of the unhedged in the

reduction in the variance of the unhedged position. A higher value of *HE* indicates a more effective hedge. For instance, an *HE* of 0.80 (or 80%) implies that the hedging strategy has reduced portfolio risk by 80% compared to the unhedged position. Conversely, a *HE* close to zero, or negative, suggests that the hedge has provided little or no risk reduction, and in some cases, may have amplified portfolio volatility.

In interpretative terms, *HE* reflects the risk mitigation power of a hedging asset (e.g. green ETFs, or cryptocurrencies) against fluctuations in another asset or portfolio. A consistently high *HE* value indicates that the chosen hedging instrument successfully stabilizes portfolio returns, especially during turbulent market periods. Conversely, time-varying or declining *HE* levels highlight the instability of the hedge and the need for adaptive or dynamic hedging strategies that adjust to evolving market conditions.

4. Data and descriptive statistics

This study uses daily data from green finance ETFs along with the two most prominent cryptocurrencies, that is, Bitcoin and Ethereum. Green ETFs refer to Exchange-Traded Funds specifically oriented toward green finance, with an investment focus on companies involved in clean energy production, renewable technologies and environmentally sustainable practices. The selection of these ETFs is based on the thematic coverage of the underlying investment funds. In our case, we use two representative instruments: the SPDR S&P Kensho Clean Power ETF (CNRG), which targets firms engaged in the development of clean power technologies, and the iShares Global Clean Energy ETF (ICLN), which provides exposure to a broad range of global companies in the clean energy sector. The daily data were collected from *Investing.com* [2], which provides comprehensive historical financial information, including prices and returns for global stock indices, commodities and ESG-related assets. The period spans from October 22, 2021 to January 5, 2024. For cryptocurrencies, data is collected from the “Coin Market Cap”. We first convert the daily closing price data into a daily return series for analysis. The choice of the sample period, starting in Q4 2021, is motivated by two main factors. First, it captures Ethereum’s transition from Proof-of-Work to Proof-of-Stake and post-COVID structural shifts in cryptocurrency–clean energy interactions. Second, it encompasses the onset of major geopolitical and macro-financial shocks, including the Russia–Ukraine war and the Gaza conflict, thus reflecting evolving volatility dynamics and stress episodes relevant for our analysis. Figure 1 illustrates the temporal evolution of the return series for Blue/Green ETFs alongside Bitcoin (BTC) and Gold (GLD).

From Table 1, the statistics indicate that ETH and BTC are negatively skewed and have significant excess kurtosis, pointing toward frequent extreme negative returns. ICLN and CNRG are positively skewed with significant excess kurtosis, suggesting frequent extreme positive returns.

The significant Jarque-Bera test results for all series confirm that they do not follow a normal distribution. The stationarity of all series is confirmed by the ERS test, which means that their statistical properties do not change over time. The significant Q2(20) statistic for ICLN suggests the presence of ARCH/GARCH effects, indicating time-varying volatility in this series. Correlation analysis shows interconnectedness among the assets. The ADF and PP tests results indicate that BTC returns are stationary, as the null hypothesis of a unit root is rejected. However, the evidence for ETH returns is less conclusive: the ADF test marginally rejects the null at the 10% significance level, while the PP test suggests nonstationarity. The KPSS test provides complementary insights, confirming stationarity for BTC and indicating non-stationarity for ETH at the 5% level. Furthermore, the ARCH test strongly rejects the null of homoskedasticity for BTC and, to a lesser extent, for ETH, highlighting the presence of conditional heteroskedasticity. ETH and BTC have moderate to strong correlations with each

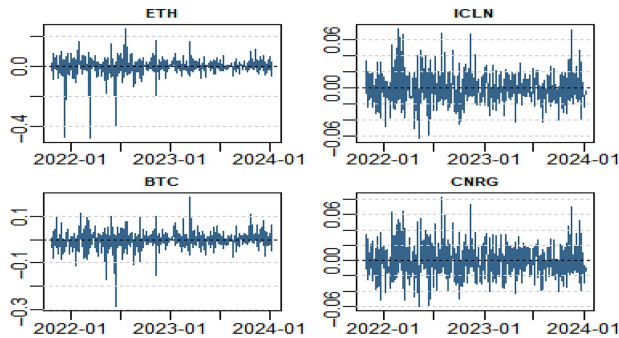


Figure 1. Time path graphs of return series

Note(s): This figure shows the returns history for each of the two cryptocurrencies – Bitcoin (BTC) and Ethereum (ETH) – and the two green assets, the iShares Global Clean Energy ETF (ICLN) and the SPDR S&P Kensho Clean Power ETF (CNRG). Returns are calculated using a log-difference transformation e.g. the first difference of the natural logarithm of the original index values. The sample covers the period from October 22, 2021 to January 5, 2024, with cryptocurrency data obtained from CoinMarketCap

Table 1. Summary statistics

Statistics/Asset	ETH	ICLN	BTC	CNRG
Mean	-0.0010798 (0.629)	-0.00083858 (0.285)	-0.000618 (0.680)	-0.000759 (0.385)
SD	0.053429	0.018744	0.035828	0.0209222
Skewness	-2.981*** (0.000)	0.536*** (0.000)	-0.923*** (0.000)	0.384*** (0.000)
Ex.Kurtosis	26.733*** (0.000)	1.654*** (0.000)	9.803*** (0.000)	0.763*** (0.003)
JB	17879.511*** (0.000)	92.522*** (0.000)	2371.671*** (0.000)	27.923*** (0.000)
Q(20)	11.169 (0.385)	16.193* (0.079)	3.875 (0.988)	8.659 (0.654)
Q2(20)	0.928 (1.000)	25.396*** (0.001)	5.589 (0.927)	13.324 (0.210)
<i>Stationarity test</i>				
ADF	0.01*** (0.000)	0.009*** (0.000)	0.01*** (0.000)	0.01*** (0.000)
PP	0.01*** (0.000)	0.01*** (0.000)	0.01*** (0.000)	0.01*** (0.000)
KPSS	0.1* (0.105)	0.1* (0.092)	0.0019** (0.032)	0.1* (0.100)
<i>Heteroskedasticity test</i>				
ARCH	0.952 (0.620)	0.008*** (0.000)	0.87 (0.422)	0.152 (0.178)
Kendall	ETH	ICLN	BTC	CNRG
ETH	1.000***	0.224***	0.571***	0.222***
ICLN	0.224***	1.000***	0.253***	0.779***
BTC	0.571***	0.253***	1.000***	0.255***
CNRG	0.222***	0.779***	0.255***	1.000***

