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**Investigating the Dependence Structure of Dirty and Clean Cryptocurrencies  
with Energy and Green Assets: Evidence from Markov-Switching Models**

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# **Investigating the Dependence Structure of Dirty and Clean Cryptocurrencies with Energy and Green Assets: Evidence from Markov-Switching Models**

## **Abstract**

The rapid growth of cryptocurrencies, characterized by high volatility, weak correlations with traditional assets, and substantial environmental impacts, has spurred interest in their interactions with energy and green financial markets. This study employs a Markov-switching generalized autoregressive conditional heteroscedasticity model with dynamic conditional correlation to examine the regime-dependent return and volatility connectedness between dirty and clean cryptocurrencies and energy and green financial assets. The empirical results reveal regime dependence in cryptocurrency dynamics, as well as differences in return and volatility connectedness across asset classes. These findings underscore the importance of accounting for regime-dependent dynamics when evaluating cross-market risk transmission and diversification properties between cryptocurrencies, energy markets, and green financial assets.

**Keywords:** dependence structure, Markov-switching models, cryptocurrencies, energy, green financial assets

**JEL:** G11, C58, C22

**Ethical statement:** This manuscript has not been published or presented elsewhere in part or in entirety and is not under consideration by another journal. We have read and understood your journal's policies, and we believe that neither the manuscript nor the study violates any of these. There are no conflicts of interest to declare.

## 1. Introduction

Global business integration and business cycle synchronization have facilitated a globally connected financial marketplace. Market participants usually seek assets that offer potential hedging or safe-haven properties to adjust their portfolios to reduce losses or maximize profits (Lewellen et al., 1977). Since the launch of Bitcoin in 2009, cryptocurrency markets have grown rapidly and gained widespread prominence. Given their high price volatility, high average returns, and limited correlations with conventional assets, cryptocurrencies have emerged as a crucial financial asset for portfolio management (Corbet et al., 2019; Guesmi et al., 2019; Hsu et al., 2024; Yermack, 2015).

Most major cryptocurrencies by market capitalization, such as Bitcoin (BTC) and Ethereum (ETH), are produced through mining, which entails substantial energy consumption and carbon emissions (Corbet & Yarovaya, 2020; De Vries et al., 2022; Rend & Lucey, 2022; Zhou et al., 2025a). Specifically, conventional dirty (energy-intensive or high-carbon) cryptocurrencies use a proof-of-work consensus algorithm with high energy usage to support mining and transactions (Corbet & Yarovaya, 2020; Ren & Lucey, 2022). Evidence from the Digiconomist Bitcoin Energy Consumption Index<sup>1</sup> indicates that, as of December 25, 2025, the annual electricity consumption of Bitcoin mining is on a scale comparable to that of Thailand, and individual Bitcoin transactions require considerably more energy than the average electricity consumption of a U.S. household. Moreover, Mora et al. (2018) indicate that CO<sub>2</sub> emissions resulting from continuous BTC usage could push global warming above 2°C in less than three decades.

Concerns over the environmental impacts of cryptocurrencies have prompted the Crypto Climate Accord, an initiative aimed at decarbonizing the industry and achieving net-zero greenhouse gas emissions by 2050. In response, a new category of clean (energy-efficient or low-carbon) cryptocurrencies has emerged, relying on energy-efficient consensus algorithms, such as proof-of-stake, to reduce energy consumption and environmental pollution (Haq et al., 2023; Jacquet & Mans, 2019; Ren & Lucey, 2022; Wendl et al., 2023; Zhou et al., 2025b). Advances in clean crypto-asset technologies and increasing emphasis on environmental protection are expected to lead to development of the clean cryptocurrency market, with the popularity and value of this market increasing over time (Alshammari et al., 2025; Ren & Lucey, 2022). More broadly, financial markets have witnessed increasing interest in sustainability-oriented and low-carbon financial assets (Goodell et al., 2022; Octopus Energy Generation,

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<sup>1</sup> <https://digiconomist.net/bitcoin-energy-consumption>

2020).

In light of growing environmental concerns surrounding cryptocurrencies and the emergence of clean digital assets, recent studies have increasingly examined the linkages between cryptocurrency markets and energy or green financial markets. This literature primarily investigates whether cryptocurrencies serve as diversifiers, hedges, or safe havens against energy price fluctuations and climate-related risks. However, cryptocurrencies are often treated as a homogeneous asset class, with most studies concentrating predominantly on “dirty” cryptocurrencies such as Bitcoin, while comparatively limited attention has been paid to clean cryptocurrencies despite their rising market importance (e.g., Duan et al., 2023, 2024; Marco et al., 2023; Mnif et al., 2025; Ren & Lucey, 2022). Emerging evidence suggests that such a homogeneous treatment may mask important cross-market dynamics. Dirty and clean cryptocurrencies differ fundamentally in their technological characteristics, volatility spillover patterns, and investor bases, as reflected in distinct co-bubble transmission mechanisms (Chen et al., 2024), asymmetric volatility spillovers (Haq et al., 2023), and heterogeneous risk preferences and environmental considerations among investors (Będowska-Sójka & Kliber, 2024). Consequently, dirty and clean cryptocurrencies may exhibit unique linkages with energy and green financial markets, with potentially important implications for portfolio diversification and risk hedging.

These heterogeneous linkages are likely to manifest not only in returns but also in volatility. Most existing studies focus on return connectedness, while paying limited attention to volatility connectedness (Ali et al., 2024; Attarzadeh & Balcilar, 2022; Nguyen et al., 2023; Ozturk, 2020; Symitsi & Chalvatzis, 2018; Xie & Cao, 2024; Yousaf et al., 2024). Yet return and volatility connectedness capture different dimensions of cross-market interactions, reflecting price co-movements and risk transmission, respectively (Attarzadeh & Balcilar, 2022; Ji et al., 2018; Yousaf et al., 2024). Evidence further indicates that volatility spillovers are often stronger than return spillovers (Ozturk, 2020; Yousaf et al., 2024), implying that return-based analyses may yield an incomplete assessment of cross-market relationships and underscoring the importance of examining both return and volatility dynamics within a unified analytical framework.

Financial markets, however, frequently undergo abrupt transitions between low- and high-volatility states, particularly during periods of economic and financial stress (Ardia et al., 2018; Bauwens et al., 2014). Capturing such behavior poses challenges for conventional empirical frameworks. Existing studies predominantly rely on conventional time-series approaches to model dynamic correlations, including DCC-GARCH (Dutta et al., 2020, 2023; Prasad Yadav et al., 2022; Ren & Lucey, 2022),

TVP-VAR (Attarzadeh & Balcilar, 2022; Naeem et al., 2023; Umar et al., 2023; Wen et al., 2022), and wavelet-based methods (Goodell et al., 2022; Husain et al., 2023; Yadav et al., 2023). While these approaches allow correlations to vary over time, they typically assume smoothly evolving parameters and do not explicitly accommodate regime shifts in dynamics. The Markov-switching GARCH framework (MS-GARCH) provides an extension by allowing model parameters to change discretely across regimes, thereby capturing nonlinear dynamics and sudden market transitions more effectively (Ardia et al., 2019a; Inayati et al., 2024). Incorporating regime shifts into dynamic conditional correlations further improves the ability to characterize extreme market fluctuations and cross-market risk transmission (Li & Miu, 2023). Accordingly, this study employs the MS-GARCH-DCC model to examine regime-dependent return and volatility connectedness among cryptocurrency, energy, and green financial markets.

This study examines regime-dependent return and volatility connectedness among five dirty and five clean cryptocurrencies, four dirty and three clean energy markets, and two green financial assets, using daily data from November 6, 2017, to April 15, 2024. The empirical results reveal regime dependence in cryptocurrency dynamics, and differences in their return and volatility connectedness with energy and green financial assets. By explicitly distinguishing between dirty and clean cryptocurrencies and analyzing both return and volatility channels, the study provides new evidence on heterogeneous spillover patterns and their implications for portfolio diversification and risk management for both investors and policymakers.

The rest of the paper is organized as follows. Section 2 reviews of the relevant literature. Section 3 discusses the mechanisms linking dirty and clean cryptocurrencies with energy and green markets. Section 4 introduces the empirical methodology. Section 5 describes the data source and variables. Section 6 presents the empirical results, followed by a discussion. Finally, Section 7 elucidates the conclusion of this study.

## **2. Literature review**

### **2.1 Relationships between cryptocurrency and energy markets**

Several studies have investigated the relationships of cryptocurrency markets with fossil fuel and carbon markets to explore whether cryptocurrencies can be considered diversifiers, hedges, or safe havens against these assets. Zeng et al. (2020) employ the VAR model and identify that the connectedness between BTC and conventional assets (stocks, oil, and gold) is weak and limited, which suggests that BTC offers diversification opportunities for investors in these assets. Rehman and Kang (2021) find that oil and gas markets have a lead-lag price connection with the BTC; however, no

co-movement can be observed between the BTC and coal markets, which suggests the existence of opportunities for diversification between BTC and coal futures in a portfolio. Moreover, Dutta et al. (2020) use the DCC-GARCH model to investigate the time-varying correlations and safe-haven properties of gold and BTC to oil markets during the COVID-19 period. They find that gold is a safe-haven asset for oil markets, whereas BTC only acts as a diversifier to these markets. Yousaf et al. (2022) show that spillover dynamics among crude oil, gold, and Bitcoin differ across normal and crisis periods, concluding that gold acts as a safe haven and hedge for the oil market, whereas Bitcoin functions primarily as a diversifier rather than a reliable hedge under extreme uncertainty. Similarly, Ozturk (2020) finds that volatility connectedness among Bitcoin, gold, and crude oil is generally stronger than return connectedness, and that diversification benefits among these assets are limited in the short term but become more attainable over longer investment horizons.

Some researchers consider cryptocurrency a hedge or safe haven for energy markets. For instance, Selmi et al. (2018) employ the quantile-on-quantile regression approach and conclude that BTC and gold can serve as a hedge, safe haven, and diversifier against oil fluctuations in a time-varying setting. Okorie and Lin (2020) employ the VAR-MGARCH-GJR-BEKK model and find that crude oil has short-term hedging potential for ETH, whereas crude oil has long-term hedging potentials for Solve, Elastos, and BitCapitalVendor. Będowska-Sójka and Kliber (2022) test the hedging properties of cryptocurrencies during the COVID-19 pandemic and report that only stablecoins (USD Coin and Tether) acted as hedges against downward movement in oil prices. However, Naeem et al. (2021) show that BTC, ETH, Litecoin (LTC), and XRP (a clean cryptocurrency) act as effective hedge and safe-haven assets for metals and agriculture but not for energy commodities. Wen et al. (2022) compare the dynamic spillover effects of gold and BTC on oil and stock markets during the COVID-19 pandemic by using the TVP-VAR model. They reveal that gold was a considerably stronger safe-haven asset for oil and stock markets than was BTC in the pandemic.

