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Research article

Interlinkages between Bitcoin, green financial assets, oil, and emerging stock markets

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Abstract: In this article, we describe the novel properties of Bitcoin and green financial assets and empirically examine the connectedness between Bitcoin and two green financial assets (i.e., carbon emissions, green bonds) and two representative markets of conventional assets (i.e., oil and emerging stock). This study also analyzes whether Bitcoin, carbon, green bonds, oil, and emerging stock assets can hedge against any market turbulence. From observed findings, Bitcoin was not an effective substitute for green bond assets. Thus, Bitcoin is not a valuable hedge instrument to substitute green bonds to mitigate climate risks. More precisely, the findings of the study show that carbon assets outperform emerging stock assets amidst the COVID-19 crisis, while the stock markets incurred significant losses. Crucially, the innovative findings also played an important role for policymakers interested in decarbonizing the crypto-assets.

Keywords: Bitcoin mining; carbon emissions; climate changes; green financial assets; portfolio optimization; wavelet coherence

JEL Codes: B23, C32, G10, Q4

Abbreviations: BTC: Bitcoin; GB: green bond; Stock: emerging stock market

1. Introduction

Globally, cryptocurrencies have experienced vast growth and naturally attracted investors' attention owing to their performance and potential diversification features (Charfeddine et al., 2020;

Huynh et al., 2021; Naeem et al., 2022; Chen et al. 2022). As of 5 February 2024, the total market cap of all crypto-assets including stablecoins and tokens reached approximately $1.63 trillion, and Bitcoin is the most traded crypto, accounting for 51.9% of the total market cap, nearing $846.49 billion (refer to CoinMarketCap; https://coinmarketcap.com/). While the Bitcoin (BTC) transaction volumes have increased, competition on the network has also risen. Energy-intensive cryptocurrency mining validates blockchains and pays miners, making it more complicated to estimate energy usage (Arfaoui, Naeem, Boubaker, Mirza, Karim, 2023).

According to a report released by the Cambridge Centre for Alternative Finance (CCAF), Bitcoin's current energy usage is about 110 terawatt-hours (TWh) yearly, which is estimated to be around 0.55% of global energy generation. The carbon footprint of all Bitcoin transactions in a year is comparable to 97.14 million tons of carbon dioxide emissions; see Carter (2021). In addition, the Bitcoin Energy Consumption Index constructed by Digiconomist demonstrates that one Bitcoin trade is equivalent to the electricity consumption of a common American household for 53 days (Pan et al., 2023). Major environmental concerns surrounding Bitcoin (BTC) mining have intensified sustainability-aware investors' dilemma to achieve the economic payoff of Bitcoin versus adopting financial backing to the green bonds' philosophy (Bariviera and Merediz-Solà, 2021).

In this spirit, the rapid increase of the potential environmental impacts associated with crypto results in global investors concentrating more on inclusive green growth investments to diversify the climate risk of crypto (Naeem and Karim, 2021). The rising of carbon emissions has quickened contemporary global warming, leading to destructive impacts on all life (Uddin et al., 2018). Accordingly, a large body of literature has emerged to tackle environmental issues, and sustainable actions have been undertaken by industry, government, and academia to decrease carbon emissions as well as fossil fuel usage to avoid global climate catastrophe (Southworth, 2009; Iqbal et al., 2022; Naeem et al., 2021). Noteworthily, the world economy and climate change are symbolized as volatile and uncertain conditions for portfolio investment. Prior literature concludes the argument and almost always considers major financial backing from green bonds or eco-friendly stocks to be a good substitute for clean energy or renewable energy stocks (Naeem and Karim, 2021; Sharma et al., 2023).

The potential interconnection between Bitcoin futures and other financial asset classes provides valuable and practical insights for investors since this interconnectedness can impact the investment decisions of market participants (Ji et al., 2019; Bouri et al., 2020; Gonzalez et al., 2021, Li et al., 2023, among others). If Bitcoin and cryptocurrencies are highly connected to other financial assets such as green bonds, carbon emissions, crude oil, and conventional stock prices, market participants then can develop a style of portfolio including a long position in green bonds and a short position in the cryptocurrencies to hedge overall portfolio risk exposure. Alternatively, in case a weak association exists, incorporating a long position in a crypto-asset in a well-designed portfolio will be broadly diversified from risky assets to safe-haven assets, leading to improving the risk of reward ratio (e.g., Baur et al., 2010). Especially, during turbulent market periods, if there are low and stable correlations among assets, then Bitcoin can play a safe-haven role for market participants by allocating part of their wealth to cryptocurrencies until the economic turmoil is over (Conlon et al., 2020; Zeng et al., 2020). Accordingly, three problems naturally appear themselves:

Contextualizing the above consideration of these issues, this study intends to respond to the following research questions:

1. Which direction of volatility interlinkages occur among the five asset classes studied in this paper, especially focusing on crypto connectedness within green financial (i.e., green bonds, carbon) assets?

2. What is the crypto connectedness among green bonds, carbon, energy, and the crypto-markets in various time frequencies, such as short, medium, and long?
3. Do these considered assets offer the potentiality of investment diversification possibilities based on considered assets?

To answer these questions, we investigate the dynamic connectedness between Bitcoin, green financial assets, oil, and emerging stock markets by using the dynamic conditional correlation (DCC) -GJR-GARCH-based connectedness approach developed by Cappiello (2006). The present work employs the DCC-GJR-GARCH model under the DCC process to measure both the optimal portfolio weights and the optimal hedging ratios (Kroner & Sultan, 1993; Kroner & Ng, 1998) for these assets. In addition, to better understand the structure in terms of volatility spillover impacts among these assets, this study utilizes the wavelet coherence analysis introduced by Torrence and Compo (1998) to visualize the volatility spillover based on wavelet spectrum (or scalogram).

Particularly, the findings of the study show that carbon assets outperformed emerging stock assets amidst the COVID-19 crisis, while the stock markets incurred significant losses. Several factors can be explained for the outperformance during the epidemic phase. For instance, (i) there is an accelerating demand for carbon assets. (ii) Since carbon assets offer environmental benefits of emission reduction, responsible investors may have consistent expectations of rising interest in this instrument of offsetting carbon footprint.

Specifically, concerning contribution to green finance-related literature, this paper ultimately extends prior research in several ways as follows.

First, unlike previous literature, this study relates the subject of green finance with Bitcoin's emissions, oil, and emerging stock prices and has awakened the attention of crypto-portfolios. Particularly, it seeks to identify the potential connectedness of Bitcoin to green finance, carbon oil, and emerging stock prices. As a result, such a portfolio analysis may be useful in guiding us to draw innovative results and key implications in terms of green finance in the post-COVID-19 era. Second, Bitcoin is not a valuable hedge for green bond assets, suggesting that Bitcoin is an inappropriate substitute for green bonds in the role of decreasing the risk of climate change. Third, the innovative findings also play an important role for policymakers interested in decarbonizing crypto-assets, thereby directing crypto technology usage toward activities dedicated to climate change mitigation.

To the best of our knowledge, this is a pioneering study to investigate the volatility linkages between sustainable finance, oil, and emerging stock markets and analyze whether the hedging strategies allocating Bitcoin and these financial assets considerably decrease portfolio risk.

The remainder of the paper is organized as follows. Section 2 provides a related studies review. Section 3 is dedicated to the methodology and econometric model. Section 4 elaborates on the data sources and the main empirical results. Section 5 outlines the main conclusions and economic implications.

2. Review of related studies

Green finance is defined as an extensive term that includes carbon finance to boost carbon emissions reductions, sustainable finance for socially inclusive green initiatives, and climate finance to mitigate climate change (Yan et al., 2022; Nguyen et al., 2021; Flammer 2020; Reboredo 2018). Broadly speaking of financial products, green bonds (GBs, hereafter) were first issued in 2007 by the European Investment Bank (EIB). Following the release of sustainable development goals (SDGs), green finance thereby had a significant boost after 2015 (Nedopil Wang et al., 2022), attracting widespread attention of investors, scholars, and policymakers. Prior literature describes the time-varying spillovers between Bitcoin and energy-relevant investments and suggests the potential of Bitcoin as a hedger and diversifier for financing conventional energy projects. (Okorie and Lin, 2020; Okorie 2021; Hou et al., 2022; Ghabri et al., 2022). Likewise, Qi and Zhang (2022) predominantly detected strong bidirectional spillovers between GBs and traditional bonds. Furthermore, in extant studies on the general spillover effect issue, a substantial body of financial literature documents asymmetric volatility spillovers among GBs and emerging markets, such as Wei et al. (1995), Beirne et al. (2013), Qi et al. (2022), and Qian et al. (2023a, 2023b). The empirical results also indicate substantial interaction between the GBs and stock markets. Moreover, regarding the diversification role of GB markets, Reboredo (2018) noted that investors in the energy and equity markets may potentially benefit from diversification through GB markets.

Despite a large body of studies that have investigated the intercorrelation between Bitcoin and conventional energy-related assets, only a few studies published to date have discovered the interconnection between Bitcoin and ESG-related assets or environmentally friendly investing. Corbet et al. (2021) reported no evidence that Bitcoin price has a positive impact on green ETFs or carbon credit, suggesting that only energy firms obtain benefits from Bitcoin's miners for energy consumption. There is weak relatedness between green financial assets and Bitcoin, indicating that green bonds and clean energy stocks can provide hedging or diversification benefits for crypto investing (e.g., Naeem and Karim, 2021; Ren et al., 2022; Chen et al. 2024). Yang and Hamori (2021) and Pham et al. (2022) further demonstrated evidence of an asymmetric tail relationship between carbon credit and cryptocurrency markets. Analyzing this dependence is crucial for investors who are searching for methods to hedge against climate risk in crypto investment.

Subsequently, while a strand of literature has used time-varying parameter vector autoregressive (TVP-VAR) approach developed by Diebold and Yilaz (2014) to investigate the connectedness between green bonds and varied financial markets, e.g. Attarzadeh and Balcilar (2022); Yadav et al. (2022) among others. The studies on incorporating blockchain-based crypto assets are still limited to a few studies and are in their early stages but rapidly expanding (Arfaoui et al., 2023). Therefore, this research seeks to bridge the gap by exploring volatility spillover from crypto to the energy and green bond market. The current article intends to add value to the studies by using dynamic conditional correlation (DCC) and wavelet coherence approaches to examine volatility spillover in the cryptocurrency, energy markets, and green bonds.

