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Towards the path of green finance: Unraveling the co-movement between green cryptocurrencies and Bitcoin

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Abstract

In this paper, we have studied the multifractal cross-correlation between green cryptocurrencies and a non-green cryptocurrency; Bitcoin, which is considered a significant polluter. The study reveals that both small and large fluctuations in Bitcoin's return affect the returns of green cryptocurrencies. Based on the study's results, investors can create their portfolios more effectively, subject to the risk they are willing to take, the time horizon of their investments, and their eco-consciousness.

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1.0 Introduction

Cryptocurrencies have been a rage recently as a financial asset and investment, garnering increased attention, Urquhart (2016). One of the first asset classes in this category is Bitcoin, launched in 2009, a year after the Global Financial Crisis. Despite initial skepticism about the asset, it has experienced significant growth in market capitalization and paved the way for introducing new crypto assets, Kumar (2019). As per CoinMarketCap (a premium cryptocurrency price tracking website) the number of cryptocurrencies has increased from 1560 currencies in April 2018 to 8848 active cryptocurrencies in 2024. This indicates that the cryptocurrency market is becoming more active and liquid as investor participation has increased. This emerging and dynamic asset class attracts investors, industrial participants, and experts to examine portfolio diversification and optimization, Goodell & Goutte (2021). Glaser et al. (2014) found that cryptocurrency users consider these assets an alternative investment vehicle rather than an alternative transactional vehicle.

As per CoinMarketCap, Bitcoin has the largest market capitalization, indicating a significant number of investors. The mechanism employed by Bitcoin for transaction validation involves solving a complex cryptographic puzzle and finding a specific input to a hash function that satisfies certain conditions. Upon successfully solving this puzzle, the participant is rewarded. This validation process is known as Proof-of-Work (PoW) and is commonly called mining. This mining process requires a substantial amount of energy generated from the hardware used to solve the complicated problem. As per the estimation of the Cambridge Bitcoin Electricity Consumption Index, Bitcoin’s global ranking is 25; hence, we can say that Bitcoin mining is an energy-intensive process.

As the sector becomes increasingly intertwined with the global financial system through the exchange and investment in digital currencies, attention must be paid to the negative environmental externalities caused by them (Chamanara, et al., 2022). The rising price of Bitcoin in recent years, leading to increased demand for Bitcoin mining, has transformed the cryptocurrency market into one of the world's leading polluting sectors. Mining is reported to consume significant electricity, resulting in substantial carbon emissions (Stoll et al., 2019). In their study, they also attempted to calculate the carbon footprint of Bitcoin and found that annual carbon emissions range from 22.0 to 22.9 $MtCO_2$, with an annual electricity consumption magnitude of 45.8 TWh.Concerns about the environmental and carbon footprints of Bitcoin have prompted the development of consensus systems worldwide to monitor, control, and mitigate environmental externalities in the cryptocurrency market. Despite the widespread acceptance of cryptocurrencies, particularly Bitcoin, as an investment (Urquhart, 2016), concerns have been raised about the energy inefficiency resulting from the mining process.

In this scenario, the search for potential diversification in the cryptocurrency market is of great importance. As a reaction to this, green blockchains and green validation processes have arisen. This has opened the doors for a new set of crypto assets called green cryptocurrencies. Out of the lot, Cardano has the highest market capitalization and is the first to use the Proof of Stake (PoS)Ouroboros consensus protocol. This protocol, unlike PoW, is designed to reduce energy consumption by eliminating the requirement of substantial computing power. Unlike Bitcoin, Cardano rewards its validators with transaction fees, reducing energy and waste footprints. Likewise, several green cryptocurrencies have emerged as a new asset class intended to reduce energy consumption. Among them, green cryptocurrencies, such as Nano, Stellar, and Algorand, not only boast significant market capitalization but also distinguish themselves by their comparatively lower energy consumption. In this study, we will be considering Cardano, Nano, Stellar, and Algorand as the major green cryptocurrencies.