Note(s): The above table reports the mean, standard deviation, skewness and excess kurtosis, along with the Jarque–Bera (JB) test for normality, the ADF, PP and KPSS tests for stationarity, Ljung–Box Q-statistics for serial correlation in returns [Q(20)] and squared returns [Q²(20)] and ARCH test for heteroskedasticity. *p*-values are in parentheses. The lower panel reports Kendall's tau correlation coefficients between assets, capturing their rank-based dependence structure. Statistical significance is denoted by ***, ** and * for the 1, 5 and 10% levels, respectively

other and also with clean energy indices (ICLN and CNRG), suggesting potential insights for portfolio diversification and risk management strategies. To sum up, the findings indicate that all series exhibit high volatility, nonnormality and varying degrees of correlation, with cryptocurrencies showing more pronounced extreme behaviors in their return distributions.

Figure 1 displays the time path historical returns for BTC and ETH and the two green assets (ICLN and CNRG) during the sample period. Figure 1 illustrates the high volatility and sensitivity of ETH and BTC and green assets (ICLN and CNRG) to global crises and market developments. Both ETH and BTC display high volatility throughout the period, with several pronounced spikes. In early 2022, these cryptocurrencies experienced significant fluctuations likely reflecting the impact of the Ukrainian war, which increased market uncertainty. This volatility persisted from late 2022 to 2023, possibly due to ongoing global economic uncertainties and regulatory developments in the cryptocurrency market. From 2023 to early 2024, volatility continued, suggesting that these assets remain highly sensitive to market news and global events. Similarly, ICLN and CNRG exhibit notable spikes in volatility, though generally less pronounced than those of cryptocurrencies. Early 2022 saw heightened volatility in these green assets, likely due to the Ukrainian war's impact on global energy markets and increased focus on energy security. From mid-2022 to 2023, periodic spikes in volatility were observed, potentially corresponding to major global events and policy shifts toward sustainable energy investments. By late 2023 to early 2024, while volatility persisted, the fluctuations were less extreme compared to cryptocurrencies, reflecting a relatively stable interest in green investments amid increasing environmental awareness and policy support. Overall, while cryptocurrencies show more extreme and frequent volatility, green assets demonstrate stability with periodic spikes, underscoring the evolving market dynamics and the growing importance of sustainable investments in the face of global uncertainties.

5. Empirical results

5.1 Total connectedness using TVP-VAR

From Table 2, the results indicate that green assets, such as ICLN and CNRG, are highly integrated within the system of clean energy and cryptocurrency markets. For instance, ICLN exhibits a high level of shock reception (53.38%) but also transmits an even greater share of shocks (55.82%), resulting in a net transmitter position (+2.44). Similarly, CNRG receives

Table 2. Average dynamic connectedness

Assets	ETH	ICLN	BTC	CNRG	FROM
ETH	58.04	6.81	28.19	6.96	41.96
ICLN	6.16	46.62	6.49	40.73	53.38
BTC	27.42	8.52	54.86	9.20	45.14
CNRG	6.12	40.49	6.92	46.47	53.53
TO	39.70	55.82	41.60	56.90	194.02
Inc.Own	97.74	102.44	96.45	103.37	cTCI/TCI
NET	-2.26	2.44	-3.55	3.37	64.67/48.50
NPT	0.00	2.00	1.00	3.00	

Note(s): The above table reports the results based on a TVP-VAR (0.99,0.99) with One lag and a 20-step ahead forecast horizon. Inc.Own (Including Own) represents the total forecast error variance explained for each variable, combining both the "From" spillovers and the variable's own variance (diagonal element). NET is calculated as the difference between "TO" and "FROM," indicating the net directional connectedness of each variable; a positive value means the variable is a net transmitter, whereas a negative value means it is a net receiver. NPT (Net Pairwise Transmitter) counts the number of pairwise connections where the variable acts as a net transmitter of shocks

53.53% of shocks while transmitting 56.90% (+3.37). These patterns highlight that green ETFs play an active role in the transmission of volatility and are influential components within cross-asset dynamics. Their strong interconnectedness suggests that they can contribute to portfolio diversification strategies, especially when combined with highly volatile assets such as Bitcoin and Ethereum.

Figure 2 shows that while green energy ETFs and conventional cryptocurrencies exhibit periods of high interconnectedness, there are also significant fluctuations and periods of decreased connectedness. These dynamics highlight the importance of continuously monitoring the interrelationships among portfolio components to optimize diversification and risk management strategies. At the beginning of 2022, the TCI starts at a high level (near 100), indicating that the connectedness between green energy ETFs and conventional cryptocurrencies was initially very high. A sharp drop occurs early in 2022, bringing the TCI down to around 60. This sharp decline indicates a sudden reduction in the interdependencies among the assets coinciding with the onset of the Russia-Ukraine war. Throughout 2023, the graph shows periods of increase, reaching around 80, before slightly declining again. This pattern indicates periods of increased correlation among assets, influenced by global events, economic policies, or significant market movements. Toward the end of 2023 and the beginning of 2024, notably coinciding with the outbreak of the Gaza war, the TCI experiences slight fluctuations but generally trends downwards, indicating a gradual decrease in the interconnectedness of green energy ETFs and conventional cryptocurrencies. This decline could imply diversification benefits as the assets' price movements become less synchronized, potentially offering risk management advantages for investors.