3. Methodology and data

3.1. The econometric model

As our major purpose is to discover the correlations in the one-to-one relationships between the pair assets' returns, thereby we use a representative bivariate model. Then, the bivariate DCC-GARCH model can be written mathematically:

$$r_{i,t} = u_{i,t} + \varepsilon_{i,t} \tag{1}$$

Where $r_{i,t}, u_{i,t}$, and $\varepsilon_{i,t} = H_{i,t}^{1/2} z_{i,t}$ denote the 2 × 1 vector of asset returns, conditional returns, and the residuals, respectively. $z_{i,t}$ refers to a 2×1 vector of *i.i.d.* errors.

$$\left\{\begin{matrix} \boldsymbol{H}_t = \sqrt{\boldsymbol{D}_t}\boldsymbol{A}_t\sqrt{\boldsymbol{D}_t} \\ \boldsymbol{D_t} = diag(h_{1,1,t}, h_{2,2,t}) \\ \boldsymbol{A_t} = diag\left(\frac{1}{\sqrt{q_{1,1,t}}}, \frac{1}{\sqrt{q_{2,2,t}}}\right)\boldsymbol{Q}_t\, diag\left(\frac{1}{\sqrt{q_{1,1,t}}}, \frac{1}{\sqrt{q_{2,2,t}}}\right) \end{matrix}\right\} \tag{2}$$

where $\boldsymbol{H}_t$ is defined as the variance-covariance matrix. $\boldsymbol{D}_t$ are the diagonal conditional variances. $\boldsymbol{A_t}$ refers to the conditional correlation matrix. Q_t represents a symmetric positive definite matrix is defined as follows.

$$\boldsymbol{Q}_t = \begin{bmatrix} q_{1,1,t} & q_{1,2,t} \\ q_{2,1,t} & q_{2,2,t} \end{bmatrix}$$

In addition, introducing Engle (2002), we specify Q_t as the following equation.

$$Q_t = (1 - a - b)\overline{\boldsymbol{Q}} + az_{t-1}z_{t-1}^T + bQ_{\boldsymbol{t-1}} \tag{3}$$

where $\overline{\boldsymbol{Q}}$ denotes the 2× 2 unconditional matrices composed by the standardized residuals $z_{i,t}$. Parameters a and b are non-negative, and the DCC process signifies mean-reverting in consideration of $a + b$< 1. The correlation estimator is then given by

$$\boldsymbol{\rho}_{1,2,t} = \frac{\boldsymbol{q}_{1,2,t}}{\sqrt{\boldsymbol{q}_{1,1,t}}\sqrt{\boldsymbol{q}_{2,2,t}}} \tag{4}$$

To analyze the asymmetric effect of positive and negative shocks on volatility, the asymmetric (A-DCC) approach was introduced by Cappiello et al. (2006), and they modified the conditional volatility model as follows.

$$h_{i,t} = \omega_{i,0} + \alpha_{i,i}\, \varepsilon_{i,t-1}^2 + \beta_i\, h_{i,t-1} + \gamma_i I_{t-1}\, \varepsilon_{i,t-1}^2 \tag{5}$$

$$I_{t-1} = \begin{cases} 1 & \text{if } \varepsilon_{i,t-1} < 0 \\ 0 & \text{if } \varepsilon_{i,t-1} > 0 \end{cases}$$

where I_{t-1} is the indicator function. Thus, a positive value for γ denotes that negative residuals tend to increase volatility more than positive residuals and then captures the "asymmetric" effect. The estimates of the model parameters can be calculated by applying the Quasi-Maximum Likelihood (QML) approach, and the log-likelihood estimation is expressed as follows:

$$logL = \sum_{t=1}^{T} -\frac{1}{2}(n \ln \pi + \ln(det\, H_t) + u_t H_t^{-1} u_t^T) \tag{6}$$

where det is the determinant of H_t. The definition of residuals u_t also extends the joint distribution of conventional DCC introduced by Engle (2002).

3.2. Asset allocation models

Assume that $\boldsymbol{w} = (\boldsymbol{w_1}, \cdots, \boldsymbol{w_N})^{\boldsymbol{T}}$ represents the weights of the assets in the portfolio. In what follows, $\boldsymbol{w} \in \boldsymbol{W}$:=$\{w \in \mathbb{R}^{\boldsymbol{N}} | \boldsymbol{w_i} \geq 0, \boldsymbol{w^T 1} = \boldsymbol{1}\}$, which indicates that the short-selling scenario is not considered here. In this note, this constraint is set only to describe a practical method for quantifying the common limitation with short-selling financial assets or cryptocurrency. This serves, as the approaches proposed in this paper are equally suitable for settings that allow it.

3.2.1. Minimum-variance portfolio

As proposed by Markowitz (1952), mean-variance portfolio optimization is considered under the assumption of normality for the returns. The weights can be achieved by solving the optimization problem as follows:

$$\underset{w}{\operatorname{argmin}}\ \boldsymbol{w^T}\boldsymbol{\Sigma}\mathbf{w} \tag{7}$$

subject to

$$\boldsymbol{w^T 1 = 1}$$

with $\boldsymbol{\Sigma}$ denoting the covariance matrix of the returns.

3.2.2. Portfolios to maximize expected utility

Subsequently, to evaluate the potential performance of Bitcoin and other assets within portfolios, we compare the trading strategy (max $\mathbf{U}$) with three benchmark trading strategies: holding Bitcoin only, holding other assets only (carbon emission…), and the well-known equal-weight portfolio (EQ, half-Bitcoin and other assets). Without loss of generality, the market participants will select the optimal weights ($\boldsymbol{w}$) to maximize the expected utility function based on the mean-variance optimal portfolio (MVO) rule. The mean-variance term and the objective function can be expressed as

$$\boldsymbol{U}(\boldsymbol{w}) = \boldsymbol{r}\boldsymbol{w^T} - \frac{\gamma}{2}\boldsymbol{w}\boldsymbol{\widehat{H}}\boldsymbol{w^T} \tag{8}$$

where r is the momentum factor (Jegadeesh and Titman 1993), γ denotes the risk aversion coefficient, and $\widehat{H}$ is the estimation of variance-covariance matrices through the preceding DCC-GJR model.

3.2.3. Equally weighted portfolio

The naïve portfolio can be written as $\boldsymbol{w} = \left(\frac{\mathbf{1}}{\boldsymbol{N}}, \cdots, \frac{\mathbf{1}}{\boldsymbol{N}}\right)^{\boldsymbol{T}}$.This portfolio requires no assumptions or estimates and is equally weighted.

3.3. Wavelet coherence analysis

To identify the dynamic linkages or spillover of Bitcoin and sustainable assets classes, we conduct the approach of wavelet coherence as follows:

The wavelet coherency proposed by Torrence and Compo (1998) takes the co-movement between two-time series, x(t) and y(t), into account in the time-frequency domain. The cross-wavelet transform of x(t)and y(t) is shown mathematically as follows:

$$W_{x,y}(u,s) = W_x(u,s)W_{y*}(u,s) \tag{9}$$

where u and s refer to the scale and position index, respectively. * represents the complex conjugate. The squared wavelet coherence between x(t) and y(t) recognizes significant co-movement through cross-wavelet power series at a given time scale, which can be written as

$$R^2(u,s) = \frac{\left|S\left(s^{-1}W_{x,y}(u,s)\right)\right|^2}{S(s^{-1}|W_x(u,s)|^2)S\left(s^{-1}\left|W_y(u,s)\right|^2\right)} \tag{10}$$

where $S(.)$ is a smoothing operator and s represents a wavelet scale, with $R^2(u,s)$ between 0 and 1, reflecting the localized correlation in a time-frequency domain in the squared specification (Mensi et al., 2020; Rubbaniy et al., 2021; Goodell et al., 2022). Since $R^2(\,,)$ is accompanied by limited positive values, the wavelet coherence phase difference is applied to identify the direction (positive/negative) of co-movements between pairs. The wavelet coherence phase formulation between two-time series can be written as follows mathematically:

$$\rho_{x,y}(u,s) = \tan^{-1}\left(\frac{lm\left[S\left(s^{-1}W_{x,y}(u,s)\right)\right]}{Re\left[S\left(s^{-1}W_{x,y}(u,s)\right)\right]}\right) \tag{11}$$

where *lm* and *Re* depict the imaginary smoothing component and the real component of the smoothing operators, respectively. (Rubbaniy et al., 2021; Anwer et al., 2023).

3.4. Data and sample

Daily data for the largest cryptocurrency (Bitcoin) as well as financial assets including green bonds, carbon emission, and Brent oil futures prices were extracted from investing.com (https://www.investing.com/commodities/). The datasets used were collected from investing.com, which is one of the top three global financial websites and a financial markets platform providing real-time data. The data used in Bitcoin futures is based on the Chicago Mercantile Exchange (CME) Group. In addition, we chose December 12, 2017, as the starting point of our research because statistical data on Bitcoin futures trading in the CME have been collected since December 10, 2017, when Bitcoin futures trading began on the Chicago Board of Exchange (CBOE) exchange. Among the prominent asset classes, the Dow Jones Emerging Markets Index is a close proxy of conventional stock markets, and carbon asset is proxied by carbon emissions (allowance) futures under this study. Where carbon emission (allowance) futures stand for carbon emissions and carbon assets (briefly denoted as Carbon in figures and tables). To do so, the data for the Dow Jones Emerging Markets Index (DJEMI) is retrieved from the S&P Dow Jones Indices LLC's data (www.spglobal.com/spdji/en/). The DJEMI is developed to measure 95% of the market cap that covers stocks traded in emerging markets. The natural logarithm returns, $R_{i,t} = ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \times 100$, is then estimated for the period from 11/12/2017 to 30/4/2023, i=Bitcoin, other assets, where $R_{i,t}$ is the return series of assets i at time t. The profile data includes 6,900 observations.

4. Empirical application and portfolio analysis

As depicted in Figure 1, a similar empirical stylized fact can also be observed from each asset's return. It is noteworthy that Bitcoin returns are more volatile compared to other assets. In contrast, the green bond is less volatile than other assets and is a more stable one. The yellow (bold) lines exhibit the considerable volatility jump risk, and all asset returns are significantly affected by shocks from the first wave of the COVID-19 outbreak that occurred in February 2020.

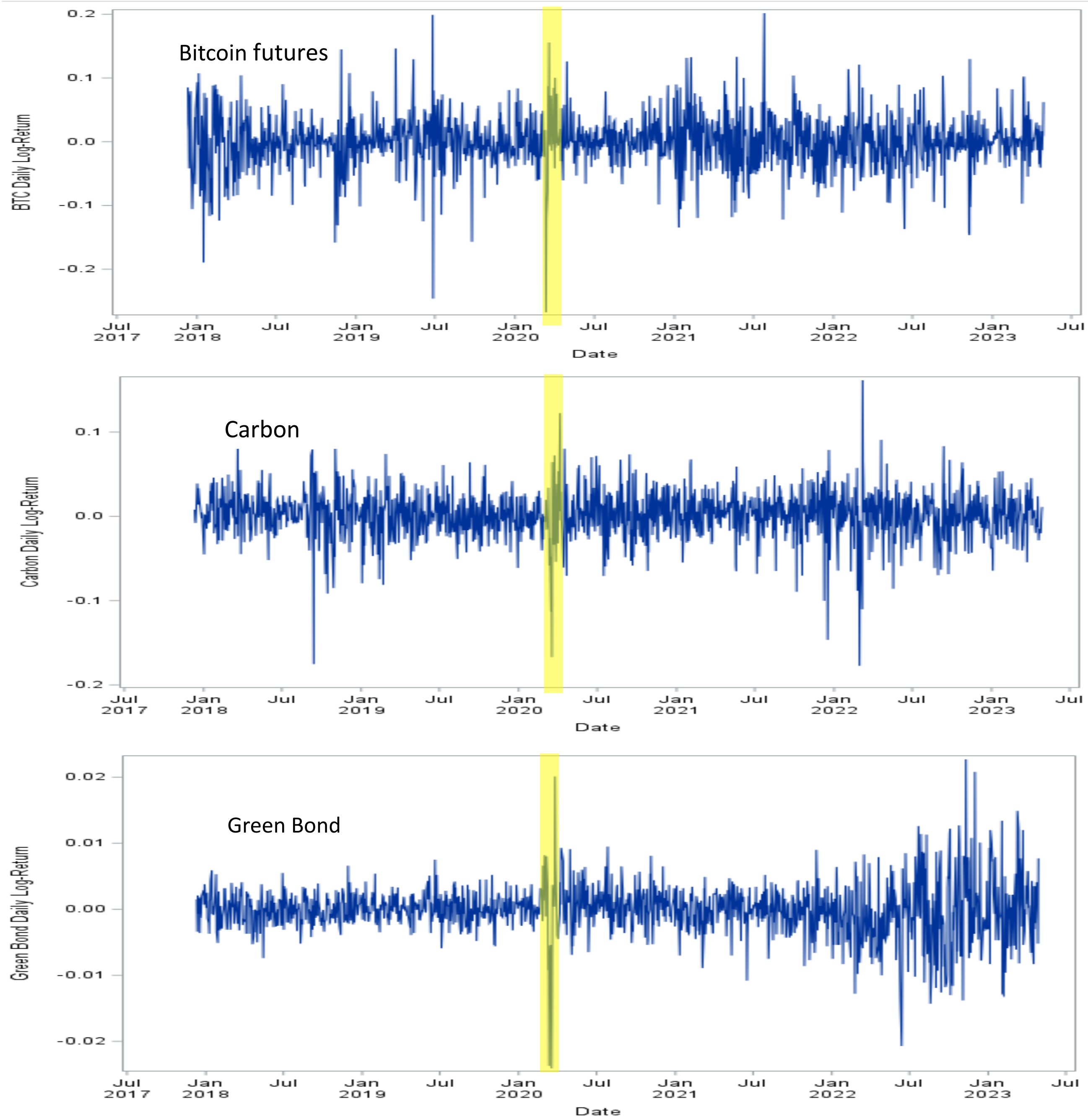


Figure 1. Time series for each financial asset's returns.