Few studies have investigated the relationships between clean cryptocurrencies and energy markets. For example, Umar et al. (2023) assess the dynamic relationship between fossil fuels and green cryptocurrencies by using the TVP-VAR model, finding that green cryptocurrencies can be considered a hedge against the fossil fuels they examined. Naeem et al. (2023) employ the CAViaR model with the TVP-VAR framework and show that clean cryptocurrencies can offer diversification benefits, particularly for energy metals and fossil fuels. Kaur (2025) employ a TVP-VAR and DCC-GARCH framework to examine static and dynamic spillovers among green cryptocurrencies, renewable energy stocks, and agricultural commodities, showing that

green cryptocurrencies, especially Cardano (ADA) and Stellar (XLM), offer portfolio diversification under normal market conditions and provide hedging benefits mainly during periods of market turmoil. However, Umar et al. (2024) state that clean cryptocurrencies have weak diversification benefits for traditional energy markets (WTI, Brent crude oil, natural gas, and coal markets). Thus, further investigation should be conducted regarding the relationships of dirty and clean cryptocurrency markets with energy markets.

## **2.2 Relationships between cryptocurrency and green markets**

Several studies have examined the relationships between cryptocurrency markets and green markets (e.g., green bond, clean energy, and renewable energy markets). For example, Goodell et al. (2022) employ network and wavelet analysis to investigate the interconnectedness of green investment funds with traditional markets (stock and commodity markets) and nontraditional markets (BTC and fintech markets); they prove that BTC is an effective diversifier for green assets. Prasad Yadav et al. (2022) use the DCC-GARCH model and find that volatility spillovers occur from the green bond market to the renewable energy and BTC markets only over the medium- and long-term, indicating that more opportunities for diversifying the portfolio in the short-term. Similarly, Yadav et al. (2023) employ the wavelet coherence model and find that green bonds offer stronger diversification benefits with energy, BTC, and carbon markets over short-term horizons than over medium- or long-term horizons.

Attarzadeh and Balcilar (2022) employ a TVP-VAR model to analyze the dynamic relationships between returns and realized volatility for BTC, fossil energy, and clean energy markets as well as the S&P 500. Their findings indicate that crude oil, clean energy, and BTC markets are weakly correlated during noncrisis periods; however, these correlations are stronger during crisis periods, such as the 2014 energy crisis, the 2018 cryptocurrency crash, and the COVID-19 pandemic. Therefore, investors can hedge their BTC portfolio with fossil fuel or clean energy investments during noncrisis periods. Pham et al. (2023) also support the viewpoint that cryptocurrencies (BTC and ETH) can be used as hedges against green energy and fossil fuel investments during noncrisis periods. Rao et al. (2022) examine the relationships among green bonds, BTC, commodities, and other financial markets during the pre-and post-COVID-19 periods. They confirm that BTC is not a suitable hedging instrument under extreme economic uncertainty.

Certain studies have explored the relationships between clean cryptocurrencies and green assets. For instance, Husain et al. (2023) perform wavelet coherence analysis to examine the dynamic connectedness between green cryptocurrencies, green

investment, conventional commodities, and equities; they identify that green cryptocurrencies do not exhibit any hedge or safe-haven properties against the other assets. Yousaf et al. (2024) employ a TVP-VAR framework and demonstrate that volatility spillovers between green cryptocurrencies and green stocks are substantially stronger and more persistent than return spillovers, particularly during periods of market stress. They further identify ADA and XLM as effective hedging instruments for green stock portfolios. Additionally, Dias et al. (2024) report that ADA and XLM exhibit moderate co-movements with dirty cryptocurrencies and clean energy stock indices, suggesting that these assets can provide meaningful diversification benefits for investors.

Few studies have examined the connections between cryptocurrency categories and other asset classes. Ren and Lucey (2022) use the DCC-GARCH model to examine the relationships of clean energy markets with clean and dirty cryptocurrency markets. They find that clean energy is not a hedging asset for dirty and clean cryptocurrencies; however, it can be a weak safe haven for these cryptocurrency markets in an extremely bearish market. Marco et al. (2023) demonstrate that dirty and clean energy stocks are valuable for long-term portfolio hedging because U.S. environmental stock market indices act as net shock receptors, whereas both dirty and clean cryptocurrencies are relatively inefficient at minimizing portfolio risk. Duan et al. (2023) adopt the TVP-VAR model and reveal that dirty and clean cryptocurrencies can provide diversification gains against most green and stock indices, with this found to be especially true during the COVID-19 pandemic period. Similarly, Duan et al. (2024) employ the quantile-on-quantile method and indicate that clean and dirty cryptocurrencies have weak and stable relationships with traditional and green financial assets, which confirms that these cryptocurrencies have a sheltering effect on traditional and green financial assets under extreme market conditions. Mnif et al. (2025) use a TVP-VAR connectedness approach to show that green bonds offer consistent hedging benefits, while clean cryptocurrencies provide context-dependent hedging in volatile markets.

The literature indicates that cryptocurrencies exhibit substantial heterogeneity in their characteristics and interactions with other asset classes (Ren and Lucey, 2022), and that return and volatility connectedness capture distinct dimensions of cross-market relationships (Ozturk, 2020; Yousaf et al., 2024). Existing evidence further shows that correlations and hedging properties vary across market conditions, particularly between tranquil and stressed periods (Attarzadeh & Balcilar, 2022; Duan et al., 2023), suggesting state dependence in cryptocurrency linkages (Li and Miu, 2023). These findings motivate an empirical framework that accounts for asset heterogeneity and

regime-dependent return and volatility dynamics when examining linkages with cryptocurrencies, energy and green financial markets.

### **3. Mechanisms Linking Dirty and Clean Cryptocurrencies with Energy and Green Markets**

This study investigates the dynamic return and volatility connectedness between dirty and clean cryptocurrencies and energy-related and green assets. A multi-theoretical perspective provides the foundation for understanding these relationships. Heterogeneous agent models emphasize that financial markets are populated by investors with diverse beliefs and decision rules, giving rise to nonlinear and time-varying price dynamics (Hommes, 2006). Building on this perspective and consistent with Li and Miu (2023), investor composition is expected to differ systematically across markets. Under normal market conditions, energy and green assets are primarily priced by fundamentalist investors responding to geopolitical developments and supply and demand fundamentals (Dokas et al., 2023), whereas cryptocurrency markets are more speculative in nature and are influenced largely by investor attention and sentiment (Baur et al., 2018; Liu & Tsyvinski, 2021; Yermack, 2015). These contrasts are reinforced by differences in market efficiency. Cryptocurrency markets exhibit lower informational efficiency and greater sensitivity to behavioral biases (Urquhart, 2016; Kristoufek, 2018), while energy and green markets are more mature and fundamentally driven. Collectively, these structural and informational differences imply that the two markets rely on distinct information sets, resulting in weak or insignificant correlations during tranquil periods.

The distinction between dirty and clean cryptocurrencies further shapes these interactions through the channel of environmental risk transmission. Environmental and climate-related risks can propagate across asset classes as changes in energy prices, regulatory pressures, and transition risks influence asset valuations and investor behavior (Barnett et al., 2020; Bolton & Kacperczyk, 2021; Giglio et al., 2021). Dirty cryptocurrencies rely on energy-intensive consensus mechanisms and are therefore directly exposed to such risks through mining costs and production profitability. Empirical evidence indicates that the valuation and volatility of proof-of-work cryptocurrencies are closely linked to electricity and energy costs (Hayes, 2017; De Vries, 2018). Consequently, fluctuations in fossil fuel prices can act as implicit signals of environmental and transition-related risks, facilitating spillovers from energy markets to dirty cryptocurrency markets and generating stronger positive correlations, particularly during periods of heightened energy market volatility. Clean cryptocurrencies, by contrast, exhibit substantially lower energy dependence and reduced exposure to environmental transition risks, leading to weaker linkages with

conventional energy markets and greater resilience to energy-related spillovers (Kuang, 2025; Zhou et al., 2025b). These contrasts underscore the heterogeneous nature of the cryptocurrency and energy nexus and the importance of technological and environmental characteristics in shaping cross-market dynamics.

Correlations may strengthen when market shocks activate cross-market transmission mechanisms. King and Wadhvani (1990) argue that volatility in one market can be interpreted as an informational signal about broader market conditions, inducing parallel adjustments in other markets. Kodres and Pritsker (2002) further show that investors respond to changes in risk exposure or liquidity pressures by rebalancing their portfolios, enabling shocks to be transmitted across otherwise unrelated markets. Even without direct fundamental linkages, these mechanisms can generate substantial spillovers between cryptocurrency and energy markets. As emphasized in Li and Miu (2023), periods of high market volatility, which are widely associated with economic and financial distress (Li, 2022), are expected to be accompanied by markedly stronger correlations between cryptocurrencies and energy assets.

Overall, these theoretical perspectives indicate that the relationship between cryptocurrencies and energy-related or green assets is inherently state dependent. Correlations are likely to be weak under normal market conditions but to strengthen during periods of market stress as contagion and portfolio rebalancing effects intensify. The MS-GARCH-DCC model is therefore particularly well suited for this study, as it allows conditional volatilities and correlations to vary across regimes, enabling a rigorous assessment of the diversification, hedging, and safe-haven properties of cryptocurrencies.

## **4. Methodology**

### **4.1 MS-GARCH-DCC model**

Traditional GARCH -based models may not adequately capture the high and low volatilities that are frequently observed in financial markets. Ignoring regime shifts in volatility dynamics can bias estimation results and considerably affect the precision of volatility forecasts (Bauwens et al., 2014; Lamoureux & Lastrapes, 1990). Thus, MS techniques have been used to analyze the dynamics of time-series data (e.g., Haas et al., 2004; Hamilton & Susmel, 1994; Krolzig et al., 2002; Li, 2008; Li & Miu, 2023). Compared with traditional GARCH models, MS-GARCH models, which use a Markov process to switch between several regimes, provide a more precise and complex representation of the underlying volatility dynamics. By identifying different regimes, researchers and practitioners can gain insights into the variation in volatility under different economic conditions.

In contrast to the TVP-VAR model, the MS-GARCH model is particularly effective at capturing regime shifts or structural breaks in data (Bauwens et al., 2014; Lamoureux & Lastrapes, 1990). The MS-GARCH model provides a straightforward method for identifying and interpreting different regimes, with this method being more intuitive than that used by the TVP-VAR model, which involves continuous parameter changes. In addition, the MS-GARCH model is robust to nonlinearities in the data because it allows abrupt changes in the model parameters (Inayati et al., 2024; Lamoureux & Lastrapes, 1990). Compared with the TVP-VAR model, the MS-GARCH model produces more accurate forecasts because MS-GARCH model captures the underlying data dynamics more accurately, particularly under the existence of structural changes. (Ardia et al., 2019a; Inayati et al., 2024). Therefore, we adopt the MS-GARCH model proposed by Ardia et al. (2018) in our empirical analysis. This model is described follows.