Nano uses a novel ledger design called block-lattice, helping it to avoid the bottleneck of a single blockchain design, resulting in a network requiring very little energy. Stellar, another major green cryptocurrency, uses a Proof of Agreement(PoA) consensus mechanism, making its network faster and more energy-efficient. The last green crypto that will be considered in this study is Algorand, which produces a new block in roughly three seconds and reaches an agreement on each block. It uses pure PoS, maintaining a clean and green system.

This emerging and dynamic asset class reflects investors' demand for energy-efficient assets in their portfolios. The adoption of sustainable green technologies supports unlocking green investments, contributing to achieving the UN Sustainable Development Goals (SDGs). This can be considered a part of green finance, broadening access to environmentally-friendly goods and services for individuals and enterprises, equalizing the transition to a low-carbon society, and resulting in more socially inclusive growth. This creates a 'great green multiplier' effect in the economy.

Within the framework of our financial system, investors engage in the simultaneous allocation of resources to both green and non-green cryptocurrencies. Nevertheless, a comprehensive understanding of these green cryptocurrencies becomes imperative for investors seeking to optimize their returns when juxtaposed with non-green crypto assets, notably exemplified by Bitcoin. The intricacies inherent in the cryptocurrency system pose a formidable challenge for mapping interconnections, given its complex and interdependent nature. Notably, the existing body of research on this complex phenomenon remains limited.

This paper addresses this scholarly void by examining and elucidating the interconnections across various scales between the returns associated with green cryptocurrencies and non-green cryptocurrency, Bitcoin. Through such an examination, our study contributes to the literature by shedding light on the intricate web of dependencies within the cryptocurrency realm. For this purpose, our study aims to use Multifractal Cross-Correlation Analysis, examining fractality and correlation at different scales, thereby offering insights into diversification benefits for investors.

The remainder of this article is structured as follows: Section 2 provides a brief review of the literature; and Section 3 discusses data and methodology employed. Section 4 shows the estimation results and their explanation, while section 5 provides the concluding remarks.

2.0 Review of Literature

2.1 Studies on Energy Consumption of Cryptocurrencies

Numerous studies have examined the energy consumption of cryptocurrencies using various methodologies. Many of them particularly reviewed the impact of Bitcoin trading on energy consumption and found that it is the largest emitter of carbon among crypto assets. The study by Krause & Tolaymat (2018) found that around 3 to 15 million tons of CO_2 emissions are generated through cryptocurrency mining. They also argued that the mining process of Bitcoin can lead to an increase in CO_2 in the atmosphere. Stoll et al. (2019) proposed a new methodology for identifying power consumption by Bitcoin and calculated the carbon footprint. They found that annual carbon emissions range from 22.0 and 22.9$MtCO_2$ and the annual electricity consumption of Bitcoin had a magnitude of 45.8TWh.Mora et al. (2018) and Howson (2019), made an argument that Bitcoin alone among all cryptocurrencies may lead to a 2-degree Celsius rise in global temperature by 2050.

The electricity consumption among this asset class is high and can have negative impacts on the environment. Based on these concerns, academicians and policymakers began to think about the carbon footprints of cryptocurrencies. The literature on the linkage between cryptocurrencies and environmental impacts began after these assets became popular among investors. The studies such as Jiang et al. (2021), Roeck & Drennen (2022), and Badea & Mungiu-Pupăzan (2021) explored the electricity consumption of Bitcoin mining. However, other studies like Mora et al. (2018), Panah et al. (2022), Pham et al. (2022), and Erdogan et al. (2022) examined and found the CO_2 emissions from the mining process of cryptocurrencies. These studies highlight the huge level of energy consumption by Bitcoin and the need to invest in alternative assets that have less energy consumption and footprints. Naeem & Karim (2021) argued that the clean energy hedging ratio and effectiveness are greater for Bitcoin, showing the potential for green cryptocurrencies in portfolio diversification. In this scenario demand for more sustainable financial assets will increase and investment in green cryptocurrencies; a new emerging asset class will become more attractive.