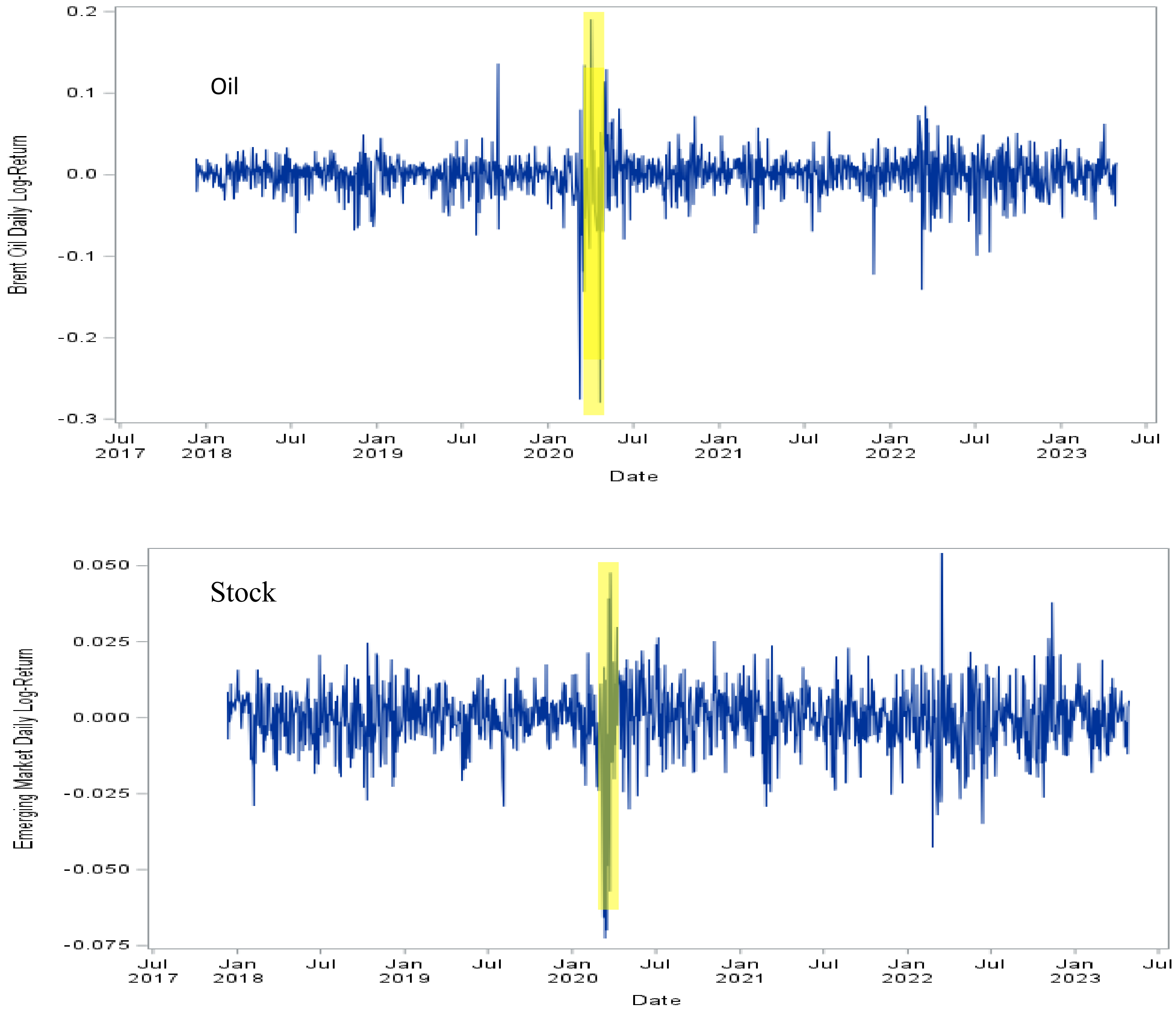


Figure 1. Time series for each financial asset's returns.

Notes:

The top panel illustrates the daily logarithmic returns (R_t) of Bitcoin futures.

The second panel plots the daily logarithmic returns (R_t) of carbon emission futures .

The third panel illustrates the daily logarithmic returns (R_t) of S & P Green Bond .

The fourth panel plots the daily logarithmic returns (R_t) of Brent oil futures.

The last panel illustrates the daily logarithmic returns (R_t) of emerging stock markets .

4.1. Evidence of dynamic conditional correlations and volatility spillovers

In terms of the estimates of variance–covariance equations in the DCC-GARCH model, the own conditional ARCH (α_{11},α_{22}) and GARCH (β_{11},β_{22}) effects can measure the dependence of short and long-term persistence, correspondingly. As shown in Table 1, the results report that patterns could be very generally observed among Bitcoin and financial assets. Unsurprisingly, our empirical results show stronger long-term persistence of own volatility than short-run persistence. These highly significant coefficients are present in most cases exactly. These findings are in line with the results of Hatem et al. (2022). The values of parameters (β_{11},β_{22}) for Bitcoin against carbon asset are 0.8608 and 0.7848, other portfolio is 0.8434, 0.9027 for the BTC/GB, and equal 0.8625, 0.8511 for the BTC/oil, respectively. The volatility sensitivity to own lagged conditional variance specification in the GARCH terms reports on statistical significance results for all Bitcoin vs. financial assets series at the 1% level.

Turning out to the findings of time-varying characteristics are reported in Table 1 for the pairs of Bitcoin/ other assets. The dynamic connectedness is positive and varies considerably over time for all asset pairs (except for DCC a of BTC-carbon, GB, and carbon/emerging), then showing similar evidence to Canh et al. (2019) and Wang et al. (2019). Likewise, the estimates of the DCC parameters (a and b) are meaningful as mass coefficients and report along with their statistical significance in most cases. For short-run persistence of the shock on the DCC, we observe the highest for BTC/Stock at 0.0537, while the greatest long-term shock persistence to the DCC is 0.98 for BTC/GB.

Regarding the hedge and diversifier properties of representative crypto, a Bitcoin asset is referred to as a hedge asset that is negatively correlated or uncorrelated with another asset. To put it another way, a hedge requires no correlation or a negative correlation between two assets on average; see Baur et al. (2010). A diversifier is an asset that has a positive (non-perfectly) correlation with another asset or portfolio on average; see Baur et al. (2010). As depicted in Table 1, dcc a corresponds to parameter a (equation 3), dcc b corresponds to parameter b, and dcc_{1_2} corresponds to the parameter $\boldsymbol{\rho}_{1,2}$ (equation 4). In addition, the parameters of conditional correlations between Bitcoin, carbon, and GB assets are positively weak (dcc_{1_2} = 0.042, for Bitcoin/carbon and dcc_{1_2} = 0.056 for Bitcoin/GB) estimated at the 5% significance level. This is evidenced in coincidence with the existence of the interlinkages or spillover effects among Bitcoin and green financial (i.e., carbon and GB) assets. As a result, we offer the interpretation that Bitcoin is an unsuitable hedge instrument to substitute green bonds in the role of decreasing the risk of climate change owing to the presence of the interlinkage effects between crypto and green financial (i.e., green bonds, carbon) assets.

To investigate the asymmetric responses in the connectedness of Bitcoin shocks, Table 1 depicts the coefficient $\gamma_{i,i}$, and the results in most examined assets support the asymmetric movements, except for BTC/emerging and GB/emerging pairs. Additionally, to visualize the news impact curve (NIC) for the DCC-GJR-GARCH model, its graphs are generalized to the "news impact curve (NIC)" (Engle and Ng 1993). As observed in Figure 2, the NICs capture the asymmetric response to volatility news because the non-Bitcoin curves are plotted with a bit steeper slope on their negative side relative to the positive side. Briefly, the aforementioned news impact curves can be representative of the asymmetric or leverage effect by accessing either the center of the news impact curve located at a point where ε_{t-1} is positive or both sides of the slope of the news impact curve to distinguish. The NICs created for the GJR-GARCH model (Figure 2) also confirm our findings that a negative shock has the potential to enhance the volatility of returns by a bit steeper than a positive shock, except in the Bitcoin - emerging stock asset pairs (Figure 2d). Summarizing all, news impact curves in the six diagrams are similar to their trends across the examined assets.

4.2. Illustration of assets' allocation

Subsequently, considering the optimal portfolio construction and hedging ratios in the existence of Bitcoin assets, the average portfolio weights suggest the optimal weights of Bitcoin and other assets for the risk-minimizing hedging strategies without reducing the expected returns. Regarding portfolio risk hedging strategies matters, Table 2 reports the average optimal weights and hedge ratios for the pairs of BTC / other assets during the sample periods, respectively. With the results calculated from these assets' portfolios, the average optimal weights are 0.6888, 0.9977, 0.7657, and 0.98488 for BTC/carbon, BTC/GB, BTC/oil, and BTC/Stock assets' portfolios, respectively. The observed findings depict that the optimal weight is 0.6888 for the pair of BTC / carbon emission, suggesting that for a \$100 portfolio of BTC - carbon emission, investors should invest \$68.88 in Bitcoin and then keep \$31.12 in carbon emission futures.

For 100 dollars of the BTC-Stock portfolio, market participants may distribute \$98.48 in Bitcoin with the remainder of \$1.52 invested in emerging stock. Considering non-short selling constraints activity, these weight optimizations appear to have lower positions in terms of emerging stocks held (positions), suggesting that market participants should allocate low weight to emerging stocks in all BTC/assets portfolios. Overall, Khaki (2023) also documented that the leading crypto (Bitcoin) should outweigh the other centralized cryptocurrencies based on portfolio weight optimization.

As shown in Table 2, the BTC/carbon portfolio reports an average hedge ratio of 0.065, which signifies that a long position (buying) of one dollar of Bitcoin could be hedged by a short position (selling) of 6.5 cents in carbon emission futures. In other cases, similarly, a long position of one dollar of Bitcoin requires investors to go short with the average hedge ratio of 0.23, which should be hedged by a short position of 23 cents in oil futures. The hedge ratios have low values apart from green bonds, indicating a highly effective hedge in the considered assets. However, a long position (buying) of one dollar of Bitcoin with an average hedge ratio of 0.837, could be hedged by a short position of 83.7 cents on green bonds. There is a high value (0.837) of the hedge ratio in this BTC-GB portfolio pair. According to the observed findings, Bitcoin is not a valuable hedge to substitute green bonds in the role of decreasing the risk of climate change. Notably, these assets' portfolios have above-zero hedge ratios.

4.3. Application and interpretation of wavelet coherence (WC) analysis

To distinguish the significant role of the dynamic linkages or spillover among these assets, we focus on the DCC and optimal weights for each portfolio. Subsequently, we study the time-scale co-movement of Bitcoin, carbon, green bonds, oil, and emerging stock in bivariate settings using wavelet coherence analysis. The time-scale wavelet coherence degree, spectral quantities computed for levels, are captured by a color spectrum, with the navy-blue rectangles implying low coherence levels. The red/pale-red rectangles exhibit medium coherence, and pale-blue zones indicate high coherence.