Let  $y_t \in \mathbb{R}$  represent time-series observations of a financial asset at time  $t$ . To simplify the exposition, Ardia et al. (2018) assumes that  $y_t$  has a mean of 0 and that its elements are not autocorrelated. To satisfy the zero-mean assumption for  $y_t$ , we calculate the difference between the original time-series observations and their mean value to obtain  $y_t$ . In the present study,  $y_t$  represents the difference between the weekly log returns or realized volatilities of a financial asset and the corresponding mean value.

The general MS-GARCH model can be represented as  $y_t | (s_t = k, I_{t-1}) \sim D(0, h_{k,t}, \xi_k)$ , where  $D(0, h_{k,t}, \xi_k)$  is a continuous distribution with a mean of 0, a time-varying conditional variance of  $h_{k,t}$  in regime  $k$ , and a vector  $\xi_k$  (the shape parameters include tail and asymmetry);  $s_t$  represents a state variable that evolves in accordance with a first-order homogeneous Markov chain with a finite number of states ( $K$ ); and  $I_{t-1}$  denotes the information set available up to time  $t - 1$ .

Ardia et al. (2018) follows the method of Haas et al. (2004) and specify the GARCH-type conditional variance  $h_{k,t} \equiv h(y_{t-1}, h_{k,t-1}, \theta_k)$  conditionally on regime  $s_t = k$  as a function of past returns and a regime-dependent vector of the parameters denoted  $\theta_k$ . Thus, the GARCH-type processes evolve independently, and the MS-GARCH model is unaffected by the path dependency problem. In the present study, we consider the symmetric GARCH (1, 1) model of Bollerslev (1986) for the conditional variance  $h_{k,t} \equiv \omega_k + \alpha_k y_{t-1}^2 + \beta_k h_{k,t-1}$ , where  $\omega_k > 0, \alpha_k > 0, \beta_k \geq 0$ ,  $\alpha_k + \beta_k < 1$  ( $k = 1, \dots, K$ ), and the innovations have a Student's  $t$ -distribution.

After estimating the MS-GARCH model and obtaining the standardized residuals of two financial assets by using this model, we employ the DCC model proposed by

Tse and Tsui (2002) to calculate the correlations between these assets. This DCC model is described as follows. Consider a multivariate time series of observations  $\{a_t\}$ , where  $t = 1, \dots, T$ , and  $K$  elements correspond to each  $t$  value; thus,  $a_t = (a_{1t}, \dots, a_{Kt})'$ . For simplicity, Tse and Tsui (2002) assumes that  $a_t$  has a mean of 0. The conditional variance of  $a_t$  is assumed to follow the time-varying structure given by  $Var(a_t|\Phi_{t-1}) = \Omega_t$ , where  $\Phi_t$  is the information set at time  $t$ . Let the variance elements of  $\Omega_t$  be  $\sigma_{it}^2$ , where  $i = 1, \dots, K$ , and let the covariance elements of  $\Omega_t$  be  $\sigma_{ijt}$ , where  $1 \leq i < j \leq K$ .  $D_t$  represents a  $K \times K$  diagonal matrix in which the  $i$ th diagonal element is  $\sigma_{it}$ , and  $\varepsilon_t = D_t^{-1}a_t$  is the standardized residual. This residual  $\varepsilon_t$  is assumed to be serially independently distributed, with its mean being 0 and variance matrix being  $\Gamma_t = \{\rho_{ijt}\}$ . The matrix  $\Gamma_t$  is also the matrix of the correlation between  $a_t$  and  $\Omega_t$ , where  $\Omega_t = D_t\Gamma_tD_t$ .

The time-varying conditional-correlation matrix  $\Gamma_t$  is generated from the following recursion:  $\Gamma_t = (1 - \theta_1 - \theta_2)\Gamma + \theta_1\Gamma_{t-1} + \theta_2\Psi_{t-1}$ , where  $\Gamma = \{\rho_{ij}\}$  is a time-invariant unconditional correlation matrix of  $\varepsilon_t$ , and  $\Psi_{t-1}$  is a local correlation matrix depending on  $\{\varepsilon_{t-1}, \dots, \varepsilon_{t-m}\}$  for some positive integer  $m$ . The parameters  $\theta_1$  and  $\theta_2$  are assumed to be nonnegative and to satisfy the following constraint:  $\theta_1 + \theta_2 \leq 1$ . Denoting  $\Psi_t = \{\psi_{ijt}\}$ ,  $\Psi_{t-1}$  is specified as follows,  $\psi_{ij,t-1} = \frac{\sum_{h=1}^m \varepsilon_{i,t-h} \varepsilon_{j,t-h}}{\sqrt{(\sum_{h=1}^m \varepsilon_{i,t-h}^2)(\sum_{h=1}^m \varepsilon_{j,t-h}^2)}}$ ,  $1 \leq i < j \leq K$ .

## 4.2 Calculation of the correlations between cryptocurrencies and energy or green financial assets

In this study, we use the *MSGARCH* package of the R software program (Ardia et al., 2019b) to estimate the MS-GARCH model. Moreover, we employ the *dccFit* function of the *MTS* package of R to calculate the correlations of dirty and clean cryptocurrencies with dirty energy markets, clean energy markets, and green financial assets. The steps in our study are described as follows.

We first calculate the weekly log returns or realized volatilities of the selected assets. To meet the zero-mean assumption of Ardia et al. (2018), we obtain the difference between the calculated weekly log returns or realized volatilities and the corresponding mean value. We then estimate this difference by using the MS-GARCH model. Subsequently, we apply the Akaike information criterion (AIC) to find the better model among MS-GARCH models with single-regime and two-regime settings. In the two-regime MS-GARCH model, the *State* function of the *MSGARCH* package of R assigns each observation to a regime of the Markov chain by using the Viterbi algorithm.

After estimating the MS-GARCH model and obtaining the standardized residuals of the difference between the weekly log returns or realized volatilities and the corresponding mean value, we use the *dccFit* function of the MTS package of R to calculate the correlations of dirty and clean cryptocurrencies with dirty energy markets, clean energy markets, and green financial assets. For each asset with best estimated MS-GARCH model being two-regimes setting, each observation is assigned to a low or high volatility regime. Therefore, three possible situations exist for an asset pair. First, if the two selected assets are better estimated using the single-regime MS-GARCH model than by using the two-regime MS-GARCH model, the assets have only one type of correlation. Second, if only one of the selected assets is better estimated with the two-regime MS-GARCH model, the two assets have two types of correlations, namely those in the low- and high-volatility regimes. Finally, if both selected assets are better estimated using the two-regime MS-GARCH model, they have four types of correlations: correlations in which both assets lie in the low-volatility regime (low-to-low-volatility regime), correlations in which the first asset lies in the low-volatility regime but the second asset lies in the high-volatility regime (low-to-high-volatility regime), correlations in which the first asset lies in the high-volatility regime but the second asset lies in the low-volatility regime (high-to-low-volatility regime), and correlations in which both assets lie in the high-volatility regime (high-to-high-volatility regime). We apply the Mann–Whitney test and Kruskal–Wallis test to investigate whether the various types of correlations are significantly different from each other at their median levels (the 50th percentile; Kruskal & Wallis, 1952; Mann & Whitney, 1947).

### **4.3 Hedging, diversification, safe-haven, and contagion properties of cryptocurrencies**

This section operationalizes the theoretical mechanisms discussed in Section 3 by defining how alternative correlation patterns between cryptocurrencies and energy or green financial assets are interpreted as hedging, diversification, safe-haven, and contagion properties within the MS-GARCH-DCC framework. First, if the returns of the selected cryptocurrency and energy or green financial asset are negatively correlated, the cryptocurrency can serve as a hedge for the asset. Second, if these returns are positively correlated but significantly lower in the high-volatility regime (high-to-high-volatility regime) than in the low-volatility regime (low-to-low volatility regime), the cryptocurrency can serve as a diversifier for the asset. The high-volatility regime is usually associated with times of economic distress and uncertainty (Li, 2022). Consequently, the aforementioned correlation condition indicates that the selected cryptocurrency is less dependent on the asset during times of economic distress and

uncertainty than during normal market conditions; thus, the cryptocurrency can serve as a diversifier for the asset.

Realized volatility indicates the risk of financial assets (Molnár, 2012), and realized volatility can be considered an index of investor fear (Cevik et al., 2022; Chen et al., 2020). According to Li (2022), if the correlation between the realized volatilities of two assets is significantly stronger in the high-volatility regime than in the low-volatility regime, the investor fear in the two asset markets is strongly correlated, particularly during times of economic distress and uncertainty. Therefore, if the realized volatilities of the selected cryptocurrency and energy or green financial asset are positively correlated and the correlation in the high-volatility regime (high-to-high-volatility regime) is significantly stronger than that in the low-volatility regime (low-to-low-volatility regime), the investor fear in the asset market spreads to the cryptocurrency market during times of economic distress and uncertainty. By contrast, if the aforementioned realized volatilities are negatively correlated, the cryptocurrency may be a safe haven for the asset. If the realized volatilities are positively correlated but the correlation in the high-volatility regime (high-to-high-volatility regime) is significantly weaker than that in the low-volatility regime (low-to-low-volatility regime), the cryptocurrency can be a diversifier for the asset.

According to Baur and Lucey (2010) and Baur and McDermott (2010), a hedge is an asset that is uncorrelated or negatively correlated on average with another asset or portfolio, a diversifier is an asset that is positively but not perfectly correlated on average with another asset or portfolio, and a safe haven is an asset that is uncorrelated or negatively correlated with another asset or portfolio in times of market stress or turmoil. Our definition for hedges matches that of Baur and Lucey (2010) and Baur and McDermott (2010). Moreover, our definition of safe havens emphasizes the situation during market stress or turmoil. If the realized volatilities of the selected cryptocurrency and other asset are negatively correlated, the cryptocurrency can be a safe haven for the asset during market stress or turmoil. Our definition of diversifiers is stronger than that of Baur and Lucey (2010) because of the estimation method used in the present study, which also distinguishes this study from relevant previous studies. A stronger definition of diversifiers may result in more rigorous analysis outcomes. According to our definition, an asset is considered a diversifier only if it has a positive correlation with another asset or portfolio and this correlation is significantly weaker in the high-volatility regime (high-to-high-volatility regime) than in the low-volatility regime (low-to-low volatility regime). This condition implies that the selected asset is less dependent on the other asset during times of economic distress and uncertainty than is the case during normal market conditions.