2.2 Studies on Green Cryptocurrencies

Moving to the studies on green cryptocurrencies, the research in this area has become dynamic only in recent years. So, the research in this field is scarce. Pham et al. (2022) examined the tail dependency of carbon pricing between green and non-green cryptocurrencies using a quantile connectedness framework. Husain et al. (2023) tested the dynamic connectedness of green cryptocurrencies, green investment, conventional commodities, and equities using wavelet coherence and found that green cryptocurrencies do not exhibit hedge or safe-haven properties, but they are good diversifiers. Ali et al. (2024), in their study, have taken a set of green and non-green crypto assets and concluded that green cryptocurrencies provide a diversification benefit that is less comparable to high energy-consuming cryptocurrencies such as Bitcoin. Similarly, Sharif et al. (2023) in their study emphasized the importance of investing in green cryptocurrencies along with non-green financial assets through the quantile spillover index. The results show that the overall nexus is stronger for clean cryptocurrencies than for dirty cryptocurrencies. All of the existing literature has highlighted the importance of investing in green crypto assets.

2.3 Studies on multifractal cross-correlation in cryptocurrencies

Fractal characteristics in the crypto market have been examined in detail by numerous studies using various methods like Detrended Fluctuation Analysis (DFA) (Alvarez et al., 2018; Costa et al., 2019 and Quintino et al., 2020), Multifractal-Detrended Fluctuation Analysis (MF-DFA) (Cheng et al., 2019; Stosic et al., 2019 and Shrestha, 2021). The studies mentioned above have found the cryptocurrency market to be fractal and multifractal.

Podobnik and Stanley (2008) extended the DFA to Detrended Cross-Correlation Analysis (DCCA), to quantify cross-correlations between non-stationary time series. DCCA has been applied and studied in the crypto market (Ferreira et al., 2020;Almeida et al., 2023). This method was later extended to multifractal series (MF-DXA, MFDCCA, MF-X-DFA). These methods are a combination of DCCA and MF-DFA and have been used in various studies in the cryptocurrency market (Ghazani & Khosravi,2020; Guangxi & Xingyu, 2021; Kakinaka & Umeno,2021).

It can be seen from the literature that there have been sparse studies on the co-movement of Bitcoin and green crypto assets.

3.0 Data and Methods

3.1 Data

The data for this study is from CoinMarketCap (a premier price tracking website for the crypto market); the green cryptocurrencies chosen based on market capitalization are Cardano, Stellar, Nano, and Algorand. Bitcoin is the non-green cryptocurrency that we have taken. The time frame for the study is from 06-22-2019 to 07-06-2023 (1476) for observations of each cryptocurrency.

3.2 Method

3.2.1 Multifractal Cross-correlation Analysis (MF-DCCA)

We have used the Modified Multifractal Detrended Fluctuation Analysis (MF-X-DFA) method based on the MF-DCCA algorithm. The Multifractal Detrended Cross-Correlation Analysis (MF-DCCA) was proposed by Zhou(2008). Let M(i) and N(i) be a two-time series of length K, representing the logarithmic returns. Estimating logarithmic returns ensures a scale-free investment measure, making it suitable for comparison. When m(t)= n(t), the MF-X-DFA collapses to Multifractal Detrended Fluctuation Analysis (MF- DFA).

Step 1: We determine the cumulative sum of m(i) and n(i) and deduct it from their respective means. This is done to find the long-term trend. This is represented in equation (1). Over here, it ranges from 1 to K.

$M(i) = \sum_{t=1}^{i}[m(t) - \widehat{m}]\ , N(i) = \sum_{t=1}^{i}[n(t) - \hat{n}]$ (1)

Step 2: Next, M(i) and N(i) are divided into $K_s \equiv int\frac{K}{s}$, non-overlapping segments of equal length s, where s is the time interval. If K is not a multiple of s, the same procedure is repeated from the opposite side. Thus, in such a situation, we obtain $2K_s$.

Step 3: We find the local trend, which is calculated using least-square fitting polynomial l_ϑ for each segment. Then, the variance is estimated, shown in equations (2) and (3).