As shown in Figure 3a, the BTC-Carbon pair shows a significant co-movement at higher energies (frequencies) in 2020 and 2022.The scalogram in Figure 3a–3d shows the presence of weak coherence in the medium scale, as depicted by a preponderance of red zones. Accordingly, where weak inter-linkage is recognized, Bitcoin is found to lead carbon asset. In the case of other asset pairs, Bitcoin is leading oil and emerging stock markets. Figure 3b reports that higher energies occur at the lower levels in the Bitcoin-Green asset pair.

Table 1. Estimates of DCC-GJR-GARCH model among pairs of Bitcoin vs financial assets.

	BTC/ Carbon			BTC/ Green Bond			BTC/ Oil			BTC/Stock			Carbon/Stock			Green Bond /Stock		
Parameter	Estimate	t-Value	Pr > |t|	Estimate	t- Value	Pr > |t|	Estimate	t-Value	Pr > |t|	Estimate	t-Value	Pr > |t|	Estimate	t-Value	Pr > |t|	Estimate	t-Value	Pr > |t|
dcc a	0.0219	1.17	0.2431	0.0002	0.05	0.9565	0.0157	1.740	0.0828	0.0537*	5.55	0.0001	0.0062	1.64	0.1092	0.0331*	2.65	0.0081
dcc b	0.8828*	5.92	0.0001	0.9898*	17.65	0.0001	0.9617*	36.84	0.0001	0.9462*	95.84	0.0001	0.9814*	105.09	0.0001	0.9179*	27.38	0.0001
dcc_{1_2}	0.0423	1.30	0.1947	0.0565†	2.05	0.0408	0.1162*	2.660	0.0080	0.9201*	41.78	0.0001	0.1406*	3.31	0.0010	0.0276*	6.83	0.0001
w_{11}	0.0001*	3.47	0.0005	0.0001*	3.50	0.0005	0.0001*	3.550	0.0004	0.0001	4.04	0.0001	0.0007*	3.22	0.0013	0.0001*	4.21	0.0001
α_{11}	0.0574*	3.19	0.0015	0.0644*	3.18	0.0015	0.0580*	3.240	0.0012	0.0678*	3.14	0.0017	0.0975*	3.77	0.0002	0.0845*	4.76	0.0001
α_{22}	0.0982*	3.71	0.0002	0.0623*	4.09	0.0001	0.0732*	4.250	0.0001	0.0705	0.63	0.5294	0.0116	0.87	0.3863	0.0184	1.29	0.1970
γ_{11}	0.0121	0.60	0.5481	0.0150	0.67	0.5043	0.0134	0.670	0.5043	-0.0001	−0.001	0.9974	0.0357	1.09	0.2746	−0.0062	−0.38	0.7074
γ_{22}	0.0401	1.20	0.2307	0.0464†	2.41	0.0161	0.1025*	3.780	0.0002	0.0067	0.07	0.9427	0.1441*	5.31	0.0001	0.1461*	5.44	0.0001
β_{11}	0.8608*	27.46	0.0001	0.8434*	24.02	0.0001	0.8625*	28.74	0.0001	0.8788*	37.02	0.0001	0.7925*	19.16	0.0001	0.9128*	63.67	0.0001
β_{22}	0.7848*	18.69	0.0001	0.9027*	59.55	0.0001	0.8511*	49.70	0.0001	0.8869*	11.61	0.0001	0.8607*	32.11	0.0001	0.8537*	33.10	0.0001
Information Criteria																		
HQC.			−15961.5			−21465.7			−16513.1			−18892.6			−20126.3			−26135.4
AIC.			−15986.9			−21491.0			−16538.6			−18917.8			−20151.5			−26160.6
SBC			−15918.9			−21423.4			−16470.6			−18850.1			−20083.8			−26092.2
log likelihood			8006.451			10758.51			8282.29			9472.03			10088.87			13093.4

Notes:

1. * and † are significant at the 1% and 5% levels, respectively.
2. HQC, AIC, and SBC denote Hannan-Quinn criterion, Akaike information criterion, and Schwarz Bayesian criterion, respectively.

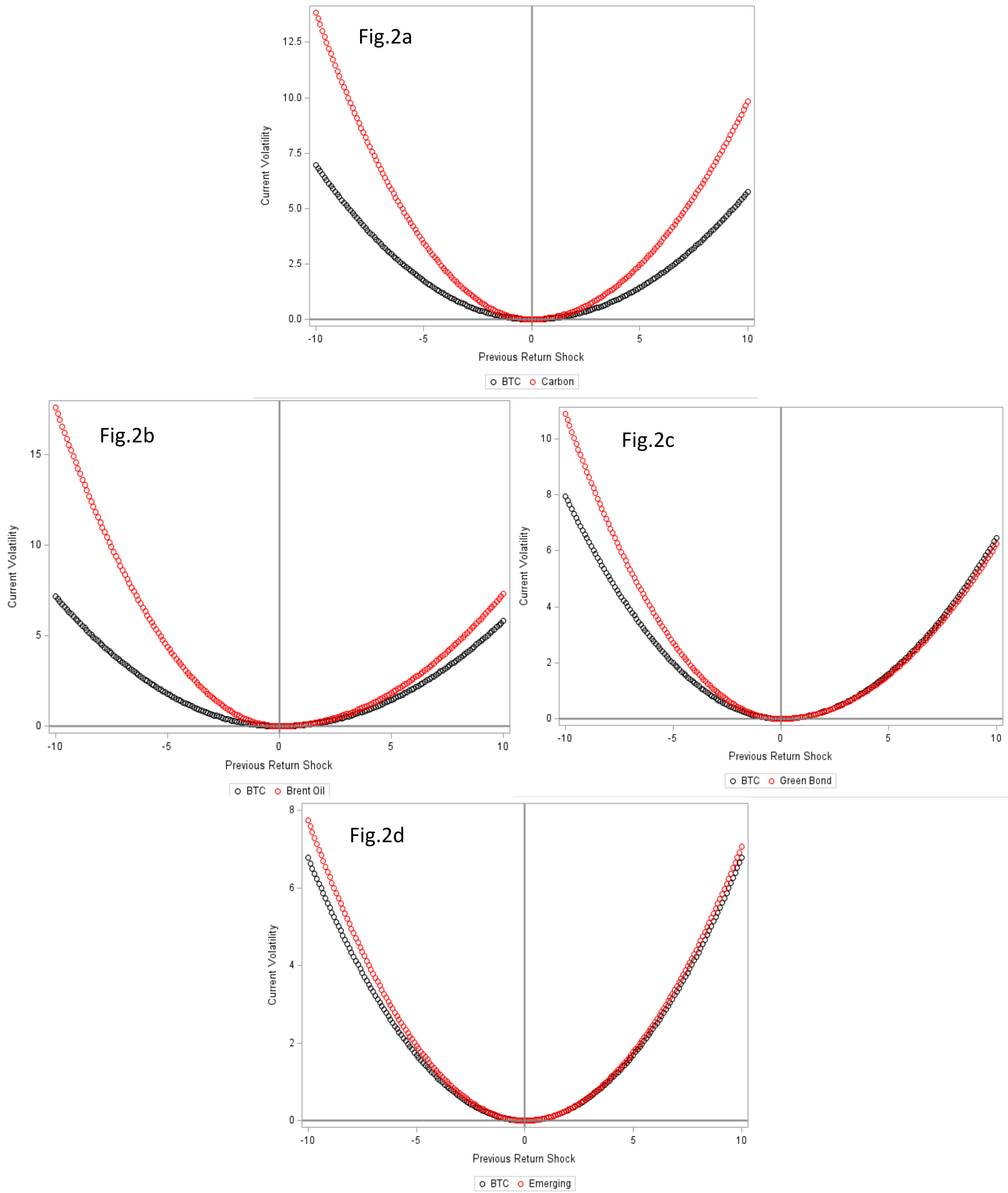


Figure 2. Typical volatility news impact curves for BTC and financial assets.

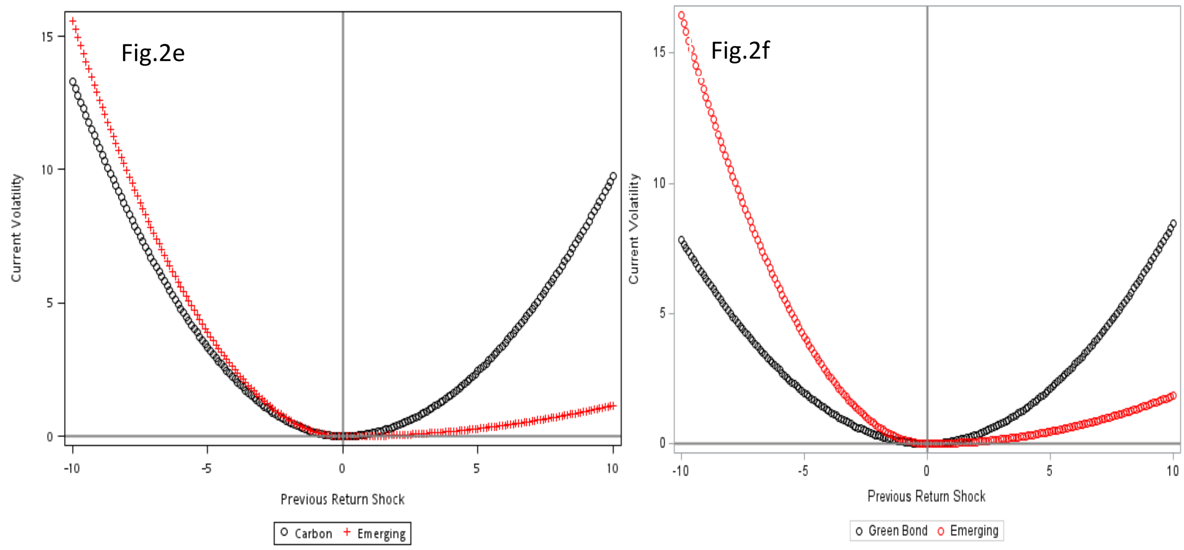


Figure 2. Typical volatility news impact curves for BTC and financial assets.

Notes: An illustrative plot of the news impact curve is displayed in Figure 2 and consists of the news impact curves for three futures portfolio pairs. It is noticed that the x axes and y axes represent daily scales.

Table 2. Descriptive statistics for optimal weights and hedge ratios among various financial assets.

	Variable	Mean	Std Dev	Std Error	Minimum	Maximum	Variance
Portfolio 1:BTC–Carbon	ow	0.6888	0.1135	0.0030	0.2089	0.9742	0.0129
	Hr	0.0657	0.0873	0.0023	−0.2466	0.8279	0.0076
Portfolio 2: BTC–Green Bond	ow	0.9977	0.0030	0.0001	0.9819	1.0008	9.2E-6
	Hr	0.8377	0.3095	0.0084	0.3554	2.0404	0.0958
Portfolio 3: BTC–Oil	ow	0.7657	0.1655	0.0044	0.0411	1.0006	0.0274
	Hr	0.2278	0.1606	0.0043	−0.1032	1.0080	0.0258
Portfolio 4: BTC–Stock	ow	0.9848	0.0474	0.0012	0.8332	1.2689	0.0022
	Hr	0.6641	0.92855	0.0249	−1.6625	4.1253	0.8622
Portfolio 5: Carbon–Stock	ow	0.9237	0.0604	0.0016	0.3244	1.0027	0.0036
	Hr	0.4199	0.1643	0.0044	0.0747	1.0682	0.0270
Portfolio 6: Green Bond	ow	0.0610	0.1142	0.0030	−0.1117	0.5494	0.0150
–Stock	Hr	0.1050	0.0647	0.0017	−0.0388	0.3718	0.0041

Note:

1. **ow** is the optimal portfolio weight in a fully invested, no-shorting portfolio. Following Kroner and Ng (1998), the risk-minimizing optimal portfolio allocation for *x* (e.g., Bitcoin) and *y* (alternative) asset is determined by

$$w_{xy,t} = \frac{h_{y,t}-h_{xy,t}}{h_{x,t}-2h_{xy,t}+h_{y,t}} \text{ under the condition that } w_{xy,t}=\begin{cases} 0 & \text{if} \quad w_{xy,t} < 0 \\ w_{xy,t} & \text{if} \quad 0 \le w_{xy,t} \le 1 \\ 1 & \text{if} \quad w_{xy,t} > 1 \end{cases}$$

where $w_{xy,t}$ denotes the estimated weight of first asset *x* in one dollar of two-asset portfolio (*x*, *y*) at time t, and $h_{xy,t}$ refers to the conditional covariance of the two assets (*x*, *y*). Apparently, the remaining weight of the second asset *y* equals 1-w_{xy} in this portfolio.