## 5. Data and variables

The data used in this study are obtained from Bloomberg and comprise daily prices of dirty and clean cryptocurrencies, fossil fuels, green energy, and green financial assets from November 6, 2017, to April 15, 2024; all data are in U.S. dollars. In accordance with the literature (Duan et al., 2023, 2024; Plam et al., 2022; Ren & Lucey, 2022; Umar et al., 2023), we focus on the top five dirty and top five clean cryptocurrencies by market capitalization. The top five dirty cryptocurrencies are BTC, ETH, Bitcoin Cash (BCH), Ethereum Classic (ETC), and LTC, and the top five clean cryptocurrencies are ADA, XRP, IOTA (MIOTA), XLM, and Nano. Moreover, this study uses data from crude oil (Brent crude and WTI crude) and natural gas (GAS) as well as the S&P Commodity Producers Oil & Gas Exploration & Production Index (SPOG) to determine the performance of global fossil fuel energy (dirty energy) investments. It also uses the ISE Global Wind Energy Index (GWE), Macerich Company Global Solar Energy Index Net Total Return (SUNIDX), and S&P Global Clean Energy Index (SPGC) to represent the performance of global clean energy investments. Finally, it considers two indices related to green financial assets: the Dow Jones Sustainability Index (DJSI) and MSCI World ESG Leaders Index (ESGL).

The daily price return is calculated as  $R_{i,t} = \ln(P_{i,t}/P_{i,t-1}) \times 100$ , where  $P_{i,t}$  and  $P_{i,t-1}$  are the daily closing prices at time  $t$  and time  $t - 1$ , respectively. Furthermore, this study follows the method proposed by Rogers and Satchell (1991) to calculate the daily realized volatility of an asset; the high (H), low (L), open (O), and close (C) prices of the asset are considered in this method. The daily realized volatility of an asset at time  $t$ , denoted  $V_{i,t}$ , is expressed as follows:

$$V_{i,t} = \ln\left(\frac{H_{i,t}}{O_{i,t}}\right) \times \left[ \ln\left(\frac{H_{i,t}}{O_{i,t}}\right) - \ln\left(\frac{C_{i,t}}{O_{i,t}}\right) \right] + \ln\left(\frac{L_{i,t}}{O_{i,t}}\right) \times \left[ \ln\left(\frac{L_{i,t}}{O_{i,t}}\right) - \ln\left(\frac{C_{i,t}}{O_{i,t}}\right) \right]$$

Table 1 presents the descriptive statistics for each transformed time series. All return series except those for BCH, MIOTA, and GAS show positive means, and ADA has the highest mean return of 0.885. The dirty and clean cryptocurrencies are the most volatile assets, with their standard deviation (SD) ranging from 10.123 to 20.500. Moreover, the dirty energy assets (SD: 5.419–8.293) are more volatile than the clean energy assets (SD: 3.164–5.638) and green financial assets (SD: 2.360–2.533). All return series except those for BCH, ETC, and LTC are negatively skewed, and all cryptocurrencies have excess kurtosis. Furthermore, the dirty energy assets (GAS, WTI, and Brent) have the highest mean realized volatility (1.184–0.465). ESGL has the highest SD of realized volatility (1.235). All realized volatility series exhibit positive skewness and have a kurtosis statistic greater than 3; thus, these series have a leptokurtic

distribution. The Jarque–Bera statistic indicates that none of the series has a normal distribution. The augmented Dickey–Fuller unit root test is significant for all series, implying that all series of returns and realized volatility are stationary.

[Table 1 goes here]

## **6. Empirical results and Discussion**

We empirically examine the dynamic correlations of dirty and clean cryptocurrencies with dirty energy markets, clean energy markets, and green financial markets by using the MS-GARCH-DCC model. Table 2 presents the AIC values obtained for the returns and realized volatilities of all considered assets when using MS-GARCH-DCC models with single-regime and two-regime settings. For the return series of BTC, LTC, ADA, XRP, and SPOG, the two-regime MS-GARCH-DCC model provides better fitting results than does the single-regime MS-GARCH-DCC model. However, the single-regime model provides better fitting results for the return series of the other assets (i.e., ETH, BCH, ETC, and so on). In addition, the two-regime model provides better fitting results for the realized volatilities of BTC, ETC, ADA, XRP, MIOTA, XLM, XNO, GAS, GWE, SPGC, and ESGL. The single-regime model provides better fitting results for the realized volatilities of only a few assets, namely ETH, BCH, LTC, Brent, WTI, SPOG, SUNIDX, and DJSI.

[Table 2 goes here]

To enable greater understanding of the potential diversification, hedging, or safe-haven roles of dirty and clean cryptocurrencies against dirty energy, clean energy, and green financial assets, our analyses report correlations of cryptocurrencies with different assets only if these correlations are significantly different for the low- versus high-volatility regime or the low-to-low-volatility versus high-to-high-volatility regimes. Tables 3 and 4 present the correlations between various cryptocurrencies and other financial assets in terms of returns and realized volatilities, respectively. These correlations are described in detail in the following text.

[Table 3 and Table 4 go here]

### **6.1 Correlations of cryptocurrencies with energy and green assets in terms of returns**

As presented in Table 3, the median coefficient of correlation between the returns of BTC and WTI is significantly lower in the high-volatility regime (0.1965173) than in the low-volatility regime (0.2071579), which indicates that BTC can be considered a diversifier for WTI (dirty energy asset). Moreover, BTC may be a diversifier for both

green financial assets (DJSI and ESGL) because the median coefficients of correlation of the returns of BTC with those of DJSI and ESGL are significantly lower in the high-volatility regime (0.1965173 and 0.2699286, respectively) than in the low-volatility regime (0.2071579 and 0.2980375, respectively). Overall, the empirical findings indicate that BTC is a suitable diversifier for WTI, DJSI, and ESGL. However, dirty cryptocurrencies do not appear to be diversifiers or hedging instruments in clean energy markets. In addition, clean cryptocurrencies fail to act as diversifiers, hedges, or safe havens for dirty energy assets, clean energy assets, or green financial assets.

## **6.2 Correlations of cryptocurrencies with energy and green assets in terms of realized volatilities**

As presented in Table 4, the median coefficients of correlation of the realized volatility of BTC with the realized volatilities of Brent, WTI, and SPOG are positive and significantly lower in the high-volatility regime than in the low-volatility regime<sup>2</sup>. Similarly, the median coefficients of correlation of the realized volatility of BTC with the realized volatilities of SUNIDX, SPGC, and DJSI are positive and significantly lower in the high-volatility regime than in the low-volatility regime<sup>3</sup>. Thus, BTC is a suitable diversifier for dirty energy (Brent, WTI, and SPOG), clean energy (SUNIDX and SPGC), and green (DJSI) assets. However, the median coefficient of correlation between the realized volatilities of BTC and GWE is positive and significantly higher in the high-to-high-volatility regime than in the low-to-low-volatility regime (0.0939399 vs. 0.0933581), indicating that investor fear spreads from clean energy markets (represented by GWE) to the BTC market during times of economic distress and uncertainty.

The median coefficients of correlation of the realized volatility of ETC with the realized volatilities of SPGC and DJSI are positive and significantly lower in the high-volatility regime than in the low-volatility regime; thus, ETC can provide financial diversification opportunities for clean energy (SPGC) and green (DJSI) assets<sup>4</sup>. Notably, the median coefficients of correlation of the realized volatility of LTC with the realized volatilities of GWE and ESGL are negative in the high-volatility regime (GWE:

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<sup>2</sup> Realized volatilities of Brent: high-volatility regime = 0.0622348, low-volatility regime = 0.0622387; realized volatilities of WTI: high-volatility regime = 0.0927166, low-volatility regime = 0.0927196; realized volatilities of SPOG: high-volatility regime = 0.2222297, low-volatility regime = 0.2222354.

<sup>3</sup> Realized volatilities of SUNIDX: high-volatility regime = 0.1283409, low-volatility regime = 0.1870612; realized volatilities of SPGC: high-to-high-volatility regime = 0.1839224, low-to-low-volatility regime = 0.2182906; realized volatilities of DJSI: high-volatility regime = 0.0832602, low-volatility regime = 0.1139407.

<sup>4</sup> Realized volatilities of SPGC: high-to-high-volatility regime = 0.0780917, low-to-low-volatility regime = 0.0851481; realized volatilities of DJSI: high-volatility regime = 0.0208814, low-volatility regime = 0.0208909.

-0.0179140; ESGL: -0.0740353). Thus, LTC has safe-haven properties for clean energy (GWE) and green (ESGL) assets.

The median coefficient of correlation between the realized volatilities of ADA and ESGL is negative in the high-to-high-volatility regime (-0.1504421); thus, ADA is a safe haven for green financial assets (represented by ESGL). Moreover, the median coefficient of correlation between the realized volatilities of XRP and GWE is negative in the high-to-high-volatility regime (-0.0250168); thus, XRP is also a safe haven for green financial assets (represented by ESGL). Investor fear spreads from clean energy (SUNIDX and SPGC) and green (DJSI) markets to the XRP markets under extreme market conditions, as the median coefficient of correlation between the realized volatilities of XRP to SUNIDX and SPGC is positive and significantly higher in the high-to-high-volatility regime than in the low-to-low-volatility regime<sup>5</sup>. The median coefficients of correlation of the realized volatility of MIOTA with the realized volatilities of clean energy assets (GWE, SUNIDX, and SPGC) are positive and significantly lower in the high-volatility regime than in the low-volatility regime<sup>6</sup>; thus, MIOTA can serve as a diversifier for clean energy assets (GWE, SUNIDX, and SPGC). In addition, the median coefficient of correlation between the realized volatilities of XLM and GWE is positive and significantly higher in the high-to-high-volatility regime than in the low-to-low-volatility regime (0.0841141 vs. 0.0272506); thus, investor fears spread from clean energy markets (GWE) to the XLM market during times of economic distress and uncertainty.

Overall, the empirical findings suggest that dirty cryptocurrencies (BTC and ETC) can act as diversifiers for some dirty energy, clean energy, and green assets. Moreover, some dirty (LTC) and clean (ADA and XRP) cryptocurrencies can act as safe havens for clean energy (GWE) and green (ESGL) assets. However, clean cryptocurrencies do not appear to offer diversification, hedging, or safe-haven against dirty energy assets. Finally, investor fear can spread from clean energy (GWE, SUNIDX, and SPGC) and green asset (DJSI) markets to dirty (BTC) and clean (XRP and XLM) cryptocurrency markets during periods of extreme market turmoil.

In conclusion, the empirical findings are broadly consistent with the proposed theoretical framework. In line with heterogeneous agent models, BTC exhibits

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<sup>5</sup> Realized volatilities of SUNIDX: high-volatility regime = 0.1120225, low-volatility regime = 0.0510861; realized volatilities of SPGC: high-to-high-volatility regime = 0.0979177, low-to-low-volatility regime = 0.0761085; realized volatilities of DJSI: high-volatility regime = 0.0204725, low-volatility regime = 0.0076233.