For $\vartheta = 1, \ldots, K_s$

$$F^2(s,\vartheta) = \frac{1}{s}\sum_{i=1}^{s} |M((\vartheta-1)s+i) - l_\vartheta| \ . |N((\vartheta\text{-}1)s+i) - l_\vartheta| \quad (2)$$

For $\vartheta = K_s+1, \ldots, 2K_s$

$$F^2(s,\vartheta) = \frac{1}{s}\sum_{i=1}^{s} |M(K-(\vartheta-K_s)s+i) - l_\vartheta| \ . |N(K\text{-}(\vartheta\text{-}K_s)s+i) - l_\vartheta| \quad (3)$$

Step 4: We average the variances over all segments to obtain the qth order fluctuation

for q $\neq$0

$$F_{q(s)} = \left\{\frac{1}{2K_s}\sum_{\vartheta=1}^{2K_s}[F_s^2(s,\vartheta)]^{\frac{q}{2}}\right\}^{\frac{1}{q}} \quad (4)$$

For q=0

$$F_{0(s)} = exp\left\{\frac{1}{4K_s}\sum_{\vartheta=1}^{2K_s} ln[F_s^2(s,\vartheta)]\right\} \quad (5)$$

Step 5: The final step is defining the scaling behavior. For each value of q, we determine the scaling behavior of the function

$$F_{q(s)} \sim s^{H_{mn}(q)} \quad (6)$$

H_{mn} is called the generalized cross-correlation exponent, it also determines the scaling behavior, if $H_{mn}(q) > 0.5$ then the cross-correlations exhibit long-range persistence, in the context of green cryptocurrencies it means that a high closing price is most probably to be followed by another high closing price and vice versa. If $H_{mn}(q) < 0.5$, it means that cross-correlations are anti-persistent. It means that a high closing price is most probably followed by a low closing price. If $H_{mn}(q)=0.5$, it means that the series does not exhibit cross-correlations. It is important to choose a scale that satisfies $10 \leq s \leq \frac{N}{4}$.In our study, we have chosen a scale of 10:100.

Renyi exponent can also be used to determine multifractality

$$\tau_{mn}(q) = H_{mn}(q)\, q-1 \quad (7)$$

If $\tau_{mn}(q)$ is linear then the correlated series is monofractal or else it can be considered as multifractal. $f_{mn}(\alpha)$ shows the singularity spectrum, the richer the spectrum the more multifractal it is.

$$\alpha_{mn(q)} = H_{mn}(q) + q\grave{H}_{mn}(q) \quad (8)$$

$$f_{mn}(\alpha) = q[\alpha_{mn} - H_{mn}(q)]+1 \quad (9)$$

The analysis for this was done using R software, with the help of a package called MF-DFA developed by Laib et al. (2019).

4.0 Results

Table I, given below, has the descriptive statistics. It can be seen that the mean returns of Bitcoin and Cardano are almost equal. The other cryptocurrencies tend to show negative mean returns. In median returns, it is seen that Stellar and Cardano are almost equal. The median returns of Nano and Algorand are negative. Bitcoin has a positive median return. In terms of skewness, it is seen that Cardano, Algorand, and Bitcoin are negatively skewed and leptokurtic, indicating possibilities of having small positive returns, fewer but higher negative returns, and kurtosis indicates that there is a significant risk of extreme events. Stellar and Nano have positive skewness and leptokurtic distributions, which indicates the possibility of having few larger positive returns and frequent small losses; the kurtosis indicates that there is a significant risk of extreme events. The Jarque-Bera(J-B) test shows that none of the selected cryptocurrencies follow a normal distribution.

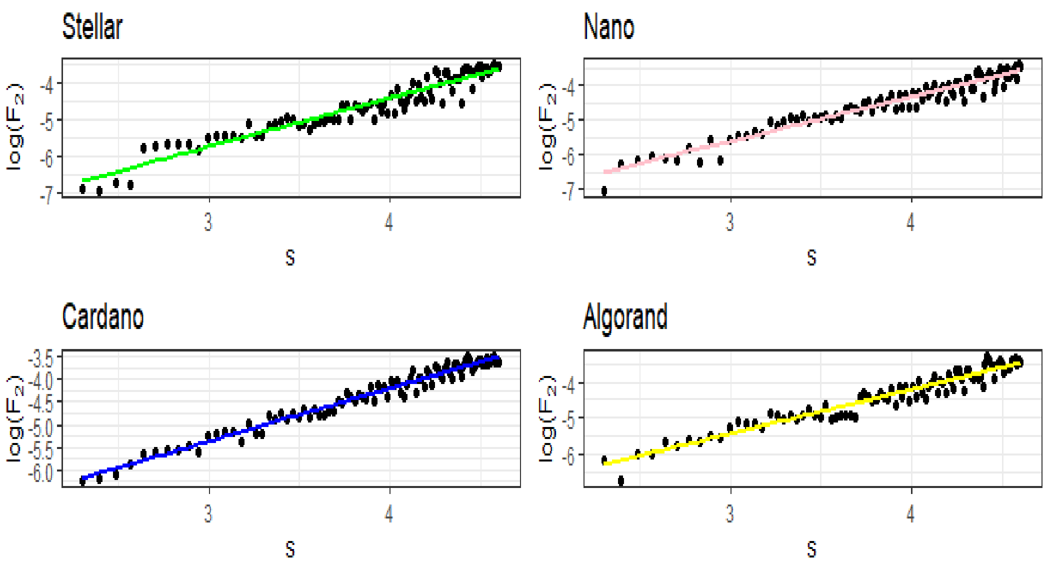
Table I: Descriptive Statistics

	Bitcoin	Stellar	Nano	Cardano	Algorand
Mean	0.0007	-0.0001	-0.0004	0.0007	-0.002
Median	0.0002	0.0007	-0.002	0.0007	-0.0004
Min	-0.464	-0.409	-0.585	-0.503	-0.650
Max	0.171	0.559	0.746	0.279	0.418
Skewness	-1.375	0.688	1.854	-0.312	-0.757
Kurtosis	21.54	19.267	29.26	10.62	13.84
Jarque-Bera	21626.72*** (0.0000)	16390.71*** (0.0000)	43276.21*** (0.0000)	3958.95*** (0.0000)	7373.30*** (0.0000)

Note:() shows the p value, *** indicates significance at 1% level

Figure 1, shows the log-on-log plots of the green cryptocurrencies with Bitcoin. It is seen that all the green cryptocurrencies fit a straight line. The figure shows that a power law exists between the return of the selected green cryptocurrencies and Bitcoin.

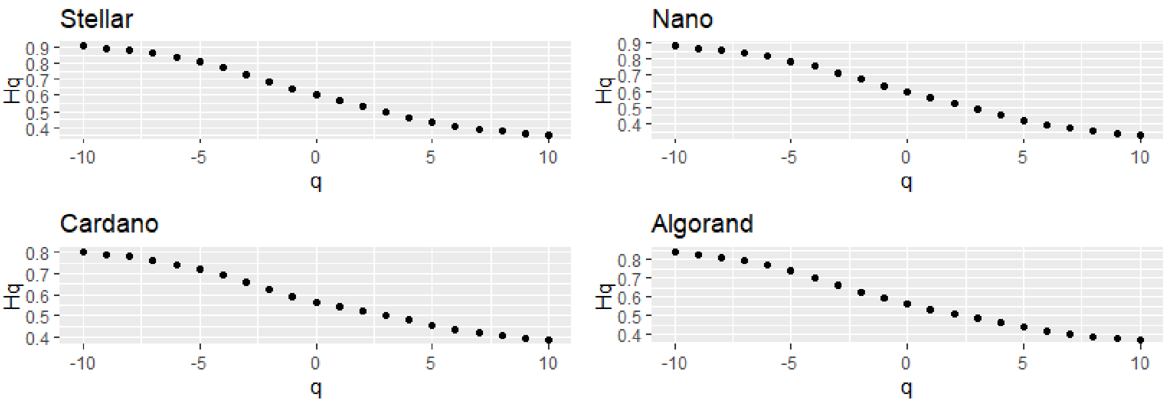
Figure 1: Log on log Plots



Note: Log on log plots used in finance for determining the power law dynamics. The above figure adheres to this.

Figure 2 shows the $H_{mn}(q)$, it is seen that $H_{mn}(q)$ for $q<0$ is larger than that for $q>0$. This shows that the cross-correlated behavior of small fluctuations tends to persist more than large fluctuations. The function is monotonically decreasing, as seen in figure 2. To sum up, from the below figure, we can say that a small fluctuation in the return of Bitcoin does cause a change in the return of the green cryptocurrencies, and that change is persistent.

Figure 2: Generalized Cross-correlation Exponent(GCE) plot



Note: The GCE plot shows the cross-correlation behavior between green crypto and Bitcoin.

Table II has the generalized cross-correlation exponent (H_{mn}). Persistent cross-correlation with Bitcoin can be seen in the negative moments, which indicates that when the fluctuations are small, the selected green cryptocurrencies and Bitcoin are cross-correlated. In positive moments of 0,1, and 2, H_{mn} is greater than 0.50, but after that, they are anti-persistent; hence in large fluctuations, they are anti cross-correlated with Bitcoin. This indicates that large positive changes in the returns of Bitcoin negatively affect the returns of the selected green cryptocurrencies and vice versa.

Table II: Generalised Cross-correlation Exponent

Moments	Stellar	Nano	Cardano	Algorand
-10	0.90	0.87	0.80	0.84
-9	0.89	0.86	0.79	0.82
-8	0.88	0.85	0.77	0.81
-7	0.86	0.83	0.76	0.79
-6	0.83	0.81	0.74	0.76
-5	0.80	0.78	0.71	0.73
-4	0.77	0.75	0.69	0.70
-3	0.72	0.71	0.65	0.66
-2	0.68	0.67	0.62	0.62
-1	0.64	0.63	0.59	0.59
0	0.59	0.59	0.56	0.55
1	0.56	0.56	0.54	0.53
2	0.52	0.52	0.52	0.50

3	0.49	0.49	0.50	0.48
4	0.45	0.45	0.48	0.46
5	0.43	0.41	0.45	0.43
6	0.40	0.39	0.43	0.41
7	0.39	0.37	0.41	0.39
8	0.37	0.35	0.40	0.38
9	0.36	0.34	0.39	0.37
10	0.35	0.33	0.38	0.36

Note: The above table the Generalised Cross-correlation Exponent at various moments.

5.0 Conclusion

Our study highlights the multifractal cross-correlation between the returns of Bitcoin and the top four green cryptocurrencies (as per market capitalization). This study adds to the current evolving literature on green cryptocurrencies by revealing that multifractal structures exist among the returns of selected green cryptocurrencies and Bitcoin. It was seen that both small and large fluctuations in the return of Bitcoin do bring about a change in the returns of green cryptocurrencies, but large fluctuations in returns negatively affects the returns of green crypto assets. This result reveals that investors have to be cautious when they have both green- cryptocurrencies and Bitcoin in their portfolio as they are persistently cross-correlated at negative values of our results contradict (Pham et al.,2022), who found green cryptocurrencies weakly connected to Bitcoin. Their study used the quantile connectedness approach, which failed to capture complex scale dependencies caused by multifractality. Our study aligns with (Zhang et al., 2018 ;Kakinaka & Umeno, 2021), who found results of multifractal cross-correlation in other cryptocurrency markets. These results enable more informed decisions that strike a compromise between return expectations, risk tolerance, and environmental values by empowering stakeholders to match their investment strategies with both financial goals and sustainability preferences. The analysis provides a more nuanced view of how these green crypto assets interact with a major non-green cryptocurrency. This we believe will help investors understand the market better and allocate their assets more efficiently; especially for eco-conscious investors.

Thus this study aims to help investors make judicious and well-informed choices. For future research, we plan to extend the analysis by looking at the alternative green finance instruments in the traditional market and their interactions with green cryptocurrencies using wavelet-based methods across different time horizons.

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