2. **Hr** denotes the risk-minimizing hedge ratio. To determine the risk-minimizing of the overall portfolio, the optimal hedge ratio of Kroner and Sultan (1993) can be formulated as

$$\delta_{xy,t} = \frac{h_{xy,t}}{h_{y,t}}$$

Where $h_{xy,t}$ is the conditional covariance between the asset pairs (x, y), and $h_{y,t}$ refers to the conditional volatility for the alternative asset (y) at time t. A one-dollar long position in asset Bitcoin (x) can be hedged by a corresponding short position in asset y (alternative asset).

In terms of Green Bond investment considering its association with Bitcoin, weak coherence is identified, as represented by many blue rectangles during the COVID-19 outbreak and 2022. This lack of correlation evidences predominant and substantial diversification options, especially to take advantage of green investment opportunities to diversify against Bitcoin and to neutralize the carbon footprint of Bitcoin mining.

On the whole, there appears to be a lower correlation at the low scales in Figure 3f, and the interaction is relatively weak. From a portfolio optimization perspective, the evidence offers diversification benefits, which are likely to be realized by constructing a portfolio including negatively or weakly interrelated assets, obtaining better risk-adjusted performance. The substantive transformation from strong to the weak correlation of green bond – emerging stock thereby provides a good diversification opportunity by involving these two asset classes in a portfolio. The low or negative connection between green bonds and emerging stock markets can be found across most of the investment time frames, these results align with Chang et al. (2023). That is likely to yield the hedging benefit of green bonds against the volatile emerging stock asset. Our finding is consistent with the result of Reboredo et al (2020), who showed the diversification benefits of green bonds with the stock market.

In general, a closer review of these dynamic optimal weights from Figure 4 (depicted in the upper part of the scalogram on each figure) suggests that more Bitcoin futures are necessary to minimize the risk of assets. Analogous results were documented by Haffar et al. (2022) finding that Bitcoin might have the crucial role of stabilizing portfolio performance, for time-varying dependence on risk exposure. Additionally, in terms of optimal weights for each portfolio, Figure 4a–4e shows that the yellow (bold) zones depict the increased volatility of BTC to impact other assets in 2020 due to the COVID-19 crisis.

4.4. The impacts of portfolio management performance

As illustrated in Table 3, portfolio performances report that the naïve strategy outperforms the max U strategy (simulation results from equation 8), measured by the average return as well as annual percentage yield (APY)**.** Furthermore, the performance of equal weighs (EQ) outperforms those acquired from the max U strategy based on the Sharpe ratio (an indicator of risk-adjusted return). Over 5 years, the final wealth in the simulation that results from applying the naïve strategy is about 4.6% more than the final wealth in performance resulting from the use of the max U strategy. Notably, we could acquire the Sharpe ratio values produced by the mean–variance (positive) strategy. As depicted in Table 3, the carbon emission futures in portfolios 1,5 generally outperformed the other assets, and the values are 0.03, 12.83, and 18.54 for Sharpe Ratio, Final Wealth, and APY (%), respectively.

To visualize the wealth paths and portfolio performances of trading strategies, Figure 5 displays the evolution of wealth (or portfolio value) of each trading strategy with time. Overall, Bitcoin is an effective hedge against other assets and a weak safe haven during the COVID-19 crisis. We also have evidence that carbon asset alone depicts the blue trajectories (highest solid lines) in portfolio 1 (top Panel) of Figure 5, outperforming all strategies before and during the COVID-19 pandemic. Thus, carbon futures (assets) offer more diversification benefits than other assets during the COVID-19 period.

Additionally**,** in portfolio 5 of Figure 5, the black line displays the highest trajectory over the last few years, which suggests that the carbon portfolio outperformed the stock assets and other strategies in the medium-long run. This may be driven in part by the growing investor demand for climate-risk matters, as evidenced by Pastor et al. (2022).

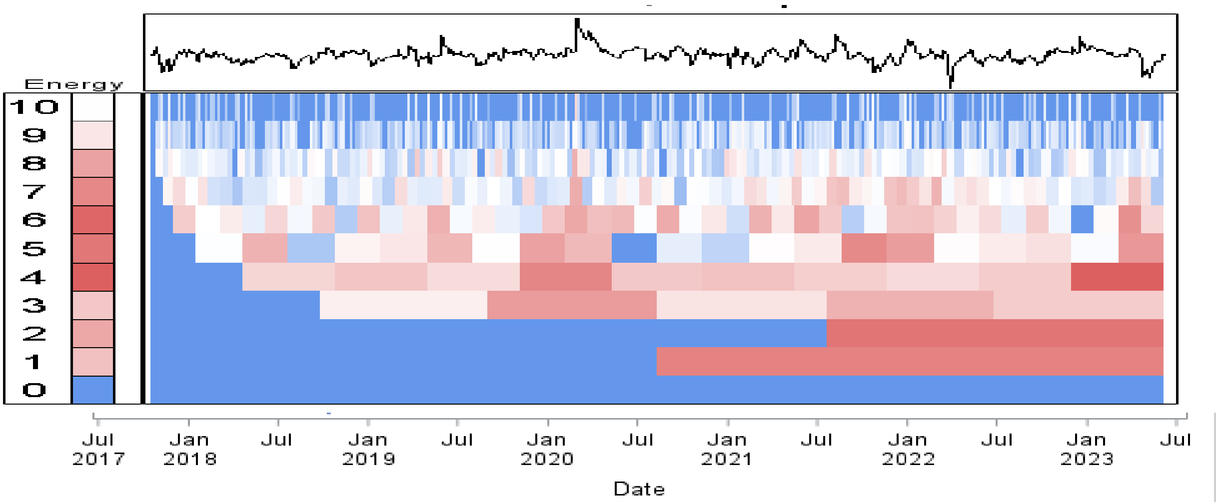


Figure 3a. Wavelet spectrum of BTC/carbon portfolio.

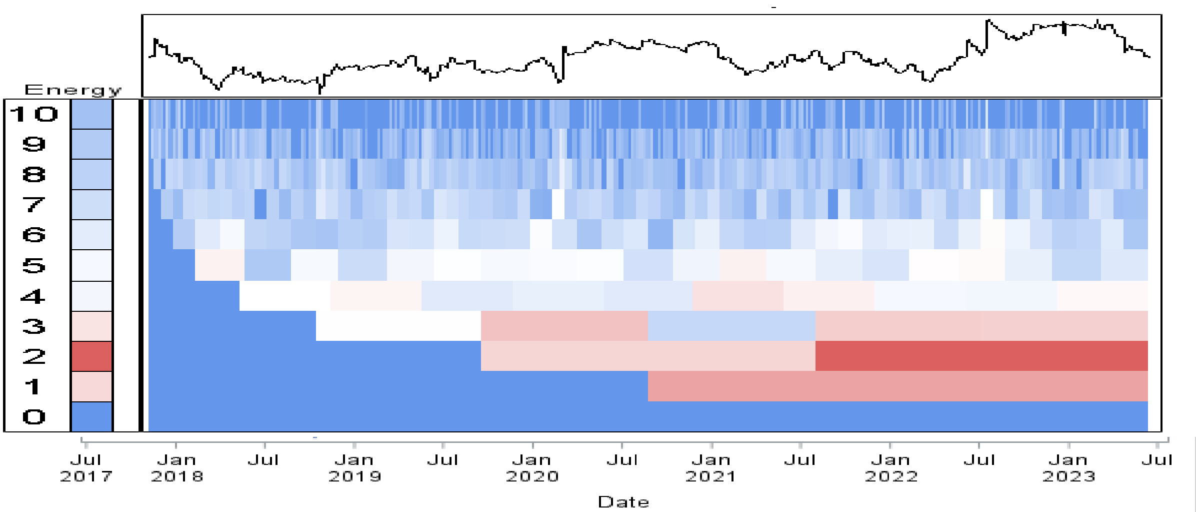


Figure 3b. Wavelet spectrum of BTC/ green bond portfolio.

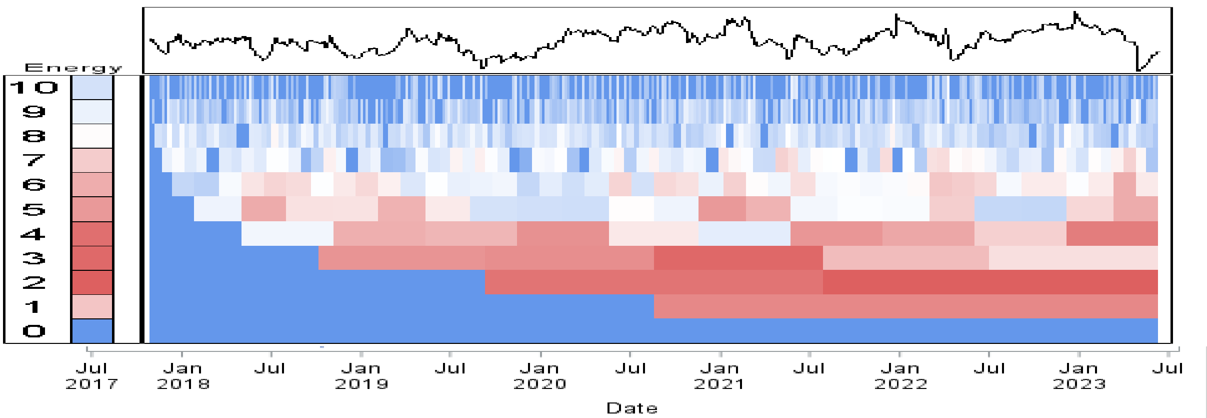


Figure 3c. Wavelet spectrum of BTC/ oil portfolio.

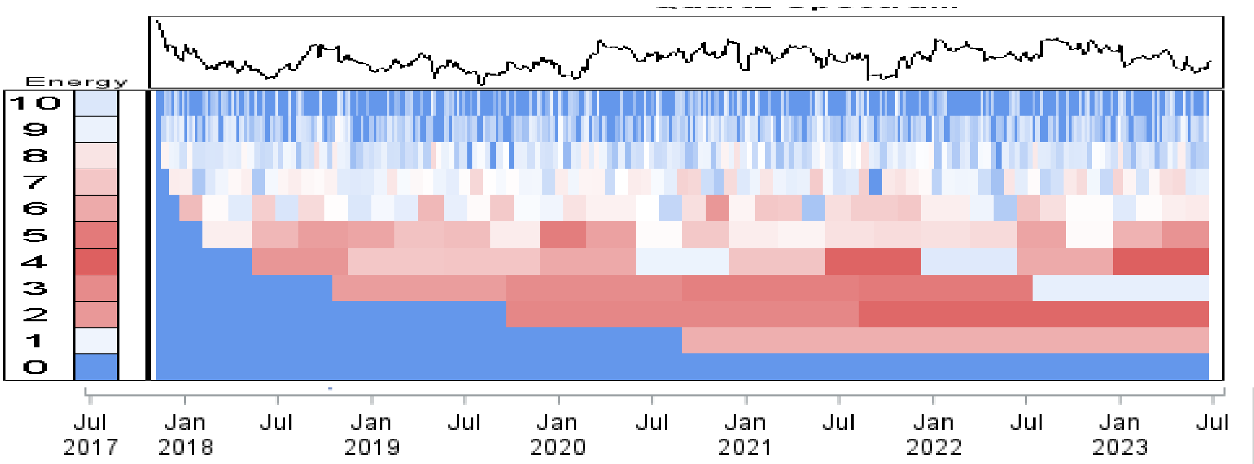


Figure 3d. Wavelet spectrum of BTC/ Stock portfolio.