<sup>6</sup> Realized volatilities of GWE: high-to-high-volatility regime = 0.0156289, low-to-low-volatility regime = 0.0156420; realized volatilities of SUNIDX: high-volatility regime = 0.1007321, low-volatility regime = 0.1007360; realized volatilities of SPGC, high-to-high-volatility regime: 0.1036058, low-to-low-volatility regime = 0.1036140.

relatively weak correlations with several energy and green financial assets in the returns dimension, supporting its role as a diversifier under normal market conditions. The limited diversification capacity of dirty cryptocurrencies in clean energy markets further accords with the environmental risk transmission mechanism, which predicts stronger linkages between energy-intensive cryptocurrencies and conventional energy assets.

The absence of hedging and safe-haven properties in the returns analysis is likewise consistent with contagion and portfolio rebalancing theories, which imply that cross-market correlations tend to rise during periods of market stress. In the realized volatility dimension, however, more nuanced patterns emerge. Although price returns become more synchronized in turbulent periods, volatility dynamics capture risk transmission and investor fear, enabling certain cryptocurrencies, particularly LTC, ADA, and XRP, to exhibit safe-haven characteristics against specific clean energy and green financial assets.

Furthermore, the observed transmission of volatility from clean energy and green markets to both dirty and clean cryptocurrencies under extreme market conditions provides direct evidence of contagion effects, as predicted by King and Wadhvani (1990) and Kodres and Pritsker (2002). These findings underscore that the diversification and safe-haven roles of cryptocurrencies are highly state dependent and differ across returns and volatility channels. Overall, the results confirm the relevance of the theoretical mechanisms outlined in Section 3 and validate the suitability of the MS-GARCH-DCC framework for capturing regime-specific dynamics in the cryptocurrency–energy nexus.

### **6.3 Discussion**

The empirical results obtained using the MS-GARCH-DCC model offer crucial insights into the behavior of cryptocurrency markets as well as the correlations of cryptocurrencies with energy and green financial assets in terms of returns and volatility. These insights are encapsulated in the following four key findings.

First, the returns and realized volatilities of certain clean and dirty cryptocurrencies exhibit regime dependence. For example, the returns of BTC, LTC, ADA, XRP, and SPOG as well as the realized volatilities of BTC, ETC, and ADA exhibit regime dependence. Ignoring regime shifts in volatility dynamics can lead to biased estimations and thus reduce the accuracy of volatility forecasts. From a regulatory and risk management perspective, this result suggest that institutional investors and policymakers should account for regime-dependent dynamics when

assessing systemic risk exposures related to digital assets, particularly during periods of market stress.

Second, the correlations of cryptocurrencies with energy and green financial assets reveal differences between returns and realized volatilities. Moreover, the results indicate that the realized volatility connectedness of cryptocurrencies with energy and green financial assets is stronger than their return connectedness, which is in agreement with the results of Ji et al. (2018), Ozturk (2020), Attarzadeh and Balcilar (2022), and Yousaf et al. (2024). Specifically, our results indicate that BTC serves as a diversifier for WTI, DJSI, and ESGL in terms of returns and for Brent, WTI, SPOG, SUNIDX, SPGC, and DJSI in terms of realized volatilities. Other cryptocurrencies, such as ETC and IOTA, can also serve as diversifiers for different energy and green financial assets (e.g., SPGC, DJSI, GWE, and SUNIDX) in terms of realized volatilities. Furthermore, LTC, ADA, and XRP can act as safe havens for GWE and ESGL. In this context, the evidence indicates that the diversification role of certain cryptocurrencies operates mainly through volatility smoothing rather than return enhancement. This pattern implies that effective portfolio construction should explicitly distinguish between return-based and volatility-based channels when evaluating the role of cryptocurrencies, and investors should avoid treating them as uniform hedging instruments.

Third, analysis of the correlations between the returns of various cryptocurrencies and assets reveals that dirty and clean cryptocurrencies assume different roles in dirty and clean energy markets under different volatility regimes. Our results indicate that the correlations of BTC with WTI, DJSI, and ESGL are weaker during periods of market volatility; thus, BTC can serve as a diversifier for dirty energy (WTI) and green financial (DJSI and ESGL) assets, which enhances its utility for risk management and portfolio diversification. These results are consistent with those of other studies (Dutta et al., 2020; Goodell et al., 2022; Yousaf et al., 2022; Zeng et al., 2020). However, the empirical results of this study also indicate that BTC and other dirty cryptocurrencies do not act as diversifiers or hedges for clean energy markets. Moreover, these results suggest that clean cryptocurrencies do not serve as diversifiers, hedges, or safe havens against energy and green assets. Thus, suitable policy interventions are required to support the development and integration of clean digital assets within the broader green finance ecosystem.

Fourth, analysis of the correlations of the realized volatilities of different cryptocurrencies with those of various energy and green financial assets reveals that not all cryptocurrencies are immune to external market volatility. Our empirical results indicate that some cryptocurrencies, such as BTC, ETC, and MIOTA, can act as diversifiers for energy and green financial assets, whereas others, such as LTC, ADA,

and XRP, may function as safe havens. However, during periods of economic stress, certain cryptocurrencies may be affected by the spread of investor fear from financial markets. For instance, BTC and XLM exhibit signs of contagion from GWE, with volatility in GWE spilling over into the BTC and XLM markets during economic turmoil or uncertainty. Moreover, investor fear may spread from SUNIDX, SPGC, and DJSI to the XRP market during market turmoil. These results highlight that not all cryptocurrencies are resistant to external market volatility. Notably, investor fear spreads from clean energy and green asset markets to markets of clean cryptocurrencies during times of economic stress and uncertainty.

This finding may be attributable to clean cryptocurrencies, clean energy, and green financial assets being emerging markets that are considered to be similar by investors. Thus, the trends in these markets tend to be similar during times of economic stress and uncertainty. Therefore, investors should closely monitor the volatility and potential contagion risks of their cryptocurrency holdings, particularly during periods of economic stress. Identifying assets with high susceptibility to external market shocks, such as BTC, XRP, and XLM, can enable timely portfolio adjustments. For policymakers, this underscores the need to monitor cross-market contagion channels when designing climate finance regulations and stress-testing frameworks. In particular, integrating cryptocurrencies into climate-related financial risk assessments may help prevent unintended amplification of volatility within the broader green finance ecosystem during periods of market turmoil.

## **7. Conclusion**

The rapid rise of cryptocurrencies has attracted growing attention from investors and researchers due to their high volatility, weak correlations with traditional assets, and environmental implications. Moreover, the increasing global emphasis on sustainability has redirected attention toward clean cryptocurrencies, necessitating a deeper understanding of the dynamic relationships between dirty and clean cryptocurrencies and their interactions with energy and green financial markets.

This study employs the MS-GARCH-DCC model to capture regime-dependent behavior in the returns and realized volatilities of various cryptocurrencies, energy assets, and green financial assets, thus providing a nuanced perspective on how cryptocurrencies interact with other financial assets under various market conditions. The empirical results of this study indicate that cryptocurrencies have regime-dependent dynamics, with differences existing in their return and volatility connectedness with energy and green financial assets. In addition, the results highlight the importance of ongoing monitoring of contagion risks for cryptocurrencies.

The promotion of clean cryptocurrencies and the integration of green finance principles into investment strategies are critical directions for future development. Policymakers should actively support the transition toward sustainable digital assets and raise the environmental awareness of cryptocurrency investors to foster a more sustainable and resilient financial ecosystem. Future research may extend the insights of the present study by investigating the dynamics of clean cryptocurrency markets and their role in advancing the global transition to a low-carbon economy.

### **Conflict of Interest Statement**

Authors declare that they do not have financial or non-financial interests that are directly or indirectly related to this work submitted for publication.

### **Data Availability Statement**

Data are contained within the article.

## Reference

- Ali, S., Yousfi, M., Chughtai, S., & Du, A. M. (2024). Return and volatility connectedness between agricultural tokens and us equity sectors. *Research in International Business and Finance*, 72, 102544.
- Alshammari, S., Abid, I., Ayadi, R., Bouazizi, T., & Soliman, A. (2025). Exploring the impact of climate change on traditional and energy cryptocurrencies: A cross-sectional approach. *International Review of Financial Analysis*, 104714.
- Ardia, D., Bluteau, K., & Rüede, M. (2019a). Regime changes in Bitcoin GARCH volatility dynamics. *Finance Research Letters*, 29, 266-271.
- Ardia, D., Bluteau, K., Boudt, K., & Catania, L. (2018). Forecasting risk with Markov-switching GARCH models: A large-scale performance study. *International Journal of Forecasting*, 34(4), 733-747.
- Ardia, D., Bluteau, K., Boudt, K., Catania, L., & Trottier, D. A. (2019b). Markov-switching GARCH models in R: The MSGARCH package. *Journal of Statistical Software*, 91(4).
- Attarzadeh, A., & Balcilar, M. (2022). On the dynamic return and volatility connectedness of cryptocurrency, crude oil, clean energy, and stock markets: a time-varying analysis. *Environmental Science and Pollution Research*, 29(43), 65185-65196.
- Barnett, M., Brock, W., & Hansen, L. P. (2020). Pricing uncertainty induced by climate change. *The Review of Financial Studies*, 33(3), 1024-1066.
- Baur, D. G., & Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *Financial review*, 45(2), 217-229.
- Baur, D. G., & McDermott, T. K. (2010). Is gold a safe haven? International evidence. *Journal of Banking & Finance*, 34(8), 1886-1898.
- Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative assets?. *Journal of International Financial Markets, Institutions and Money*, 54, 177-189.
- Bauwens, L., Dufays, A., & Rombouts, J. V. (2014). Marginal likelihood for Markov-switching and change-point GARCH models. *Journal of Econometrics*, 178, 508-522.
- Będowska-Sójka, B., & Kliber, A. (2022). Can cryptocurrencies hedge oil price fluctuations? A pandemic perspective. *Energy Economics*, 115, 106360.
- Będowska-Sójka, B., & Kliber, A. (2024). Do investors in dirty and clean cryptocurrencies care about energy efficiency in the same way?. *Finance Research Letters*, 105852.
- Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3), 307-327.