To explicitly analyze results during periods of market turbulence (Hypothesis H2), we emphasize that the dynamic measures derived from the TVP-VAR, namely the TCI and the

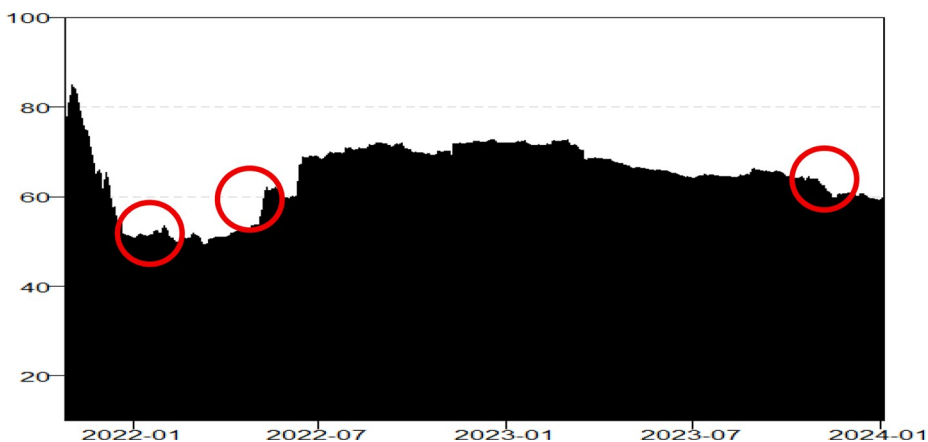


Figure 2. Dynamic total connectedness

Note(s): The results are based on a TVP-VAR (0.99,0.99) model with lag length of order 1 (BIC) and a 20-step-ahead forecast. Figure 2 illustrates the dynamic total connectedness over time, showing how the overall interconnectedness among the variables evolves from early 2022 through the end of 2023. The vertical axis represents the level of total connectedness, which fluctuates between approximately 40 and 85, indicating periods of higher or lower systemic interdependence. Notably, connectedness peaks at the beginning of 2022 and stabilizes at a relatively high level through 2022 and early 2023 before gradually declining toward the end of the period. This temporal pattern reflects changes in the intensity of spillover effects and volatility transmission within the system across the observed timeframe

net total directional connectedness, exhibit clear surges during periods of market turbulence. As shown in [Figure 2](#), connectedness intensifies markedly around major crisis episodes, including the Russia–Ukraine war (February–March 2022), the crypto-market collapse triggered by the Terra–Luna failure (May–June 2022), and the Gaza conflict (late 2023–early 2024). These peaks in TCI coincide with heightened volatility transmission, confirming that linkages between green ETFs and cryptocurrencies strengthen under stress, thereby supporting *H2*. This crisis-driven behavior is further reflected in the dynamic NTCI patterns, where both green ETFs and major cryptocurrencies assume stronger transmitter or receiver roles depending on the shock environment. Together, these time-varying dynamics validate our hypothesis and demonstrate the robustness of the TVP-VAR framework in capturing regime-dependent interdependencies.

To further ensure the robustness of our results, we evaluate the impact of major crises on market connectedness using Welch's *t*-test to compare the TCI before and during each crisis, without assuming equal variances between the periods. Welch's *t*-test is a statistical method used to compare the means of two independent samples when the assumption of equal variances may not hold ([Welch, 1947](#)). Unlike the classical student's *t*-test, Welch's *t*-test does not require homogeneity of variance and adjusts the degrees of freedom based on sample variances and sizes, making it more robust in the presence of unequal variances or unequal sample sizes ([Ruxton, 2006](#)). In the context of financial connectedness, the variability of the TCI may differ across periods, especially during turbulent crisis events. Therefore, Welch's *t*-test provides a more reliable assessment of mean differences in TCI between pre-crisis and crisis periods. The analysis reveals heterogeneous effects across events. During the FTX crisis, the average TCI declined from 46.17 before the event to 39.16 during the crisis, a highly significant reduction ($t = 10.589$, $df = 51.09$, $p < 0.001$, 95% CI [5.68, 8.34]), indicating a marked decrease in connectedness. In contrast, the Russia–Ukraine war led to a substantial increase in TCI, rising from 40.96 prior to the crisis to 50.61 during it, with the difference strongly significant ($t = -14.726$, $df = 97.99$, $p < 0.001$, 95% CI [-10.95, -8.35]). Finally, the Gaza crisis showed no statistically significant change in connectedness, with the TCI shifting slightly from 53.83–53.60 ($t = 1.564$, $df = 88.05$, $p = 0.121$, 95% CI [-0.06, 0.52]). These findings suggest that the effect of crises on systemic connectedness is highly dependent on the nature and intensity of the event, with some crises triggering significant network adjustments while others exert negligible impact.

[Figure 3](#) displays the net total directional connectedness to analyze categorizing cryptocurrencies as either net transmitters or net receivers of shocks throughout the sample period. The findings reveal distinct trends in the roles of various assets as transmitters or receivers of shocks over the period studied. In early 2022, ETH, BTC, ICLN and CNRG predominantly act as strong transmitters of shocks, as evidenced by their positive net TCI values, likely due to significant market events. Moving into mid-2022, the net TCI values for all assets begin to hover around zero, indicating a shift toward a balanced transmission and reception of shocks. This balanced state continues through the end of 2023, with most assets maintaining net TCI values close to zero. Over 2023, the NET connectedness values for all assets gradually converge toward zero. This convergence indicates that the roles of these assets as net transmitters or receivers of shocks are becoming more balanced over time. A NET value close to zero does not necessarily imply reduced risk, but rather that the directional influence among these assets is symmetric, suggesting neither clear dominance in transmitting nor receiving shocks. Consequently, while the convergence may indicate a balanced shock transmission, alternative interpretations, such as an increase in systemic risk or a decrease in diversification benefits, should also be considered in a comprehensive risk assessment. However, there are subtle shifts: by the end of 2023, ETH, BTC and CNRG