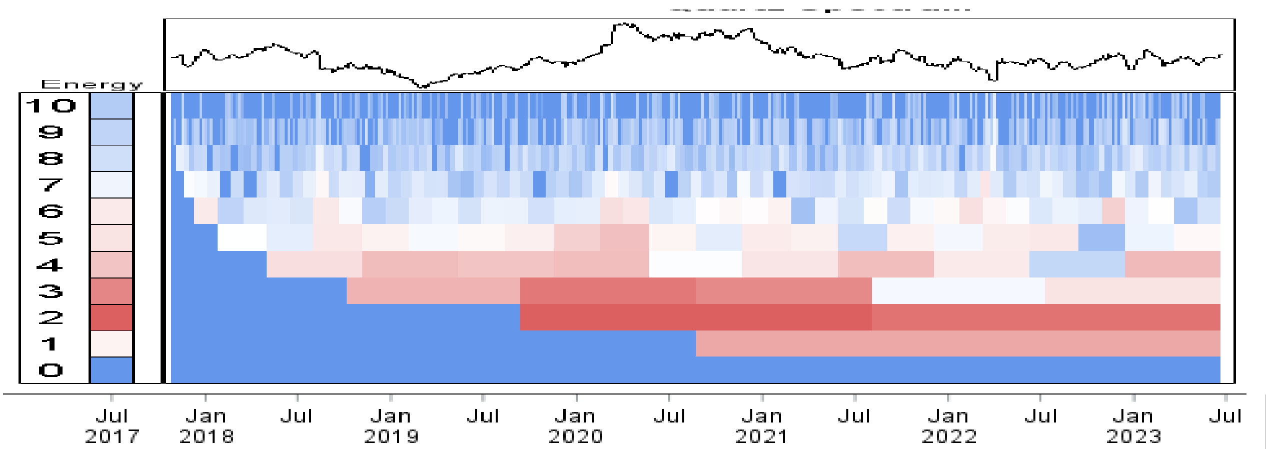


Figure 3e. Wavelet spectrum of Carbon- Stock portfolio.

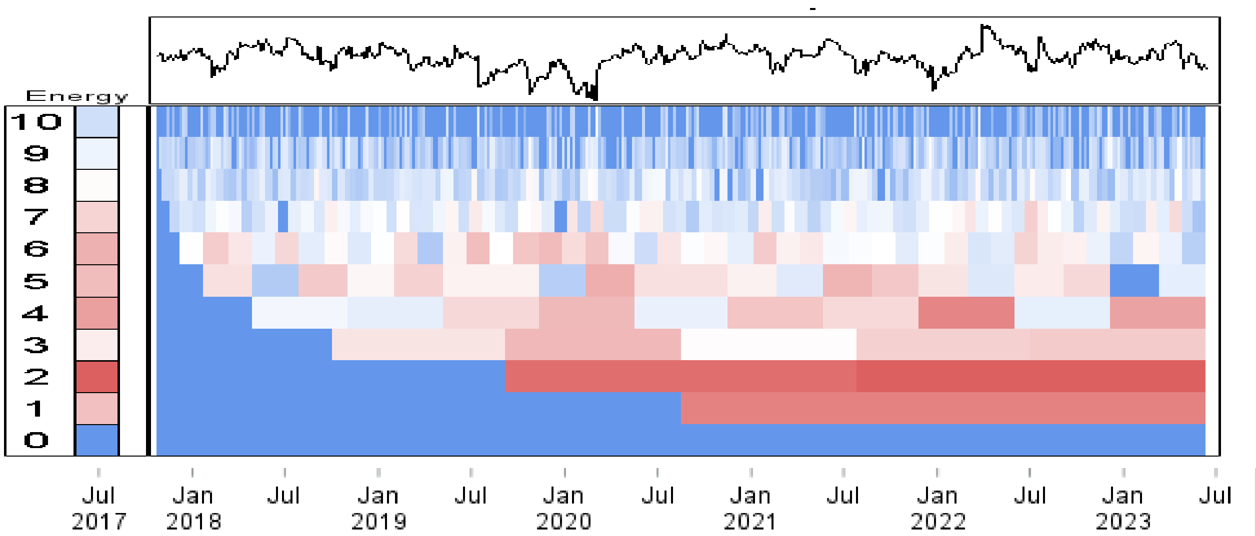


Figure 3f. Wavelet spectrum of GB-Stock portfolio.

Figure 3. Dynamic conditional correlations for BTC/financial assets through wavelet coherence.

Note: For each portfolio, the wavelet coherence allows one to quantify time-frequency dependence among asset classes. In each Figure, the warmer colors with reddish imply areas with higher interlinkages while colder colors with bluish signify lower interdependence.

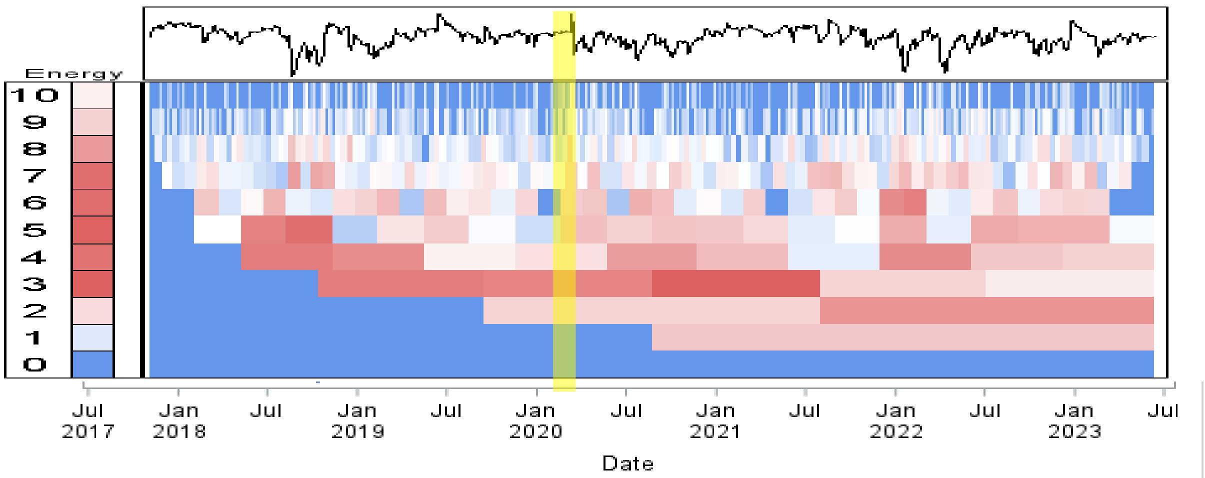


Figure 4a. Wavelet spectrum of BTC/carbon portfolio.

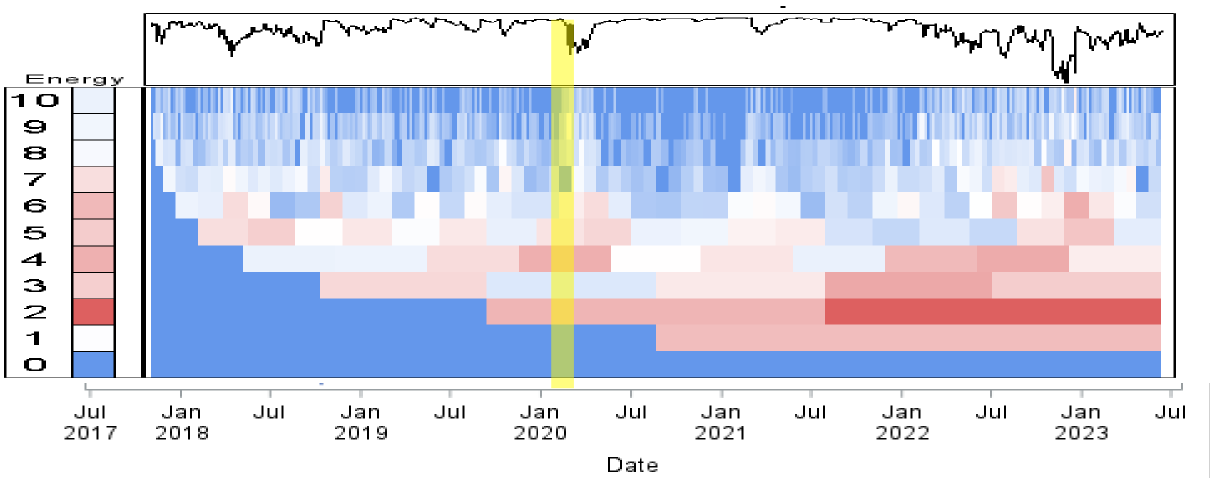


Figure 4b. Wavelet spectrum of BTC/ green bond portfolio.

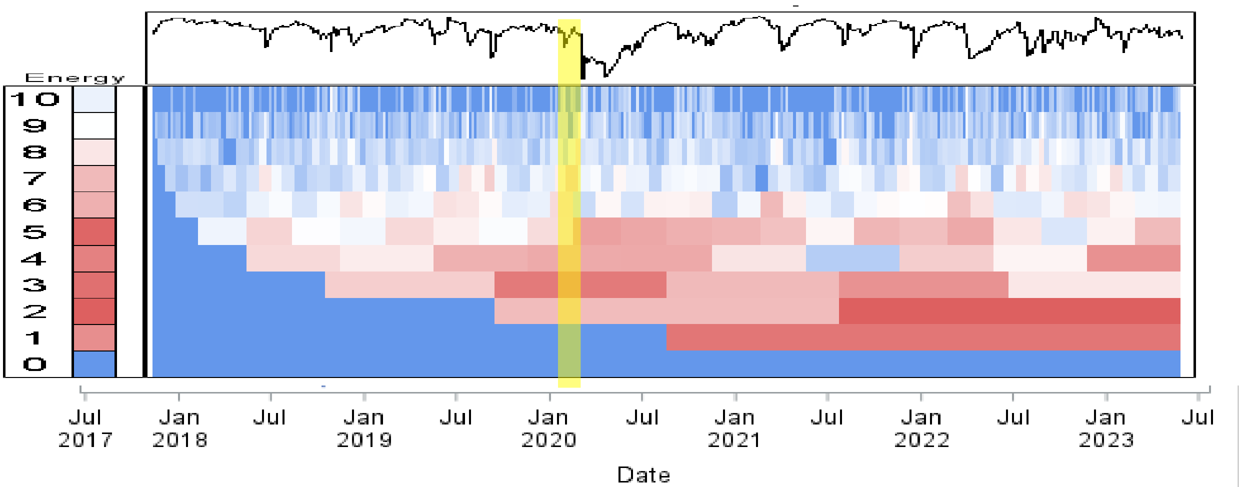


Figure 4c. Wavelet spectrum of BTC/ oil portfolio.