- Bolton, P., & Kacperczyk, M. (2021). Do investors care about carbon risk?. *Journal of financial economics*, 142(2), 517-549.
- Cevik, E., Kirci Altinkeski, B., Cevik, E. I., & Dibooglu, S. (2022). Investor sentiments and stock markets during the COVID-19 pandemic. *Financial Innovation*, 8(1), 69.
- Chen, Y., Zhao, H., Li, Z., & Lu, J. (2020). A dynamic analysis of the relationship between investor sentiment and stock market realized volatility: Evidence from China. *PloS one*, 15(12), e0243080.
- Corbet, S., & Yarovaya, L. (2020). The environmental effects of cryptocurrencies. *Cryptocurrency and blockchain technology*, 1(149).
- Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis*, 62, 182-199.
- De Vries, A. (2018). Bitcoin's growing energy problem. *Joule*, 2(5), 801-805.
- De Vries, A., Gallersdörfer, U., Klaaßen, L., & Stoll, C. (2022). Revisiting Bitcoin's carbon footprint. *Joule*, 6(3), 498-502.
- Dias, R., Chambino, M., Galvão, R., Alexandre, P., & Irfan, M. (2024). Side Effects and Interactions: Exploring the Relationship between Dirty and Green Cryptocurrencies and Clean Energy Stock Indices. *International Journal of Energy Economics and Policy*, 14(3), 411-416.
- Dokas, I., Oikonomou, G., Panagiotidis, M., & Spyromitros, E. (2023). Macroeconomic and uncertainty shocks' effects on energy prices: A comprehensive literature review. *Energies*, 16(3), 1491.
- Duan, K., Zhang, L., Urquhart, A., Yao, K., & Peng, L. (2024). Do clean and dirty cryptocurrencies connect financial assets differently? The perspective of market inefficiency. *Research in International Business and Finance*, 70, 102351.
- Duan, K., Zhao, Y., Urquhart, A., & Huang, Y. (2023). Do clean and dirty cryptocurrencies connect with financial assets differently? The role of economic policy uncertainty. *Energy Economics*, 127, 107079.
- Dutta, A., Das, D., Jana, R. K., & Vo, X. V. (2020). COVID-19 and oil market crash: Revisiting the safe haven property of gold and Bitcoin. *Resources Policy*, 69, 101816.
- Giglio, S., Kelly, B., & Stroebel, J. (2021). Climate finance. *Annual review of financial economics*, 13(1), 15-36.
- Goodell, J. W., Corbet, S., Yadav, M. P., Kumar, S., Sharma, S., & Malik, K. (2022). Time and frequency connectedness of green equity indices: Uncovering a socially important link to Bitcoin. *International Review of Financial Analysis*, 84, 102379.
- Guesmi, K., Saadi, S., Abid, I., & Ftiti, Z. (2019). Portfolio diversification with virtual

- currency: Evidence from bitcoin. *International Review of Financial Analysis*, 63, 431-437.
- Haas, M., Mittnik, S., & Paoletta, M. S. (2004). A new approach to Markov-switching GARCH models. *Journal of Financial Econometrics*, 2(4), 493-530.
- Hamilton, J. D., & Susmel, R. (1994). Autoregressive conditional heteroskedasticity and changes in regime. *Journal of econometrics*, 64(1-2), 307-333.
- Haq, I. U., Ferreira, P., Quintino, D. D., Huynh, N., & Samantreeporn, S. (2023). Economic policy uncertainty, energy and sustainable cryptocurrencies: investigating dynamic connectedness during the COVID-19 pandemic. *Economies*, 11(3), 76.
- Hayes, A. S. (2017). Cryptocurrency value formation: An empirical study leading to a cost of production model for valuing bitcoin. *Telematics and informatics*, 34(7), 1308-1321.
- Hsu, S. H., Cheng, P. K., & Yang, Y. (2024). Diversification, hedging, and safe-haven characteristics of cryptocurrencies: A structural change approach. *International Review of Financial Analysis*, 93, 103211.
- Husain, A., Yii, K. J., & Lee, C. C. (2023). Are green cryptocurrencies really green? New evidence from wavelet analysis. *Journal of Cleaner Production*, 417, 137985.
- Inayati, S., Iriawan, N., & Irhamah. (2024). A Markov Switching Autoregressive Model with Time-Varying Parameters. *Forecasting*, 6(3), 568-590.
- Jacquet, P. and Mans, B. (2019). Green mining: Toward a less energetic impact of cryptocurrencies. In Proceedings of the INFOCOM 2019—IEEE Conference on Computer Communications Workshops, INFOCOM WKSHPS, Paris, France, 29 April–2 May 2019.
- Ji, Q., Zhang, D., & Geng, J. B. (2018). Information linkage, dynamic spillovers in prices and volatility between the carbon and energy markets. *Journal of Cleaner Production*, 198, 972-978.
- Kaur, R., Kumar, P., Radulescu, M., Mohd, S., & Dascalu, N. (2025). Spillover Nexus among Green Cryptocurrency, Sectoral Renewable Energy Equity Stock and Agricultural Commodity: Implications for Portfolio Diversification. *Economics*, 19(1), 20250138.
- King, M. A., & Wadhvani, S. (1990). Transmission of volatility between stock markets. *The review of financial studies*, 3(1), 5-33.
- Kodres, L. E., & Pritsker, M. (2002). A rational expectations model of financial contagion. *The journal of finance*, 57(2), 769-799.
- Kristoufek, L. (2018). On Bitcoin markets (in) efficiency and its evolution. *Physica A: statistical mechanics and its applications*, 503, 257-262.
- Krolzig, H. M., Marcellino, M., & Mizon, G. (2002). A Markov-switching vector

- equilibrium correction model of the UK labour market. *Empirical Economics*, 27(2), 233-254.
- Kruskal, W. H., & Wallis, W. A. (1952). Use of ranks in one-criterion variance analysis. *Journal of the American statistical Association*, 47(260), 583-621.
- Kuang, W. (2025). Greening crypto portfolios: the diversification and safe haven potential of clean cryptocurrencies. *Humanities and Social Sciences Communications*, 12(1), 1-23.
- Lamoureux, C. G., & Lastrapes, W. D. (1990). Persistence in variance, structural change, and the GARCH model. *Journal of Business & Economic Statistics*, 8(2), 225-234.
- Lewellen, W. G., Lease, R. C., & Schlarbaum, G. G. (1977). Patterns of investment strategy and behavior among individual investors. *The Journal of Business*, 50(3), 296-333.
- Li, L. (2022). The dynamic interrelations of oil-equity implied volatility indexes under low and high volatility-of-volatility risk. *Energy Economics*, 105, 105756.
- Li, L., & Miu, P. (2023). Are cryptocurrencies a safe haven for stock investors? A regime-switching approach. *Journal of Empirical Finance*, 70, 367-385.
- Li, M. Y. (2008). Hybrid versus highbred: combined economic models with time-series analyses. *Quantitative Finance*, 8(6), 637-647.
- Liu, Y., & Tsyvinski, A. (2021). Risks and returns of cryptocurrency. *The Review of Financial Studies*, 34(6), 2689-2727.
- Mann, H. B., & Whitney, D. R. (1947). On a Test of Whether one of Two Random Variables is Stochastically Larger than the Other. *The Annals of Mathematical Statistics*, 18(1), 50-60.
- Marco, T., Mighri, Z., Tiwari, A. K., & Sarwar, S. (2023). A quantile-time-frequency connectedness investigation through the dirty and clean cryptocurrencies spillover. *Journal of Cleaner Production*, 425, 138889.
- Mnif, E., Zghidi, N., & Jarboui, A. (2025). Evaluating the effectiveness of green bonds and clean cryptocurrencies as hedging tools in volatile financial environments. *Management of Environmental Quality: An International Journal*, 36(3), 681-705.
- Molnár, P. (2012). Properties of range-based volatility estimators. *International Review of Financial Analysis*, 23, 20-29.
- Mora, C., Rollins, R. L., Taladay, K., Kantar, M. B., Chock, M. K., Shimada, M., & Franklin, E. C. (2018). Bitcoin emissions alone could push global warming above 2 C. *Nature Climate Change*, 8(11), 931-933.
- Naeem, M. A., Farid, S., Balli, F., & Hussain Shahzad, S. J. (2021). Hedging the downside risk of commodities through cryptocurrencies. *Applied Economics Letters*, 28(2), 153-160.

- Naeem, M. A., Nguyen, T. T. H., Karim, S., & Lucey, B. M. (2023). Extreme downside risk transmission between green cryptocurrencies and energy markets: the diversification benefits. *Finance Research Letters*, 58, 104263.
- Nguyen, A. P. N., Mai, T. T., Bezbradica, M., & Crane, M. (2023). Volatility and returns connectedness in cryptocurrency markets: Insights from graph-based methods. *Physica A: Statistical Mechanics and its Applications*, 632, 129349.
- Octopus Energy Generation (2020). Renewables and the recovery: accelerating investment in a post-pandemic world, November 2022.
- Okorie, D. I., & Lin, B. (2020). Crude oil price and cryptocurrencies: evidence of volatility connectedness and hedging strategy. *Energy economics*, 87, 104703.
- Ozturk, S. S. (2020). Dynamic connectedness between bitcoin, gold, and crude oil volatilities and returns. *Journal of Risk and Financial Management*, 13(11), 275.
- Pham, L., Huynh, T. L. D., & Hanif, W. (2023). Time-varying asymmetric spillovers among cryptocurrency, green and fossil-fuel investments. *Global Finance Journal*, 58, 100891.
- Prasad Yadav, M., Pandey, A., Taghizadeh-Hesary, F., Arya, V., & Mishra, N. (2022). Volatility Spill-Over of Green Bond with Renewable Energy and Crypto Market: An Application of Battery of Test. Available at SSRN 4185434.
- Rao, A., Gupta, M., Sharma, G. D., Mahendru, M., & Agrawal, A. (2022). Revisiting the financial market interdependence during COVID-19 times: a study of green bonds, cryptocurrency, commodities and other financial markets. *International Journal of Managerial Finance*, 18(4), 725-755.
- Rehman, M. U., & Kang, S. H. (2021). A time–frequency comovement and causality relationship between Bitcoin hashrate and energy commodity markets. *Global Finance Journal*, 49, 100576.
- Ren, B., & Lucey, B. (2022). A clean, green haven?—Examining the relationship between clean energy, clean and dirty cryptocurrencies. *Energy Economics*, 109, 105951.
- Rogers, L. C. G., & Satchell, S. E. (1991). Estimating variance from high, low and closing prices. *The Annals of Applied Probability*, 504-512.
- Selmi, R., Mensi, W., Hammoudeh, S., & Bouoiyour, J. (2018). Is Bitcoin a hedge, a safe haven or a diversifier for oil price movements? A comparison with gold. *Energy Economics*, 74, 787-801.
- Stensås, A., Nygaard, M. F., Kyaw, K., & Treepongkaruna, S. (2019). Can Bitcoin be a diversifier, hedge or safe haven tool?. *Cogent Economics & Finance*, 7(1), 1593072.
- Symitsi, E., & Chalvatzis, K. J. (2018). Return, volatility and shock spillovers of Bitcoin with energy and technology companies. *Economics Letters*, 170, 127-130.