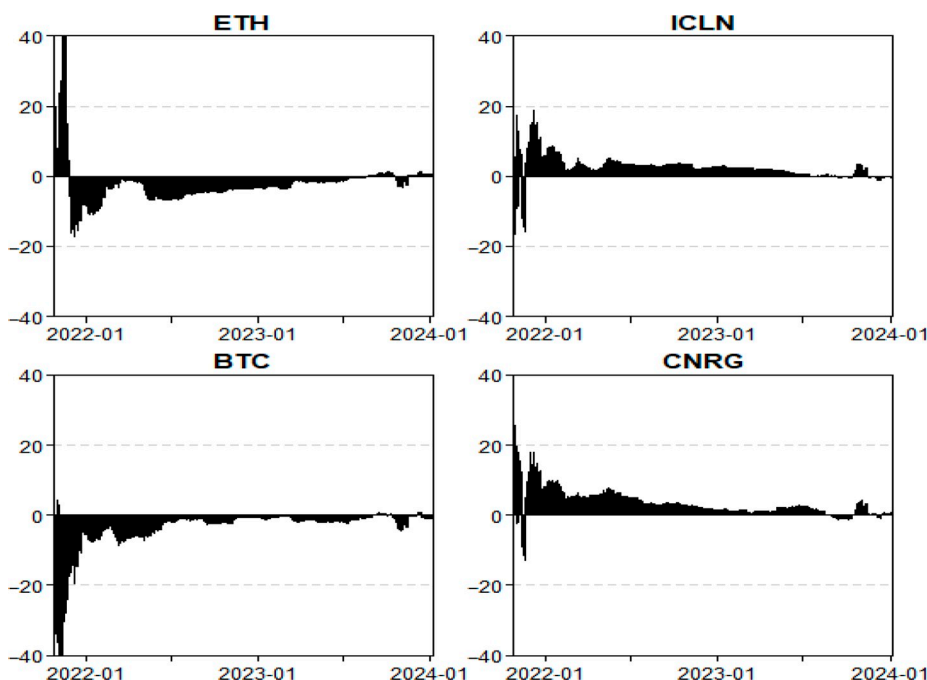


Figure 3. NET total directional connectedness

Note(s): The results are derived from a time-varying parameter vector autoregression (TVP-VAR) model with forgetting factors set at 0.99 for both the state and covariance equations and one lag included. The NET connectedness measures the net spillover effects, calculated as the difference between the directional connectedness “TO” and “FROM” each variable, indicating whether a variable is a net transmitter or receiver of shocks over time

slightly become net receivers of shocks, as indicated by their negative net TCI values, whereas ICLN remains relatively balanced, with a slight tendency toward being a receiver. This analysis can help investors understand the dynamic interactions between green energy ETFs and conventional cryptocurrencies, aiding in the development of diversified and resilient investment strategies.

5.2 Dynamic portfolios

Table 3 reports the optimal portfolio weights and corresponding HE for ETH, BTC, ICLN and CNRG across four multivariate portfolio frameworks—MVP, MCP, MCoP and RPP. The MVP assigns a dominant weight to ICLN due to its lower volatility, although its HE remains small and statistically insignificant, indicating limited hedging ability despite its sizeable allocation. In contrast, ETH and BTC exhibit strong and significant HE values even when assigned relatively modest weights, highlighting their capacity to reduce portfolio risk within a variance-minimizing structure. Under the MCP and MCoP strategies, weights are more balanced across assets; however, ETH and BTC consistently maintain positive and significant HE , confirming their effectiveness in mitigating risks associated with low-correlation and low-connectedness regimes. Conversely, ICLN and CNRG display strongly

Table 3. Multivariate portfolio weights

Assets/Statistics	Mean	SD	5%	95%	HE	<i>p</i> -value
<i>Minimum variance portfolio (MVP)</i>						
ETH	0.00	0.00	0.00	0.01	0.88	0.00
ICLN	0.84	0.07	0.70	0.93	0.07	0.42
BTC	0.14	0.05	0.04	0.21	0.74	0.00
CNRG	0.02	0.05	0.00	0.14	0.25	0.00
<i>Minimum correlation portfolio (MCP)</i>						
ETH	0.29	0.05	0.21	0.36	0.72	0.00
ICLN	0.26	0.07	0.16	0.38	−1.26	0.00
BTC	0.26	0.03	0.21	0.31	0.38	0.00
CNRG	0.18	0.10	0.00	0.31	−0.81	0.00
<i>Minimum connectedness portfolio (MCoP)</i>						
ETH	0.30	0.05	0.23	0.36	0.72	0.00
ICLN	0.26	0.06	0.16	0.34	−1.28	0.00
BTC	0.26	0.04	0.20	0.31	0.38	0.00
CNRG	0.19	0.09	0.01	0.32	−0.83	0.00
<i>Risk-parity portfolio</i>						
ETH	0.14	0.01	0.12	0.17	0.84	0.00
ICLN	0.35	0.01	0.33	0.37	−0.30	0.00
BTC	0.19	0.01	0.18	0.22	0.64	0.00
CNRG	0.31	0.01	0.30	0.33	−0.04	0.62

Note(s): The above table presents the mean, standard deviation, 5th and 95th percentiles, hedge effectiveness (HE) and *p*-values for asset’s weights corresponding to cryptocurrencies and renewable energy ETF pairs. The pairs include Ethereum (ETH), Bitcoin (BTC), iShares Global Clean Energy ETF (ICLN) and SPDR S&P Kensho Clean Power ETF (CNRG). The data highlights the statistical characteristics and significance of their return distributions and relationships

negative *HE* under both approaches, suggesting that clean-energy ETFs may amplify portfolio risk when the objective is to minimize correlation or connectedness. The RPP distributes weights more evenly, yet the pattern remains the same: cryptocurrencies deliver robust risk-reduction benefits while clean-energy ETFs fail to provide consistent hedging and at times exhibit slightly negative *HE*. Overall, the evidence across all strategies reveals a clear and stable hierarchy in risk-mitigation capacity—ETH and BTC act as reliable and effective hedging assets throughout the full sample, whereas ICLN and CNRG contribute mainly to diversification but do not consistently reduce portfolio risk, indicating that their hedging performance is conditional and regime-dependent.

Figures 4 displays the optimal weights of portfolios. For the MVP approach, the weight of ETH (MVP ETH) fluctuates slightly but remains relatively low, suggesting a preference for lower exposure to ETH due to its volatility. In contrast, BTC (MVP BTC) shows more stability in its weight, indicating a steadier contribution to minimizing portfolio variance. The weights for ICLN (MVP ICLN) and CNRG (MVP CNRG) are also relatively stable, reflecting their roles in reducing overall portfolio risk. When distinguishing between market regimes, ETH’s low weight remains consistent during both stable and crisis periods, particularly during the Russia-Ukraine war (February 2022–June 2022) and the Gaza escalation (October 2023–January 2024), highlighting its high volatility, whereas BTC and green ETFs (ICLN and CNRG) maintain more stable contributions across regimes, demonstrating their resilience. Based on the MCP approach, the weights of ICLN (MCP ICLN) and BTC (MCP BTC) are