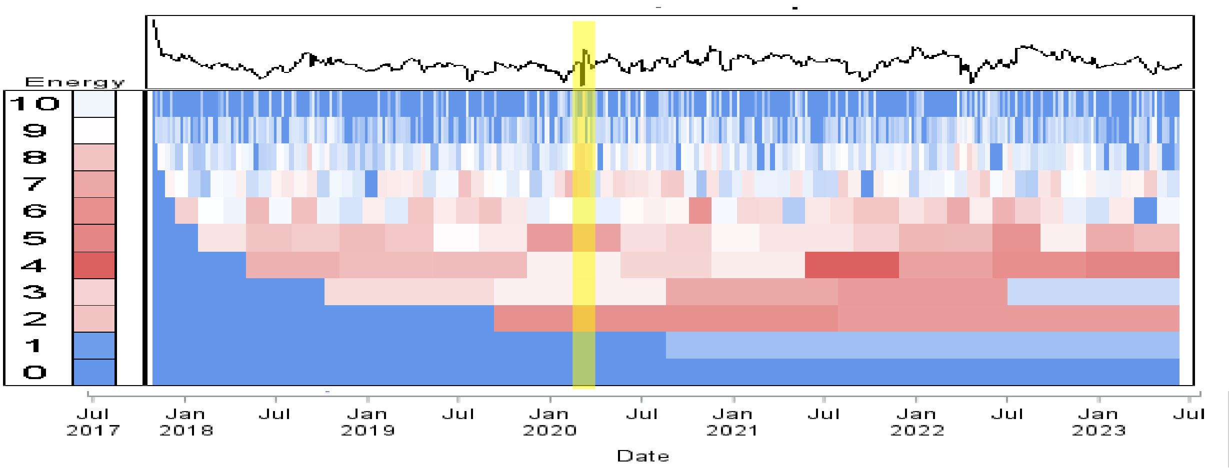


Figure 4d. Wavelet spectrum of BTC/Stock portfolio.

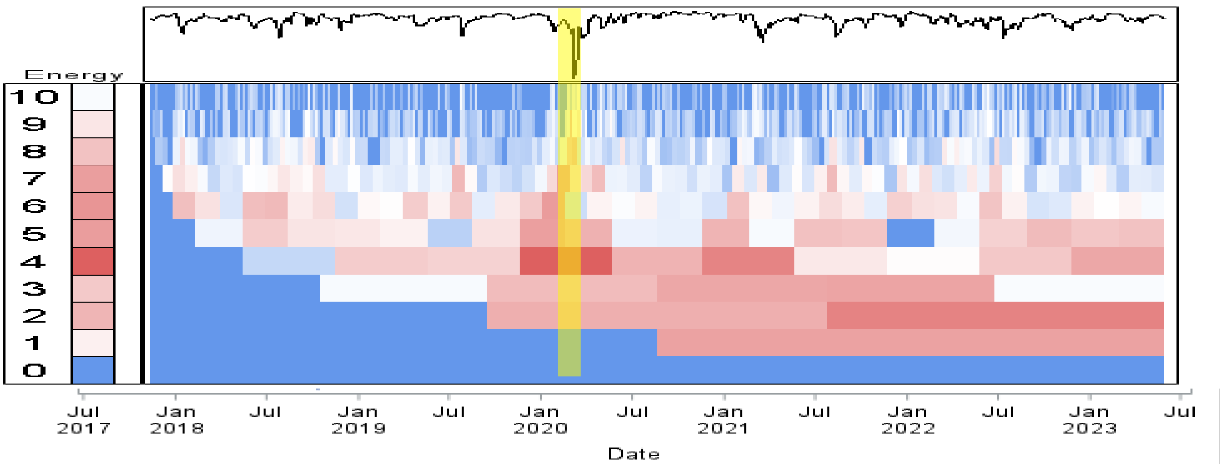


Figure 4e. Wavelet spectrum of Carbon- Stock.

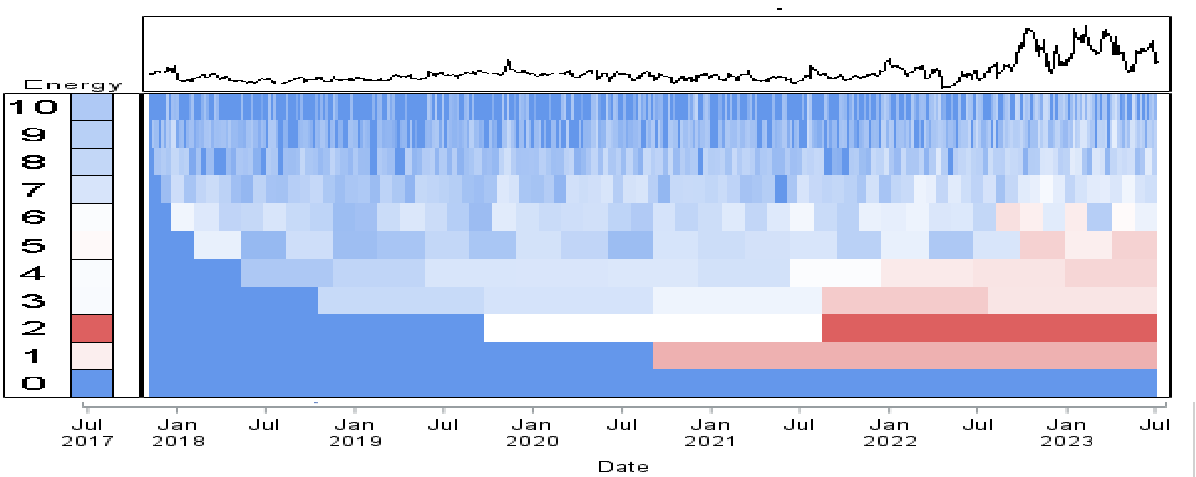


Figure 4f. Wavelet spectrum of Green Bond- Stock.

Figure 4. Illustrative plot of dynamic optimal portfolio weights through wavelet coherence.

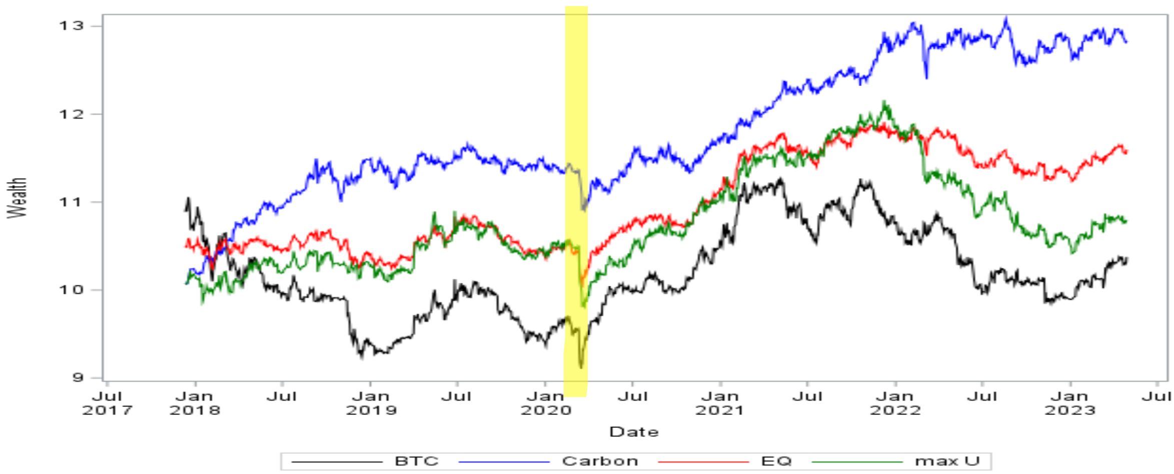
Note: In each figure, the warmer colors with red imply areas with higher interlinkages while colder colors with blue signify lower interdependence.

Table 3. The portfolios' performances for portfolios 1–6.

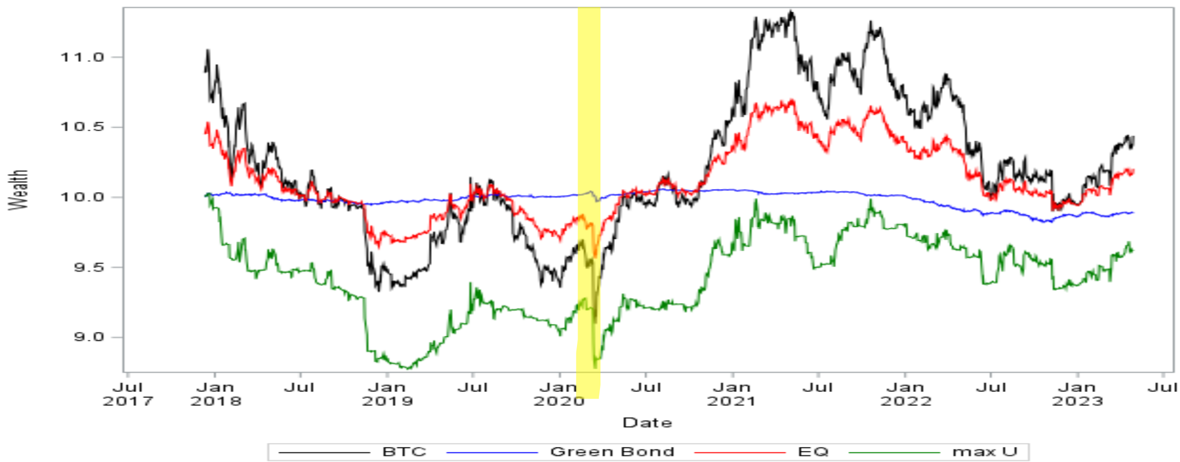
Portfolio 1	Measure	BTC	Carbon	EQ	max U
BTC–Carbon (Emissions)	Average Return	0.0071	0.0068	0.0069	0.0066
	Standard Dev.	0.2662	0.2444	0.2553	0.2444
	Sharpe Ratio	0.0268	0.0277	0.0272	0.0271
	Final Wealth	10.3762	12.8346	11.5986	10.7974
	APY(%)	16.5492	18.5474	17.7498	17.1893
Portfolio 2	Measure	BTC	Green Bonds	EQ	max U
BTC–GBs	Average Return	0.0073	0.0067	0.0070	0.0067
	Standard Dev.	0.2700	0.2460	0.2580	0.2460
	Sharpe Ratio	0.0272	0.0273	0.0272	0.0272
	Final Wealth	10.4397	9.8948	10.2034	9.6259
	APY(%)	16.5492	16.5092	16.7481	16.2954
Portfolio 3	Measure	BTC	Oil	EQ	max U
BTC–Oil	Average Return	0.0071	0.0067	0.0069	0.0066
	Standard Dev.	0.2662	0.2478	0.2570	0.2478
	Sharpe Ratio	0.0268	0.0270	0.0269	0.0267
	Final Wealth	10.3762	10.3083	10.3885	9.4852
	APY(%)	16.5492	16.8277	16.8881	16.1814
Portfolio 4	Measure	BTC	Stock	EQ	max U
BTC– Stock	Average Return	0.0071	0.0066	0.0069	0.0066
	Standard Dev.	0.2662	0.2446	0.2554	0.2444
	Sharpe Ratio	0.0268	0.0269	0.0269	0.0270
	Final Wealth	10.3819	9.9974	10.2264	10.2367
	APY(%)	16.8831	16.5894	16.7656	16.7734
Portfolio 5	Measure	Carbon	Stock	EQ	max U
Carbon– Stock	Average Return	0.0068	0.0066	0.0067	0.0066
	Standard Dev.	0.2444	0.2446	0.2445	0.2444
	Sharpe Ratio	0.0277	0.0269	0.0273	0.0271
	Final Wealth	12.8346	9.9974	11.3439	10.7429
	APY(%)	18.5474	16.5894	17.5757	17.1497
Portfolio 6	Measure	Green Bonds	Stock	EQ	max U
GBs– Stock	Average Return	0.0065	0.0066	0.0066	0.0066
	Standard Dev.	0.2427	0.2446	0.2436	0.2446
	Sharpe Ratio	0.0269	0.0269	0.0269	0.0268
	Final Wealth	9.9178	9.9974	9.9593	9.8499
	APY(%)	16.5273	16.5894	16.5597	16.4740