- Tse, Y. K., & Tsui, A. K. C. (2002). A multivariate GARCH model with time-varying correlations. *Journal of Business and Economic Statistics*, 20, 351-362.
- Umar, Z., Choi, S. Y., Teplova, T., & Sokolova, T. (2023). Dynamic spillovers and portfolio implication between green cryptocurrencies and fossil fuels. *PloS one*, 18(8), e0288377.
- Umar, Z., Usman, M., Umar, M., & Ktaish, F. (2024). Interdependencies and risk management strategies between green cryptocurrencies and traditional energy sources. *Energy Economics*, 136, 107742.
- Urquhart, A. (2016). The inefficiency of Bitcoin. *Economics Letters*, 148, 80-82.
- Wen, F., Tong, X., & Ren, X. (2022). Gold or Bitcoin, which is the safe haven during the COVID-19 pandemic?. *International Review of Financial Analysis*, 81, 102121.
- Wendl, M., Doan, M. H., & Sassen, R. (2023). The environmental impact of cryptocurrencies using proof of work and proof of stake consensus algorithms: A systematic review. *Journal of Environmental Management*, 326, 116530.
- Xie, W., & Cao, G. (2024). Volatility and returns connectedness between cryptocurrency and China's financial markets: A TVP-VAR extended joint connectedness approach. *The North American Journal of Economics and Finance*, 74, 102231.
- Yadav, M. P., Kumar, S., Mukherjee, D., & Rao, P. (2023). Do green bonds offer a diversification opportunity during COVID-19?—an empirical evidence from energy, crypto, and carbon markets. *Environmental Science and Pollution Research*, 30(3), 7625-7639.
- Yermack, D., (2015). Is Bitcoin a Real Currency? An Economic Appraisal. In: Chuen, D. L. K. (Eds.), *Handbook of Digital Currency: Bitcoin, Innovation, Financial Instruments and Big Data*. Academic Press: New York.
- Yermack, D., (2015). Is bitcoin a real currency? An economic appraisal. In: Chuen, D. L. K. (Eds.), *Handbook of digital currency: bitcoin, innovation, financial instruments and big data*. Academic Press: New York.
- Yousaf, I., Ali, S., Bouri, E., & Saeed, T. (2022). Information transmission and hedging effectiveness for the pairs crude oil-gold and crude oil-Bitcoin during the COVID-19 outbreak. *Economic Research-Ekonomska Istraživanja*, 35(1), 1913-1934.
- Yousaf, I., Cui, J., & Ali, S. (2024). Dynamic spillover between green cryptocurrencies and stocks: A portfolio implication. *International Review of Economics & Finance*, 103661.
- Zeng, T., Yang, M., & Shen, Y. (2020). Fancy Bitcoin and conventional financial assets: Measuring market integration based on connectedness networks. *Economic Modelling*, 90, 209-220.

- Zhou, X., Guo, X., & Ji, J. (2025a). Exploring the impact of cryptocurrency and energy markets on global carbon emissions: a wavelet quantile analysis. *Environment, Development and Sustainability*, 1-26.
- Zhou, X., Guo, X., & Chen, Y. (2025b). Analyzing the interconnections between clean and dirty cryptocurrency and energy markets. *Physica A: Statistical Mechanics and its Applications*, 674, 130769.

Table 1 Summary statistics

	BTC	ETH	BCH	ETC	LTC	ADA	XRP	MIOTA	XLM	XNO	Brent	WTI	GAS	SPOG	GWE	SUNIDX	SPGC	DJSI	ESGL
<b>Returns</b>																			
Mean	0.706	0.683	-0.318	0.161	0.094	0.885	0.279	-0.267	0.410	0.645	0.095	0.114	-0.180	0.090	0.053	0.143	0.108	0.123	0.147
Min	31.110	48.854	88.426	96.086	76.265	153.727	112.134	134.043	80.450	152.097	31.352	27.576	21.835	16.191	11.236	16.361	16.571	8.997	10.198
Max	-40.789	-53.097	-74.265	-59.049	-72.601	-56.937	-67.529	-132.648	-66.375	-59.221	-29.071	-34.686	-27.630	-38.786	-21.481	-30.863	-24.720	-13.400	-13.187
SD	10.123	13.034	16.970	16.350	14.197	18.862	17.062	20.021	15.693	20.500	5.800	6.191	8.293	5.419	3.164	5.638	4.275	2.360	2.533
Skew.	-0.456	-0.405	0.332	0.840	0.084	2.545	1.393	1.097	1.061	2.155	-0.315	-0.546	-0.577	-1.307	-0.843	-0.389	-0.352	-0.810	-0.787
Kur.	4.875	5.543	8.090	7.841	7.231	21.700	12.797	24.619	8.895	15.817	9.234	8.797	4.046	11.373	9.648	5.443	7.001	8.901	9.075
J-B	60.8*	99.8*	368.9*	367.5*	251.0*	5258.6*	1452.5*	6610.5*	549.6*	2559.7*	549.6*	487.1*	34.0*	1077.1*	658.6*	92.0*	231.0*	524.3*	551.3*
ADF	-16.5*	-16.8*	-17.7*	-17.5*	-17.7*	-17.8*	-16.7*	-21.6*	-16.6*	-13.2*	-17.6*	-15.8*	-18.2*	-15.9*	-18.5*	-18.5*	-11.2*	-19.0*	-19.0*
<b>Realized Volatility</b>																			
Mean	0.010	0.015	0.025	0.027	0.019	0.028	0.026	0.006	0.027	0.044	0.465	0.510	1.184	0.174	0.210	0.394	0.202	0.087	0.225
Min	0.189	0.221	0.804	0.569	0.255	0.292	0.337	0.132	0.392	1.000	3.600	3.182	10.094	1.310	2.514	1.765	1.040	0.530	22.711
Max	0.000	0.000	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.047	0.020	0.125	0.001	0.020	0.034	0.007	0.007	0.010
SD	0.017	0.024	0.056	0.052	0.032	0.044	0.051	0.012	0.050	0.093	0.385	0.411	0.847	0.140	0.187	0.230	0.132	0.066	1.235
Skew.	5.219	4.569	9.047	5.562	4.797	3.453	3.897	6.924	4.014	5.987	3.394	3.226	3.951	2.839	6.565	1.794	2.210	2.724	17.991
Kur.	42.009	30.511	113.718	44.775	30.924	16.406	19.370	64.677	21.883	50.000	20.407	17.318	38.335	18.178	72.858	9.329	11.630	14.480	328.039
J-B	22897.5*	11800.4*	176727.9*	26242.3*	12241.7*	3193.3*	4615.8*	56108.0*	5911.9*	33031.6*	4901.5*	3463.1*	18408.6*	3687.7*	70945.1*	743.2*	1320.1*	2267.1*	1501691.0*
ADF	-12.71*	-13.61*	-23.44*	-6.38*	-13.60*	-11.46*	-4.31*	-4.00*	-7.19*	-13.89*	-5.80*	-5.87*	-6.89*	-8.31*	-9.55*	-8.21*	-6.92*	-6.26*	-18.24*

Note: SD, Skew. and Kurt. refer to the values of standard deviation, the skewness and kurtosis coefficients. J-B is the Jarque-Bera test statistic of normality. ADF is Augmented Dickey–Fuller unit root test. \* denotes significance at the 1% level.

Table 2 AIC of single assets

Model	Return		Realized Volatility	
	Single-regime model	Two-regimes model	Single-regime model	Two-regimes model
Dirty cryptocurrencies				
BTC	2442.728	<b>2441.319</b>	-2290.571	<b>-2304.887</b>
ETH	<b>2605.690</b>	2615.788	<b>-2005.133</b>	-1989.251
BCH	<b>2728.418</b>	2733.614	<b>-1727.348</b>	-1521.202
ETC	<b>2721.747</b>	2736.512	-1590.367	<b>-1614.015</b>
LTC	2663.645	<b>2656.725</b>	<b>-1882.308</b>	-1693.830
Clean cryptocurrencies				
ADA	2736.012	<b>2735.183</b>	-1625.437	<b>-1633.132</b>
XRP	2619.834	<b>2616.099</b>	-1582.155	<b>-1607.092</b>
MIOTA	<b>2672.782</b>	2675.521	-2750.259	<b>-2779.692</b>
XLM	<b>2643.644</b>	2654.927	-1627.192	<b>-1634.424</b>
XNO	<b>2752.967</b>	2756.502	-1295.963	<b>-1319.283</b>
Fossil Fuel Energy				
Brent	<b>2000.862</b>	2011.525	<b>110.992</b>	116.500
WTI	<b>2053.915</b>	2063.027	<b>164.215</b>	165.336
GAS	<b>2334.405</b>	2336.691	853.582	<b>837.065</b>
SPOG	2007.138	<b>2006.336</b>	<b>-463.755</b>	-461.779
Clean Energy				
GWE	<b>1640.165</b>	1648.473	-336.321	<b>-347.315</b>
SUNIDX	<b>2072.971</b>	2075.169	<b>38.610</b>	48.596
SPGC	<b>1829.351</b>	1834.704	-387.735	<b>-390.273</b>
Green Financial Asset				
DJSI	<b>1426.970</b>	1433.413	<b>-993.458</b>	-986.110
ESGL	<b>1461.770</b>	1467.887	-441.509	<b>-477.396</b>

Table 3 Correlations of cryptocurrencies with energy and green assets in terms of returns

Assets	Selected percentiles				<i>p</i> -value <sup>a</sup>	Roles
	25 <sup>th</sup>	50 <sup>th</sup>	75 <sup>th</sup>	95 <sup>th</sup>		
<b>Bitcoin (BTC) v.s.</b>						
WTI					0.034**	
Low-volatility regime	0.1719973	0.2071579	0.2332573	0.2502013		Diversifier
High-volatility regime	0.1528699	0.1965173	0.2270028	0.2514464		
SPOG					0.001***	
Low-to-low-volatility regime	0.2080621	0.2496487	0.2723600	0.2928284		-
Low-to-high-volatility regime	0.2193878	0.2193878	0.2193878	0.2193878		
High-to-low-volatility regime	0.1802471	0.2246625	0.2575937	0.2864701		
High-to-high-volatility regime	0.2540990	0.2660572	0.2762463	0.2850832		
DJSI					<0.001***	
Low-volatility regime	0.2671415	0.2954236	0.3197669	0.3360930		Diversifier
High-volatility regime	0.2063249	0.2605328	0.3089446	0.3349070		
ESGL					<0.001***	
Low-volatility regime	0.2629166	0.2980375	0.3191034	0.3345293		Diversifier
High-volatility regime	0.2068436	0.2699286	0.3076540	0.3325022		
<b>Bitcoin Cash (BCH) v.s.</b>						
SPOG					0.024**	
Low-volatility regime	0.1787574	0.1834077	0.1868141	0.1898086		-
High-volatility regime	0.1859635	0.1885703	0.1887539	0.1899059		
<b>Ethereum Classic (ETC) v.s.</b>						
SPOG					0.016**	
Low-volatility regime	0.1651569	0.1802773	0.1920343	0.2001974		-
High-volatility regime	0.1908760	0.1954571	0.1978757	0.2020820		
<b>Ripple (XRP) v.s.</b>						
WTI					0.062*	
Low-volatility regime	0.1013523	0.1067258	0.1110850	0.1141550		-
High-volatility regime	0.1031061	0.1086701	0.1120204	0.1145822		
<b>Stellar (XLM) v.s.</b>						
SPOG					0.049**	
Low-volatility regime	0.2242939	0.2275833	0.2310085	0.2331105		-
High-volatility regime	0.2284249	0.2316265	0.2329432	0.2331711		

Note: <sup>a</sup> Comparison of different regimes by Mann-Whitney test or Kruskal-Wallis test.