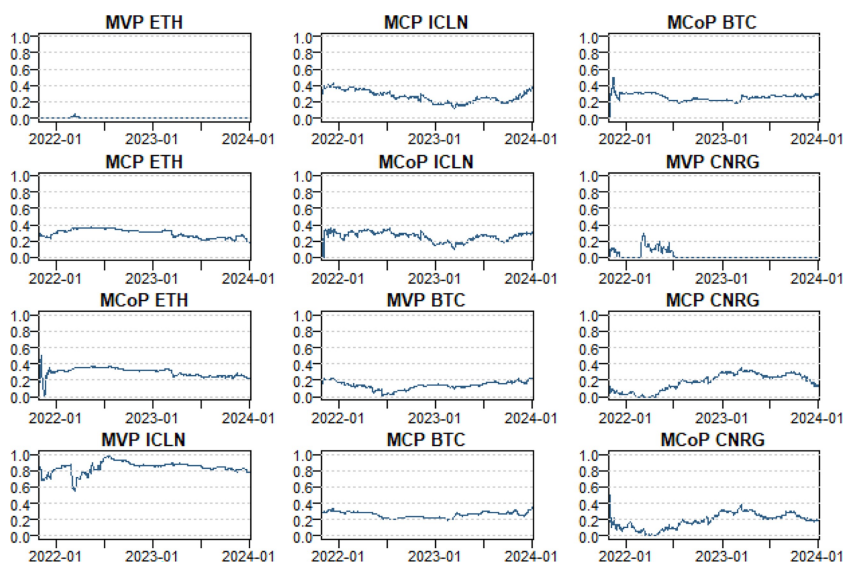


Figure 4. Dynamic multivariate portfolio weights

Note(s): The empirical results are based on the time-varying variance-covariance matrices retrieved from the TVP-VAR (0.99,0.99) with one lag. MVP refers to the minimum variance portfolio, MCP refers to the minimum correlation portfolio, RPP refers to the risk-parity portfolio, and MCoP to minimum connectedness portfolio)

notable. ICLN's weight increases significantly toward the end of the period, suggesting a growing correlation within the portfolio, whereas BTC's weight shows more stability, similar to the MVP approach. ETH (MCP ETH) maintains a lower weight, indicating consistent correlation patterns. Under crisis periods, the MCP strategy tends to allocate more weight to ICLN, suggesting that green ETFs may provide a safe-haven asset during market stress, whereas the allocation is more balanced during stable periods. In the MCoP approach, the weights of BTC (MCoP BTC) and ICLN (MCoP ICLN) exhibit more significant fluctuations, highlighting the importance of managing connectedness within the portfolio. ETH (MCoP ETH) and CNRG (MCoP CNRG) show minor changes in weights, suggesting a balanced contribution to minimizing connectedness. Notably, during crisis phases, the MCoP approach increases allocations to BTC and ICLN, indicating a dynamic adjustment to heightened systemic connectedness and volatility spillovers. These patterns indicate that the MCoP approach dynamically adjusts allocations in response to market regime shifts, particularly increasing BTC and ICLN weights during periods of higher market connectedness or stress. Finally, the weights in the RPP approach are not explicitly shown, but the variations in the other three approaches underscore the necessity of different strategies in managing risk, correlation and connectedness in a diversified portfolio of cryptocurrencies and green ETFs. Each method offers unique insights into the optimal allocation of assets, with adjustments reflecting different market regimes, thus enhancing their practical relevance in both crisis and stable periods.

Figure 5 depicts the cumulative portfolio returns for green ETFs and cryptocurrencies, using time-varying variance-covariance matrices. The trends show an overall decline across all portfolios, with significant fluctuations observed in mid-2021 and early 2022. The MVP demonstrates more stable returns compared to the MCP, RPP and MCoP, which exhibit

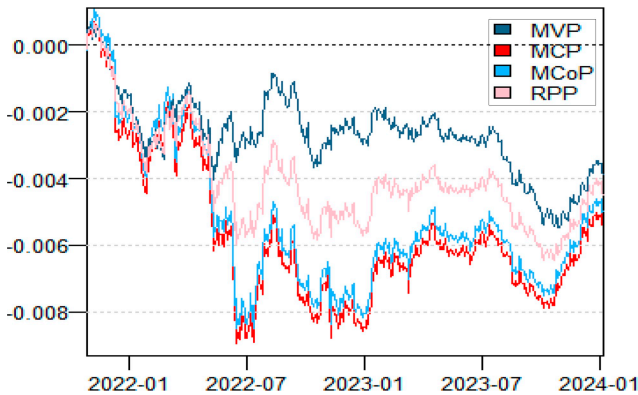


Figure 5. Cumulative portfolio returns

Note(s): The empirical results are based on the time-varying variance covariance matrices retrieved from the TVP-VAR(0.99,0.99) with one lag. MVP refers to the minimum variance portfolio, MCP refers to the minimum correlation portfolio, RPP refers to the risk-parity portfolio and MCoP to the minimum connectedness portfolio. The dotted gray lines depict returns on individual bond indices

similar patterns. Notably, the MVP outperforms the other portfolios from mid-2022 onward. The stability and superior performance of the MVP highlight the advantages of a balanced approach, especially during market fluctuations.

Figure 6 illustrates the dynamic hedge ratios for a variety of bivariate portfolios composed of different cryptocurrency pairs, including both green ETFs and cryptocurrencies. Each sub-graph within the figure represents the hedge ratio between two specific assets, showing how one asset (typically the second in the title) is used to hedge the risk associated with the other (the first in the title). For instance, in the graph labeled “ETH-ICLN,” the hedge ratio indicates the amount of ETH required to effectively mitigate the risk of ICLN over time. By examining these hedge ratios across the different asset pairs, Figure 6 provides valuable insights into the stability and effectiveness of various cryptocurrencies as hedging instruments. Certain pairs demonstrate more consistent and predictable hedge ratios, suggesting they require less frequent adjustment, while others exhibit greater variability, necessitating more active management.

The hedge ratio captures the extent to which one asset can offset the risk of another, with higher values indicating stronger *HE*. Ratios above 1 suggest over-hedging, while values close to 0 reflect weak protection. In the ETH-ICLN and ETH-CNRG portfolios, Ethereum demonstrates notable hedging capacity during the early 2022 crisis, with ratios rising above 1.0 and remaining elevated around 0.8–1.2 until mid-2022. This indicates that ETH could effectively mitigate the risks of green ETFs in turbulent periods. However, by late 2023, the ratios decline toward 0.4–0.5, reflecting reduced *HE* under more stable conditions. The ICLN-BTC and ICLN-CNRG pairs show consistently weak hedge ratios, fluctuating close to 0.1–0.3 throughout the sample. Even during volatile episodes in 2022, ICLN provided little additional hedging benefit, suggesting limited safe-haven potential of green ETFs *vis-à-vis* both crypto assets and other green ETFs. In contrast, BTC-CNRG and BTC-ETH exhibit stronger and more responsive hedge ratios. For example, during the mid-2022 crypto crash, the BTC-ETH hedge ratio increased sharply toward 1.0, highlighting Bitcoin’s role in offsetting Ethereum’s risks under market stress. This pattern clearly indicates, in line with Figure 6, that cryptocurrencies consistently outperform green ETFs in hedging capacity during periods of turmoil. Similarly,

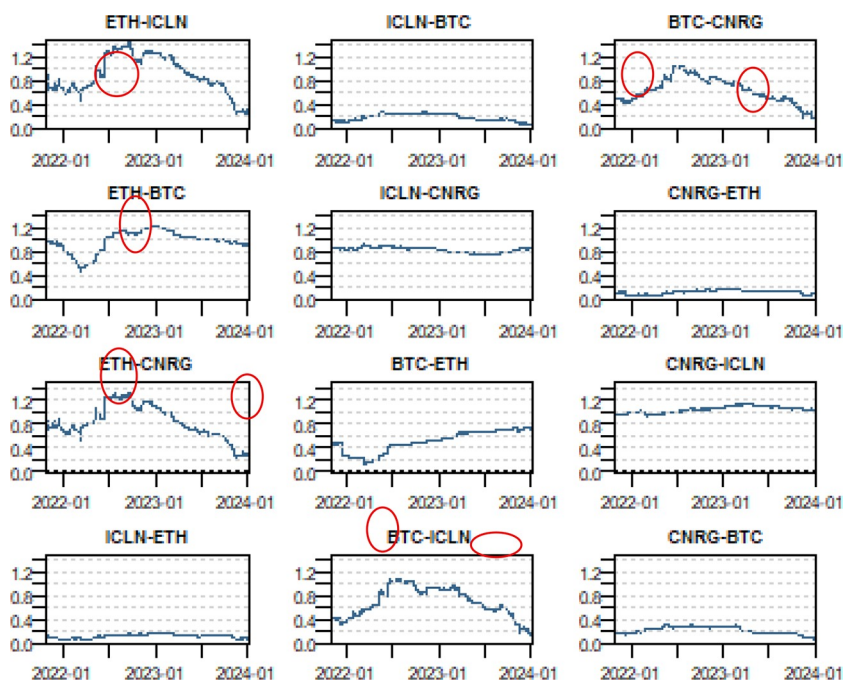


Figure 6. Dynamic hedge ratios for green and conventional cryptocurrency bivariate portfolios

Note(s): The time-varying hedge ratios estimated for bivariate portfolios combining ETFs (e.g. ICLN, CNRG) and conventional cryptocurrencies (e.g. ETH, BTC). Each subplot shows the dynamic hedge ratio between pairs of assets over the period from October 2021 to January 2024. The hedge ratio quantifies the optimal proportion of the second asset needed to hedge one unit of the first asset in the portfolio, reflecting changing risk dynamics and co-movement patterns over time

BTC–CNRG ratios peaked around 0.9 in the same period, before moderating to 0.5–0.6 in late 2023, suggesting that Bitcoin temporarily provided protection against green ETFs during crises. The CNRG–ICLN pair displays more stable ratios around 0.6–0.7, indicating moderate but persistent intra-ETF hedging. Nevertheless, these values remain noticeably below those observed for crypto-based pairs, further confirming that green ETFs play only a secondary and conditional hedging role. Notably, during major geopolitical and economic events – such as the Russia–Ukraine war (February–June 2022) and the Gaza crisis (October 2023–January 2024) – hedge ratios increase significantly, indicating that green ETFs become more effective hedging tools when BTC volatility intensifies. However, even in these episodes, their hedge ratios do not exceed those of crypto pairs, underscoring that any ETF hedging improvement remains relatively modest. In contrast, the ETH–CNRG and ETH–ICLN pairs exhibit higher and more volatile hedge ratios, often exceeding 1.0, implying that ETH requires over-hedging positions due to its heightened exposure to market shocks. This over-hedging behavior is consistent with evidence from Kuang (2025) and Kliber and Będowska-Sójka (2024), who find that “clean” cryptocurrencies reduce tail risk during market stress, while “dirty” cryptocurrencies remain highly sensitive to shocks, necessitating stronger hedging strategies. These crisis-driven fluctuations in hedging performance align with previous literature on the asymmetric behavior of hedging assets during turbulent periods (e.g. Baur and Lucey, 2010; Reboredo, 2013), which

emphasizes that asset correlations and hedge effectiveness tend to vary substantially across market regimes.

To sum up, the evidence shows that ETH and BTC provide stronger, more responsive and more consistent hedging capacity than green ETFs, especially during periods of heightened volatility in 2022, where hedge ratios often approached or exceeded unity. Figure 6 clearly illustrates this superiority, with crypto–crypto and crypto–ETF pairs exhibiting substantially higher hedge ratios than ETF–ETF combinations. By contrast, green ETFs exhibit weaker and more static hedging roles, with ratios rarely exceeding 0.5. These findings demonstrate that while green ETFs offer diversification benefits and show improvements during crises, their *HE* remains conditional and significantly lower than that of cryptocurrencies, fully aligning our discussion with the empirical patterns observed in Figure 6.

Table 4 reports the mean returns, standard deviations and Sharpe ratios (SR) for the four portfolio strategies: MVP, MCP, MCoP and RPP. Across all strategies, mean returns are negative, while return volatility remains non-negligible, leading to uniformly negative Sharpe ratios. The negative Sharpe ratios indicate that, over the full sample period, none of the portfolio strategies generated excess returns sufficient to compensate for their associated risk. This outcome reflects an environment dominated by persistent market stress and heightened uncertainty, during which downside risk outweighed potential diversification benefits. Among the four strategies, the MVP exhibits the least negative Sharpe ratio (−0.02078), suggesting relatively better risk containment, whereas the MCP, MCoP and RPP display more pronounced negative risk-adjusted performance.

Importantly, these Sharpe ratios are computed using full-sample averages, which implies that they capture only the overall, unconditional performance of each portfolio. As such, the static Sharpe ratio masks substantial time-varying dynamics in returns and volatility, particularly across different market regimes. In periods of severe market turmoil, elevated volatility combined with depressed returns mechanically drives Sharpe ratios into negative territory, even when portfolio strategies remain effective in limiting losses.

Therefore, while Table 4 provides a useful benchmark of average risk-adjusted performance, it does not allow for a distinction between crisis and non-crisis periods, nor does it capture potential improvements in performance during relatively stable market phases. This limitation motivates the adoption of a dynamic Sharpe ratio framework, which enables the analysis of how risk-adjusted returns evolve over time and across regimes. By moving to a dynamic perspective, we are able to show that negative Sharpe ratios are predominantly concentrated during crisis episodes, while periods of relative market calm may exhibit improved and occasionally positive, risk-adjusted performance. This dynamic approach

Table 4. Sharpe ratio results

Statistic	MVP	MCP	MCoP	RPP
Mean	−0.000651	−0.000828	−0.0008470	−0.0007624
SD	0.031365	0.027154	0.027765	0.024071
SR	−0.02078	−0.030517	−0.0305089	−0.031673

Note(s): The above table reports the average Sharpe Ratios obtained from back testing Four different portfolio optimization strategies: Minimum Variance Portfolio (MVP), Minimum Correlation Portfolio (MCP), Minimum Connectedness Portfolio (MCoP) and Risk Parity Portfolio (RPP). The Sharpe Ratios are computed using the mean and standard deviation of daily portfolio returns. The analysis is based on the time-varying variance–covariance matrix estimated via the TVP-VAR model, following the approach of Antonakakis *et al.* (2020). This back testing assumes that the investor can access clean cryptocurrency indices through investable instruments and is open to globally diversified exposure

therefore provides a more accurate and informative assessment of portfolio behavior and supports agile, regime-dependent portfolio management.

5.3 Agile investment strategies: integrating green ETFs and traditional cryptocurrencies

The analysis of daily Sharpe ratios for four portfolio strategies – MVP, MCoP, MCP and RPP – offers crucial insights for adaptive investment strategies, especially under extreme market conditions. This study aims to evaluate these Sharpe ratios to assess the performance of these portfolios across various periods, particularly during major events such as the COVID-19 pandemic in 2020, the war in Ukraine in 2022 and the Gaza war from late 2023 to April 2024 (Figure 7).

The overall figures imply that a dynamic allocation strategy, where investors switch between the RPP and MVP based on market conditions, could enhance overall portfolio performance. During periods of global instability or crises, the RPP's robust performance makes it a valuable asset, providing higher risk-adjusted returns. Conversely, during stable market conditions, the MVP's superior performance makes it an attractive option for consistent and stable returns.

Early 2022 to mid-2022 was characterized by elevated volatility and depressed returns, driven by the overlapping effects of post-COVID macroeconomic tightening and the outbreak of the Russia–Ukraine war. In this context, the MVP displays comparatively more stability than the other portfolios, although its return remains insufficient to generate a positive risk-adjusted performance, explaining its negative Sharpe ratio during this phase. From mid-2022 to the end of 2022, the market gradually adapted to prevailing macro-financial stress, resulting in more stable portfolio dynamics with intermittent peaks. Despite lower volatility, persistent downward pressures on returns kept the Sharpe ratios in negative territory across all strategies.

The RPP consistently outperforms the other strategies across several regimes. Its relatively higher Sharpe ratio, although still negative, reflects its superior ability to distribute risk more evenly during periods of market turbulence, particularly around the FTX collapse in late 2022. Meanwhile, the MVP becomes more volatile throughout 2023, reflecting its

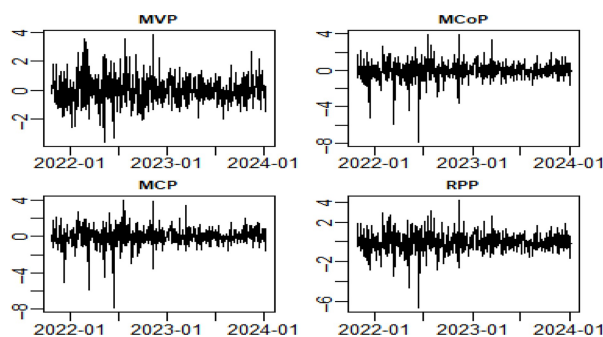


Figure 7. Daily Sharpe ratio

Note(s): The figure displays the daily Sharpe ratios for four portfolio strategies: Minimum Variance Portfolio (MVP), Maximum Correlation Portfolio (MCP), Maximum Correlation Portfolio with optimization (MCoP), and Risk Parity Portfolio (RPP) from 2023 to 2025. Red circles highlight periods of significant volatility in Sharpe ratios, corresponding to major market disruptions: early 2023 (banking crisis, visible across all strategies), and early 2024 (monetary policy shifts, particularly impacting MCP and MCoP strategies). These extreme fluctuations represent critical stress periods where risk-adjusted returns were most severely affected

increased sensitivity to shifts in correlation and variance structures. Toward the end of 2023 and early 2024, the Gaza conflict introduced renewed uncertainty. During this episode, the RPP again provides the least deterioration in Sharpe performance, illustrating its resilience when returns are compressed and volatility spikes. Importantly, this dynamic Sharpe ratio behavior is fully consistent with the connectedness results obtained from the TVP-VAR framework. In particular, the periods associated with the most negative Sharpe ratios coincide with significant increases in the TCI, indicating intensified volatility transmission across assets. This interpretation is further statistically validated by the Welch's *t*-test results, which reveal significant differences in the TCI between crisis and non-crisis regimes.

Overall, the persistence of negative Sharpe ratios across all strategies is primarily driven by synchronized global shocks, heightened risk aversion and declining asset valuations during the crisis regimes analyzed. These findings underscore the need for agile and regime-sensitive portfolio management. Specifically, switching between RPP (during crises) and MVP (during relatively calmer phases) allows portfolios to better absorb volatility and mitigate drawdowns.

6. Discussion and conclusion

This study explores the volatility connectedness and *HE* between green ETFs (SPDR S&P Kensho Clean Power ETF and iShares Global Clean Energy ETF) and cryptocurrencies (Bitcoin and Ethereum) using a TVP-VAR model. Overall, the results reveal a nuanced but coherent pattern of interactions between green ETFs and cryptocurrencies that goes beyond simple correlation analysis.

First, the TVP-VAR connectedness measures show that Bitcoin and Ethereum act as persistent net transmitters of volatility, particularly during periods of systemic stress such as the 2022 inflation shock, subsequent monetary tightening and the Gaza conflict, while ICLN and CNRG behave mainly as net receivers with only episodic transmitting roles. This configuration is consistent with the view of cryptocurrencies as high-beta speculative assets that propagate shocks to the rest of the system, whereas green ETFs, despite their growth potential, retain a more defensive profile. Second, portfolio-level evidence confirms that these connectedness patterns have material consequences for risk management: ICLN systematically lowers portfolio variance in the MVP, and green ETFs improve risk-adjusted performance in dynamic Sharpe-ratio analysis whenever market conditions deteriorate, highlighting their conditional hedging and partial safe-haven capabilities. By contrast, BTC and ETH contribute positively to diversification in the MCP and MCoP but simultaneously increase tail risk, implying that they are better suited as return enhancers than as stand-alone hedging instruments. Third, the time-varying Sharpe ratios and agile-strategy results indicate that no single allocation rule dominates across regimes; instead, switching between MVP-type allocations in calm periods and more balanced, risk-parity-oriented portfolios during crises yields superior performance, underscoring the value of regime-dependent, adaptive portfolio design.

The empirical findings also show that green ETFs serve as valuable hedging assets within balanced portfolios, particularly under economic stress, as demonstrated by the MVP, where ICLN consistently mitigates portfolio risk. Cryptocurrencies provide effective diversification, especially within the MCP and MCoP, but tend to be speculative rather than stable. The analysis confirms that Ethereum and Bitcoin act as net transmitters of shocks, particularly during global crises such as the Russia–Ukraine conflict, thereby amplifying systemic risk. However, cryptocurrencies systematically demonstrate superior *HE* and more dynamic diversification power relative to green ETFs (see [Table 5](#) and [Figure 6](#)). While ICLN absorbs

Table 5. Significance of total connectedness index (TCI) under different crisis regimes

Crisis	Mean before crisis	Mean during crisis	t-statistic	df	p-value	95% CI of difference
FTX	46.17	39.16	10.589	51.09	1.73e-14	[5.68, 8.34]
Russia-Ukraine	40.96	50.61	-14.726	97.99	<2.2e-16	[-10.95, -8.35]
Gaza	53.83	53.60	1.564	88.05	0.1214	[-0.06, 0.52]

Note(s): df refers to degrees of freedom in Welch's t-test. CI is the Confidence interval

part of these shocks, its stabilizing role appears weaker and less adaptive over time compared to the dominant hedging capacity of cryptocurrencies.

Our empirical results confirm those of [Kuang \(2021\)](#), [Ben Ameer *et al.* \(2024\)](#), [ElBannan and Löffler \(2024\)](#) and [Gökgöz *et al.* \(2025\)](#). Indeed, our findings highlight the different levels of connectedness between sustainable ETFs and other asset classes, consistent with previous studies showing dissimilar levels of static and dynamic connectedness and shock transmission across asset classes. On average, the connectedness among Blue/Green ETFs and volatility indices is low, but contagious spillovers between different asset classes are pronounced during turbulent times. Our results corroborate prior work demonstrating the resilience of sustainable funds, their ability to reduce extreme portfolio risk, and enhance reward-risk ratios, particularly for strategic investors. Nevertheless, our findings do not confirm Jeribi and Béjaoui's results, where Bitcoin was identified as a net receiver of volatility, highlighting the context-specific nature of crypto-asset connectedness.

Previous studies have shown that gold often acts as a safe-haven asset against cryptocurrencies during turbulent periods, while the S&P 500 serves as a proxy for overall market risk sentiment. Similarly, bond portfolios – particularly US Treasuries – assess hedging and diversification performance of emerging assets. Empirical evidence from [Gökgöz *et al.* \(2025\)](#) also supports this framework, showing that gold provides partial hedging benefits for Blue Economy and Green Finance ETFs, while Bitcoin exhibits time-varying diversification potential relative to equity benchmarks. Consistent with these findings, our analysis integrates these traditional benchmarks to position cryptocurrency–green ETF strategies within the broader investment landscape, enhancing interpretability and comparative relevance.

Our empirical findings offer valuable managerial and policy insights. They demonstrate that green ETFs consistently exhibit effective hedging properties during periods of financial turbulence, while cryptocurrencies provide notable diversification benefits within balanced portfolios. These dynamics indicate that green ETFs can function as stabilizing instruments under stress, partially mitigating risk, whereas cryptocurrencies' speculative behavior underscores the importance of measured regulatory oversight, transparent risk disclosure and investor education.

Specifically, incorporating sustainability-oriented assets in crypto portfolios enhances returns relative to risk and improves portfolio stability during turbulent periods. Ethereum and Bitcoin offer complementary diversification advantages, but they also transmit shocks, meaning flexible hedging approaches and adaptive monitoring systems are essential to reduce systemic risk. A dynamic allocation strategy that prioritizes Risk-Parity (RPP) during crises and MVP during calmer phases demonstrates superior performance across regimes. Such adaptive strategies enable investors to capture the growth potential of clean energy assets while mitigating risks associated with digital currencies, ultimately enhancing risk-adjusted returns.

From a policy perspective, the findings advocate for regulatory support for green financial assets to promote market stability and sustainable investment flows. Enhancing

transparency, accessibility and liquidity of green ETFs would strengthen their role as stabilizing components in diversified portfolios, while regulatory frameworks should remain evidence-based, proportional and adaptive, particularly given the rapid growth of digital asset markets.

Finally, while this study provides important cross-asset insights, its scope remains limited to specific assets and regions. Future research should extend this framework to include diverse global markets, emerging green instruments and the behavioral influence of investor sentiment on the resilience of green finance portfolios.

Notes

- [1.] Based on the Bayesian information criterion, we use the first-order VAR model.
- [2.] Data retrieved from *Investing.com*, a widely-used platform providing financial data, including historical prices, returns and indicators for global markets. available at: www.investing.com.

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