Note:
1.Table 3 reports descriptive statistics for portfolios' performance, and APY % represents the annual percentage yield.
2.EQ denotes equal weight, i.e., Naïve (1:1) hedge

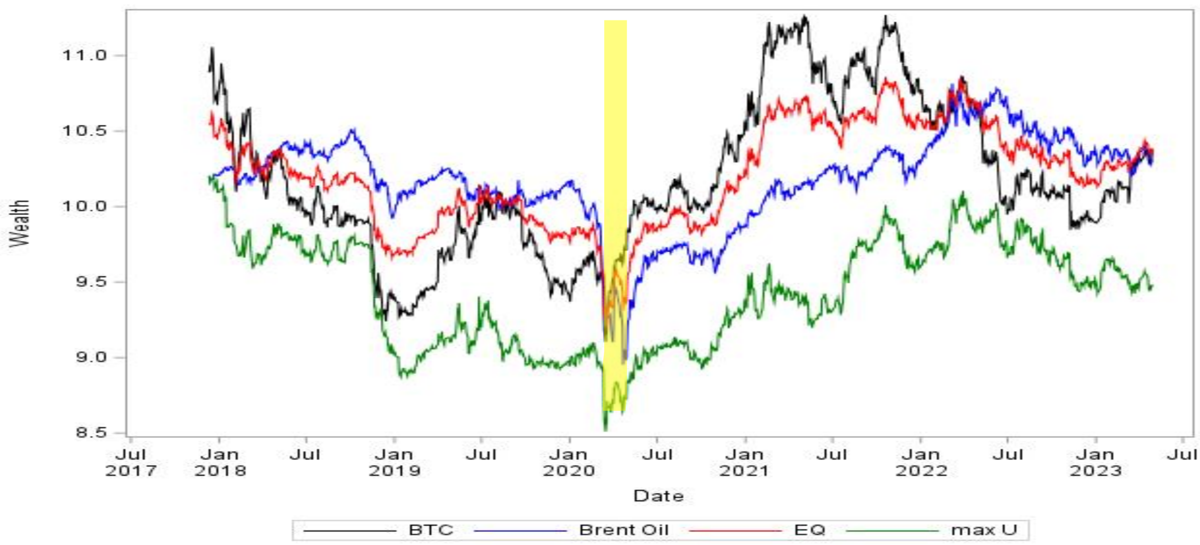
Particularly, carbon asset outperformed emerging stock assets amidst the COVID-19 crisis, while the stock market incurred significant losses (e.g., Mukanjari et al., 2020; Alexakis et al., 2021; Pastor et al., 2022; Yadav et al., 2023). Several factors can be explained for the outperformance during the epidemic phase. For instance, (i) there is an accelerating for carbon assets, and (ii) Since carbon asset offers environmental benefits of emission reduction, thus, investors may have consistent expectations of rising interest in offsetting these carbon emission instruments.



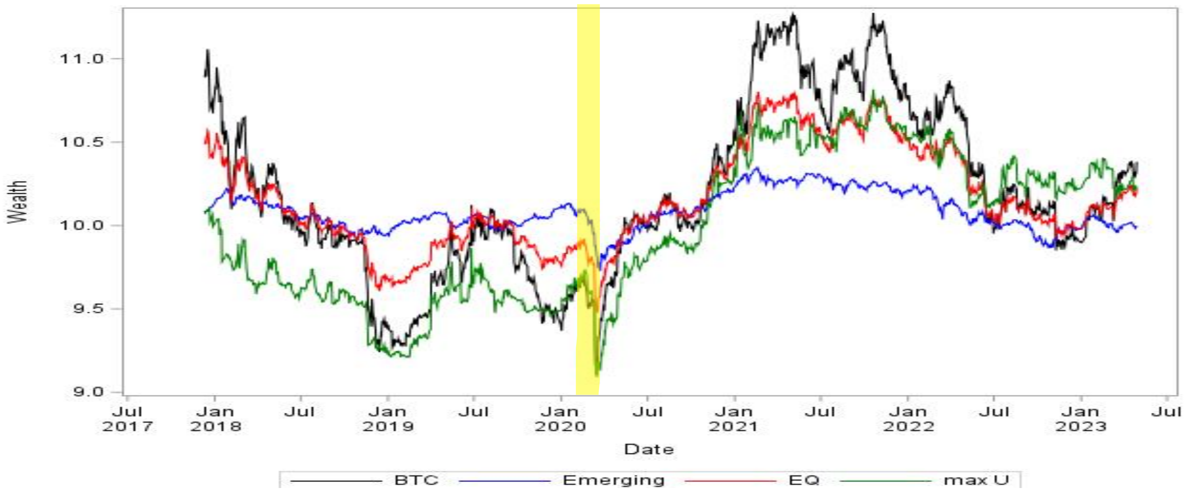
Portfolio 1. BTC–carbon (emissions).



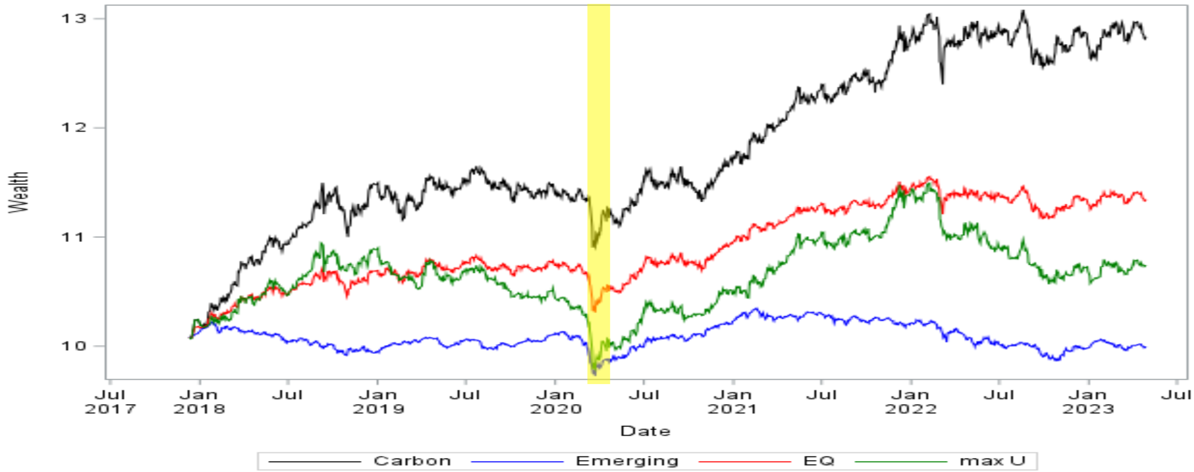
Portfolio 2. BTC–green bond.



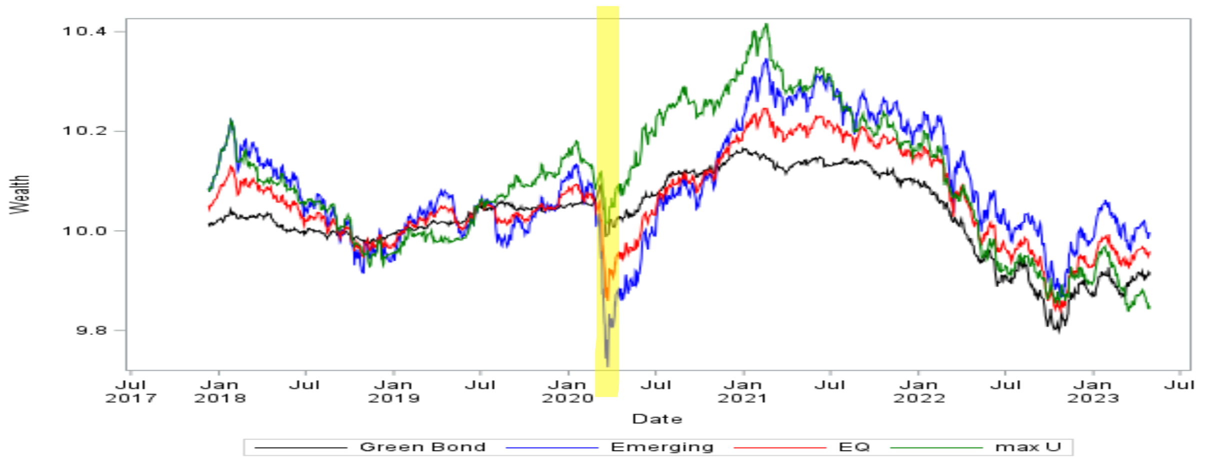
Portfolio 3. BTC–oil.



Portfolio 4. BTC–Stock.



Portfolio 5. Carbon–Stock.



Portfolio 6. Green Bond–Stock.

Figure 5. Final wealth path and performance measures for various trading strategies.

Notes: These figures report the performance measures of four trading strategies involving Naïve (1:1), hedge portfolio optimization weights (%) for each asset allocation which is estimated under an alternative MV framework. The vertical (y) axis represents the wealth path, and the wealth values are measured on quantitative scales.

In light of the COVID-19 crisis, policymakers and investors must assess the risk spillovers between Bitcoin and other assets when markets are bullish or bearish scenarios to construct optimal crypto-portfolios in regard to maximizing returns and minimizing risks, as shown in Table 3. Above all, as depicted in the yellow (bold) lines of Figure 5, the trajectories of this wealth path are found to plunge significantly due to the COVID-19 outbreak at the start of 2020.

5. Conclusions and policy implications

All in all, cryptocurrencies are undoubtedly here to stay and will surely continue to be prevalent as time passes. This is particularly true given the unpredictability of the economic environment and the advances of fintech streams.

Summarizing all, this study synthesizes the above results and depicts an overview of the capability performance of Bitcoin with financial assets. Overall, this research offers practical implications for investors' portfolios constructed from their crypto portfolios that include financial assets.

First, the study presents new evidence of Bitcoin being a hedge against carbon emissions, oil, and emerging stocks. Comparably, Bitcoin provides greater hedging capability than most traditional assets.

Second, empirically, carbon emission can play a role as a financial diversifier for most conventional assets and Bitcoin.

Third, comparably, Bitcoin against green bond assets is lacking hedge effectiveness, indicating that Bitcoin is not a valuable hedge to substitute green bonds in the role of decreasing the risk of climate change, since the green asset is less volatile than crypto, oil, and stock assets.

The study sheds light on the pairwise connectedness between Bitcoin, green/sustainable assets, energy, and emerging stock returns using more specialized techniques to simultaneously specify time and frequency variation. Firstly, we applied the DCC-GJR-GARCH model to capture the time-varying connectedness in volatility between Bitcoin and the prominent assets' returns. Second, we employed wavelet coherence analysis to describe the time-frequency connectedness between these assets. Our findings highlighted some interesting insights, along with dynamics in conditional correction between the leading cryptocurrency, Bitcoin, and prominent financial assets. Ultimately, these findings have crucial implications for crypto enthusiasts, green investors, and portfolio managers regarding crypto allocation, hedging strategy, portfolio diversification, and risk management.

Regarding future studies, a crucial question left is how to use more renewable energy to reduce Bitcoin's carbon footprint. After the unprecedented COVID-19 pandemic, what should the position hold for carbon or green bond assets as a diversifier or a hedging instrument? Thus, this work will be left to further research.

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Use of AI tools declaration

The author declare they have not used artificial intelligence (AI) tools in the creation of this article.

Conflict of interest

The authors declare no conflict of interest.

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