\*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4 Correlations of cryptocurrencies with energy and green assets in terms of realized volatilities

Assets	Selected percentiles				<i>p</i> -value <sup>a</sup>	Roles
	25 <sup>th</sup>	50 <sup>th</sup>	75 <sup>th</sup>	95 <sup>th</sup>		
<b>Bitcoin (BTC) v.s.</b>						
Brent					0.098*	
Low-volatility regime	0.0622304	0.0622387	0.0622454	0.0622514		Diversifier
High-volatility regime	0.0622272	0.0622348	0.0622432	0.0622515		
<b>WTI</b>						
					0.097*	
Low-volatility regime	0.0927115	0.0927196	0.0927279	0.0927336		Diversifier
High-volatility regime	0.0927102	0.0927166	0.0927220	0.0927342		
<b>SPOG</b>						
					0.066*	
Low-volatility regime	0.2222273	0.2222354	0.2222434	0.2222480		Diversifier
High-volatility regime	0.2222261	0.2222297	0.2222397	0.2222470		
<b>GWE</b>						
					0.020**	
Low-to-low-volatility regime	0.0547093	0.0933581	0.1379428	0.1643720		Contagion of fear
Low-to-high-volatility regime	0.0730660	0.1303719	0.1593396	0.1690977		
High-to-low-volatility regime	0.0434591	0.0778025	0.1234772	0.1432678		
High-to-high-volatility regime	0.0938809	0.0939399	0.0939989	0.0940462		
<b>SUNIDX</b>						
					0.001***	
Low-volatility regime	0.1096936	0.1870612	0.2540494	0.3300807		Diversifier
High-volatility regime	0.0713952	0.1283409	0.1745467	0.2556562		
<b>SPGC</b>						
					0.001***	
Low-to-low-volatility regime	0.1511983	0.2182906	0.2657144	0.3001333		Diversifier
Low-to-high-volatility regime	0.1293732	0.1713283	0.2559553	0.2983416		
High-to-low-volatility regime	0.1262903	0.1514850	0.1871935	0.2201648		
High-to-high-volatility regime	0.1571235	0.1839224	0.2214956	0.2579970		
<b>DJSI</b>						
					0.004***	
Low-volatility regime	0.0698742	0.1139407	0.1491692	0.1718808		Diversifier
High-volatility regime	0.0564273	0.0832602	0.1062588	0.1630605		
<b>ESGL</b>						
					<0.001***	
Low-to-low-volatility regime	-0.0440314	0.0220003	0.0892211	0.1757541		
Low-to-high-volatility regime	-0.1099935	-0.0915657	-0.0649784	-0.0196367		
High-to-low-volatility regime	-0.0880264	-0.0354815	-0.0093567	0.1157184		
High-to-high-volatility regime	-	-	-	-		

Note: <sup>a</sup> Comparison of different regimes by Mann-Whitney test or Kruskal-Wallis test.

\*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4 Correlations of cryptocurrencies with energy and green assets in terms of realized volatilities  
(continued)

Assets	Selected percentiles				<i>p</i> -value <sup>a</sup>	Roles
	25 <sup>th</sup>	50 <sup>th</sup>	75 <sup>th</sup>	95 <sup>th</sup>		
<b>Ethereum Classic (ETC) v.s.</b>						
SPGC					0.081*	
Low-to-low-volatility regime	0.0472311	0.0851481	0.1217427	0.1478399		Diversifier
Low-to-high-volatility regime	0.0655923	0.0909060	0.1175529	0.1436176		
High-to-low-volatility regime	0.1121559	0.1253827	0.1429138	0.1468004		
High-to-high-volatility regime	0.0642114	0.0780917	0.0841925	0.1218611		
DJSI					0.017**	
Low-volatility regime	0.0208779	0.0208909	0.0209028	0.0209484		Diversifier
High-volatility regime	0.0208649	0.0208814	0.0208912	0.0208999		
ESGL					0.013***	
Low-to-low-volatility regime	-0.0292225	0.0439381	0.1128027	0.2738595		-
Low-to-high-volatility regime	-0.0326329	-0.0202253	-0.0175209	-0.0038036		
High-to-low-volatility regime	-0.0945352	-0.0136012	0.0534226	0.1311541		
High-to-high-volatility regime	-	-	-	-		
<b>Litecoin (LTC) v.s.</b>						
GWE					0.050**	
Low-volatility regime	-0.0302108	0.0112294	0.0548012	0.0827869		Safe haven
High-volatility regime	-0.0450459	-0.0179140	0.0259822	0.0720616		
ESGL					0.094*	
Low-volatility regime	-0.0940523	-0.0298892	0.0452322	0.1120109		Safe haven
High-volatility regime	-0.0833073	-0.0740353	-0.0716800	-0.0584948		
<b>Cardano (ADA) v.s.</b>						
ESGL					0.006***	
Low-to-low-volatility regime	-0.0875902	-0.0053370	0.1177726	0.3647843		Safe haven
Low-to-high-volatility regime	-0.1492729	-0.1287174	-0.1153104	-0.0898640		
High-to-low-volatility regime	0.0067965	0.0553717	0.1003521	0.1297870		
High-to-high-volatility regime	-0.1504421	-0.1504421	-0.1504421	-0.1504421		
<b>Ripple (XRP) v.s.</b>						
GWE					<0.001***	
Low-to-low-volatility regime	-0.0508523	-0.0059421	0.0279810	0.0649210		Safe haven
Low-to-high-volatility regime	-0.0111990	0.0092659	0.0421209	0.0628997		
High-to-low-volatility regime	-0.0182169	0.0279757	0.0576217	0.0788340		
High-to-high-volatility regime	-0.0432441	-0.0250168	0.0547986	0.0749905		

Note: <sup>a</sup> Comparison of different regimes by Mann-Whitney test or Kruskal-Wallis test.

\*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4 Correlations of cryptocurrencies with energy and green assets in terms of realized volatilities  
(continued)

Assets	Selected percentiles				<i>p</i> -value <sup>a</sup>	Roles
	25 <sup>th</sup>	50 <sup>th</sup>	75 <sup>th</sup>	95 <sup>th</sup>		
<b>Ripple (XRP) v.s.</b>						
SUNIDX					<0.001***	
Low-volatility regime	-0.0046120	0.0510861	0.0982398	0.1701173		Contagion of fear
High-volatility regime	0.0679635	0.1120225	0.1534016	0.2000599		
<b>SPGC</b>						
					0.003***	
Low-to-low-volatility regime	0.0477631	0.0761085	0.1049611	0.1458150		Contagion of fear
Low-to-high-volatility regime	0.0487589	0.0913104	0.1222182	0.1622223		
High-to-low-volatility regime	0.0594778	0.1117608	0.1493224	0.1705242		
High-to-high-volatility regime	0.0688164	0.0979177	0.1557317	0.1720724		
<b>DJSI</b>						
					0.003***	
Low-volatility regime	-0.0053499	0.0076233	0.0287598	0.04213878		Contagion of fear
High-volatility regime	-0.0010369	0.0204725	0.0370227	0.0487157		
<b>ESGL</b>						
					<0.001***	
Low-to-low-volatility regime	-0.0529093	-0.0210582	0.0046825	0.0311510		-
Low-to-high-volatility regime	-0.0241304	-0.0219965	-0.0167578	-0.0060545		
High-to-low-volatility regime	-0.0365555	-0.0059277	0.0220465	0.1138154		
High-to-high-volatility regime	-	-	-	-		
<b>IOTA (MIOTA) v.s.</b>						
<b>GAS</b>						
					<0.001***	
Low-to-low-volatility regime	-0.0583351	0.0210230	0.0851041	0.1803334		-
Low-to-high-volatility regime	-0.0524735	-0.0084762	0.0029158	0.0120293		
High-to-low-volatility regime	-0.1146181	-0.0705542	-0.0278972	0.0665846		
High-to-high-volatility regime	-	-	-	-		
<b>GWE</b>						
					0.014**	
Low-to-low-volatility regime	0.0156333	0.0156420	0.0156503	0.0156557		Diversifier
Low-to-high-volatility regime	0.0156337	0.0156387	0.0156496	0.0156547		
High-to-low-volatility regime	0.0156368	0.0156436	0.0156498	0.0156536		
High-to-high-volatility regime	0.0156268	0.0156289	0.0156296	0.0156322		
<b>SUNIDX</b>						
					0.047**	
Low-volatility regime	0.1007288	0.1007360	0.1007437	0.1007495		Diversifier
High-volatility regime	0.1007251	0.1007321	0.1007406	0.1007499		

Note: <sup>a</sup> Comparison of different regimes by Mann-Whitney test or Kruskal-Wallis test.

\*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4 Correlations of cryptocurrencies with energy and green assets in terms of realized volatilities  
(continued)

Assets	Selected percentiles				<i>p</i> -value <sup>a</sup>	Roles
	25 <sup>th</sup>	50 <sup>th</sup>	75 <sup>th</sup>	95 <sup>th</sup>		
<b>IOTA (MIOTA) v.s.</b>						
SPGC					<0.001***	
Low-to-low-volatility regime	0.1036063	0.1036140	0.1036242	0.1036313		Diversifier
Low-to-high-volatility regime	0.1036113	0.1036189	0.1036249	0.1036289		
High-to-low-volatility regime	0.1036132	0.1036191	0.1036252	0.1036300		
High-to-high-volatility regime	0.1036040	0.1036058	0.1036095	0.1036161		
<b>ESGL</b>						
Low-to-low-volatility regime	-0.0793091	0.0105925	0.0988119	0.2670408	0.050**	
Low-to-high-volatility regime	0.0820193	0.1064796	0.1175594	0.1257697		
High-to-low-volatility regime	-0.1421787	-0.0167069	0.0867028	0.2247168		-
High-to-high-volatility regime	-	-	-	-		
<b>Stellar (XLM) v.s.</b>						
GWE					0.002***	
Low-to-low-volatility regime	-0.0084984	0.0272506	0.0715038	0.1089505		Contagion of fear
Low-to-high-volatility regime	-0.0176225	0.0230976	0.0782389	0.0880792		
High-to-low-volatility regime	-0.0324308	0.0034859	0.0336588	0.0726683		
High-to-high-volatility regime	0.0150949	0.0841141	0.1078428	0.1161393		

Note: <sup>a</sup> Comparison of different regimes by Mann-Whitney test or Kruskal-Wallis test.

\*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively.