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Efficiency of traditional and green cryptocurrencies: A comparative analysis

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Abstract

The main objective of this research is to evaluate the efficiency, in its weak form, of digital currencies classified as "dirty", such as Bitcoin (BTC) and Ethereum (ETH), and the green ones, namely Lisk (LISK), Metaverse (METAVERSE), Quantum (QTUM), Litecoin (LTC), Augur (REP), Cardano (ADA), Dash (DASH), EOS (EOS), Quantum (QTUM), Litecoin (LTC), Ripple (XRP), Augur (REP), Cardano (ADA), Dash (DASH), EOS (EOS), IOTA (IOTA), Monero (XMR), Neo (NEO), Omisego (OMG), Stellar (XLM) and Zcash (ZEC), for the period from 1 January 2018 to 23 November 2023. The results show that Bitcoin (BTC), Metaverse, Litecoin (LTC) and Cardano (ADA) have persistent behaviour with a long memory, which favours long-term strategies. Long memories indicate that markets are less efficient, where trends tend to continue, making long-term strategies more effective. On the other hand, cryptocurrencies such as Lisk, Quantum, Ethereum (ETH), Ripple (XRP), Augur, Dash, EOS, IOTA, Monero, Neo, Omisego, Stellar and Zcash show anti-persistent behaviour, with rapid correction of deviations, suggesting more efficient markets, but with less predictability. This favours short-term strategies such as arbitrage and scalping. The analysis reveals that cryptocurrencies with long memory, such as BTC, LTC and ADA, are more predictable in the long term, while most others, such as ETH and XRP, are more suitable for short-term trading, reflecting structural differences in the market.

Keywords: *Cryptocurrencies; Long Memories; Trading Strategies; Portfolio Rebalancing.*

Introduction

The rapid development of cryptocurrencies has increased demand, but cryptocurrencies with high energy consumption, known as "dirty", have raised concerns due to their ecological impact. The "Proof of Work" (PoW) mechanism used in digital currencies such as Bitcoin (BTC) and Ethereum (ETH) results in major environmental damage. The study by Mora et al. (2018) warns that Bitcoin's carbon emissions could contribute to global warming of more than two degrees Celsius in 30 years. Bitcoin's annual energy consumption is estimated at 169.98 TWh, more than that of Poland, with each transaction consuming the equivalent of an American family's energy in 62 days. Growing concern about this impact has led to an appreciation of "clean" cryptocurrencies, such as Cardano and Solana, which already have significant market capitalisations (Corbet et al., 2021).

Cryptocurrencies are decentralised forms of digital currency that use cryptography to authenticate transactions. Market efficiency is one of the crucial concepts widely studied in neoclassical finance. In the past, the author Fama (1965, 1970) introduced the phenomenon of market efficiency and the Efficient Markets Hypothesis (EMH). According to Fama (1965, 1970), markets are considered efficient when prices immediately and completely reflect all available information. This concept, based on the Efficient Markets Hypothesis (EMH), is distinguished into three forms of efficiency: weak, where prices incorporate historical information, such as past prices and trading volumes; semi-strong, where they also reflect public

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information, such as financial reports and economic events; and strong, which encompasses public and private information, even eliminating the possibility of advantage for investors with access to inside information. In practical terms, it is impossible to consistently obtain abnormal returns in efficient markets, as any new information is quickly incorporated into prices. This implies that technical or fundamental analysis strategies would be ineffective in weak and semi-strong markets, while in strongly efficient markets, not even insider information would result in returns above the market average.

This research aims to evaluate the efficiency, in its weak form, of "dirty" cryptocurrencies such as Bitcoin (BTC) and Ethereum (ETH) and "green" cryptocurrencies such as Lisk (LISK), Metaverse (METAVERSE), Litecoin (LTC), Ripple (XRP), Cardano (ADA), among others, over the period from 1 January 2018 to 23 November 2023. The results indicate that Bitcoin (BTC), Metaverse, Litecoin (LTC) and Cardano (ADA) show persistent behaviour with long memories, favouring long-term strategies since markets are less efficient and trends tend to continue. On the other hand, cryptocurrencies such as Lisk, Quantum, Ethereum (ETH), Ripple (XRP) and others show anti-persistent behaviour, with rapid correction of deviations, suggesting that the markets appear more efficient.

This research contributes significantly to the existing literature by exploring the market efficiency of cryptocurrencies in their weak form, introducing the distinction between "dirty" and "green" cryptocurrencies. The "dirty" ones, such as Bitcoin (BTC) and Ethereum (ETH), use technologies such as proof-of-work, which consume high energy and have a greater environmental impact. In contrast, the "green" ones, such as Cardano (ADA), Ripple (XRP) and Lisk (LISK), adopt more sustainable mechanisms, such as proof-of-stake, making them attractive options for environmentally conscious investors. The study covers the period from 2018 to 2023 and reveals significant differences between the two groups. "Dirty" cryptocurrencies exhibit persistent behaviour, with long memories and lower market efficiency, favouring long-term strategies. "Green" cryptocurrencies show anti-persistent behaviour, with rapid price corrections, indicating greater efficiency and attracting short-term strategies. This multidimensional approach innovates by considering environmental and technological factors, expanding the understanding of cryptocurrency market dynamics. In addition, it reinforces the relevance of the Adaptive Markets Hypothesis (AMH) by demonstrating that market efficiency varies with asset characteristics and market conditions, thus contributing to debates on sustainability, innovation and investment strategies.

After this introduction, the rest of the study is organised as follows. Section 2 presents the literature review, and section 3 describes the data and the methodology used in the analysis. Section 4 presents the empirical results, and section 5 concludes and discusses the study's implications.

Literature Review

The Efficient Market Hypothesis (EMH) advocates that asset prices reflect all available information, making it impossible for investors to obtain returns above the market average based on this information alone. This concept is crucial for investors, financial institutions and regulators, as it influences investment strategies and the development of regulatory measures for organised markets. Various authors, such as Poterba and Summers (1988) and Fama and French (1988), have analysed the efficiency of markets, investigating the predictability of returns and patterns of mean reversion.

The pandemic and events such as the 2018 crash have highlighted the cryptocurrency market's volatility. This market analysed from a functional perspective (economic relations in cyberspace) and an institutional perspective (participants in transactions), has experienced strong fluctuations. After the WHO declared the pandemic, Bitcoin fell 46.5 per cent in one day but quickly began a recovery, culminating in a period of highs that lasted almost a year, with daily increases of up to 59.6 per cent (Malkina & Ovchinnikov, 2020).

The authors Hawaldar et al. (2019) analysed the efficiency, in its weak form, of the cryptocurrencies Bitcoin and Litecoin in relation to the US dollar from 2013 to 2017, concluding that they exhibit random walk characteristics. Meanwhile, the authors Ballis and Drakos (2020) investigated imitation behaviour in the cryptocurrency market between August 2015 and December 2018, identifying that investors act irrationally,

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copying other people's decisions without basing them on their own beliefs, which reveals signs of (in)efficiency in the market.

The authors Kakinaka and Umeno (2022) and Abdullah et al. (2023) examined the efficiency, in its form, of digital currencies during significant events in the global economy. Kakinaka and Umeno (2022) showed that during the pandemic, cryptocurrencies were more multifractal in the short term and less so in the long term. On the other hand, the authors Abdullah et al. (2023) concluded that between 2018 and 2022, gold was the most efficient asset, followed by halal tourism stocks, which outperformed green stocks in efficiency.

Later, the authors Dias et al. (2023) analysed the period from March 2018 to March 2023, looking at efficiency in its weak form in 12 cryptocurrencies. The authors revealed the presence of positive and negative autocorrelations, showing the presence of long memories, which allow investors to carry out long-term trading strategies. Agrawal et al. (2024) analysed the relationship between the year cryptocurrencies were introduced and their market capitalisation and volatility using EGARCH and GJR-GARCH models. The results show that capitalisation varies with the maturity of the cryptocurrencies, while negative news impacts Bitcoin, Ethereum, BNB and Solana more, showing short-term memories, while Tether shows persistence in its returns.

2024 Galvão and Dias (2024) analysed the efficiency of clean energy indices and 'dirty' cryptocurrencies (BTC, ETH, ETH Classic and LTC) in 2020 and 2023. The authors show that both the clean energy indices and the 'dirty' cryptocurrencies show autocorrelation in their returns, which means that current returns are related to past returns. This behaviour indicates the presence of temporal dependencies in the data, contrary to the efficiency hypothesis, in its weak form, which assumes the independence of prices over time. In a complementary way, the authors Alexakis et al. (2024) investigated the increase in cryptocurrency trading during geopolitical crises, observing that trading increases in situations of devaluation of national currencies or financial constraints. However, EU sanctions against Russia in 2022 reduced trade when crypto services were included in the restrictions.

Methodology

Data

The digital currencies used in the research can be categorised into two main groups: "dirty" cryptocurrencies and "green" cryptocurrencies. "Dirty" cryptocurrencies, such as Bitcoin (BTC) and Ethereum (ETH), are so called because of the high energy consumption associated with their mining and transaction validation, which uses methods such as Proof of Work (PoW). On the other hand, "green" cryptocurrencies include projects such as Lisk (LISK), Metaverse (METAVERSE), Quantum (QTUM), Litecoin (LTC), Ripple (XRP), Augur (REP), Cardano (ADA), Dash (DASH), EOS (EOS), IOTA (IOTA), Monero (XMR), Neo (NEO), Omisego (OMG), Stellar (XLM) and Zcash (ZEC). These are classified as "green" due to their lower energy consumption, as they use more efficient mechanisms such as Proof of Stake (PoS), variants of Proof of Authority (PoA) or Directed Acyclic Graphs (DAG), which require less energy to process transactions and guarantee security. The period analysed in the study covers the years from 1 January 2018 to 23 November 2023, and the choice of these cryptocurrencies reflects the intention to differentiate the environmental impact associated with their underlying technologies in the study on efficiency, in its weak form, in the financial markets.

Tabela 1. Specific information on the cryptocurrencies used in the study.

Crypto	Code	Type	Description
Bitcoin	BTC	Dirty	BTC is the pioneer among cryptocurrencies, known as "digital gold"; it uses Proof of Work (PoW) and is highly decentralised but has high energy consumption.

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Crypto	Code	Type	Description
Ethereum	ETH	Dirty	ETH is a leading smart contract platform that has partially migrated to Proof of Stake (PoS) but still has a significant environmental impact.
Lisk	LISK	Green	LISK is a platform aimed at blockchain-based applications and uses a Delegated Proof of Stake (DPoS) variant.
Metaverse	METAVERSE	Green	METAVERSE is a cryptocurrency for virtual reality and blockchain applications designed for efficiency and lower energy consumption.
Quantum	QTUM	Green	QTUM combines the security of Bitcoin with the flexibility of Ethereum, using Proof of Stake (PoS).
Litecoin	LTC	Green	LTC can be described as the "light" version of Bitcoin, which allows for fast and efficient transactions with less energy consumption than Bitcoin.
Ripple	XRP	Green	XRP is a cryptocurrency focused on fast global payments and transfers. It does not use mining and consumes little energy.
Augur	REP	Green	REP is a blockchain-based market forecasting platform that uses smart contracts for decentralised forecasting.
Cardano	ADA	Green	ADA is a third-generation blockchain platform that uses Proof of Stake (PoS) and is designed for scalability and sustainability.
Dash	DASH	Green	DASH aims to make fast, private payments and uses a hybrid system of Proof of Work (PoW) and Proof of Stake (PoS).
EOS	EOS	Green	EOS is a platform for developing decentralised applications based on Delegated Proof of Stake (DPoS).
IOTA	IOTA	Green	IOTA is designed for the Internet of Things (IoT) and uses the Tangle (DAG) system, which does not depend on mining.
Monero	XMR	Green	XMR is focused on privacy and anonymity and uses Proof of Work (PoW) with optimisations that reduce energy consumption.
Neo	NEO	Green	NEO, known as the "Chinese Ethereum", uses Delegated Byzantine Fault Tolerance (dBFT), making it a more efficient system.
Omisego	OMG	Green	OMG is aimed at decentralised payments and financial transfers and uses the Proof of Stake (PoS) protocol.
Stellar	XLM	Green	XLM is a cryptocurrency aimed at facilitating international payments, efficiency, and low energy consumption.
Zcash	ZEC	Green	ZEC is a digital currency focused on the privacy and security of transactions, using mechanisms to reduce environmental impact.

Method

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The research will be carried out in several stages. Initially, the sample will be characterised using descriptive statistics to check whether the data follows a normal distribution. To assess whether the time series show white noise behaviour (mean equal to zero and constant variance), panel unit root tests will be applied, namely the methods of Breitung (2000), Levin, Lin, and Chu (2002), Im et al. (2003), which postulate the same null hypothesis (presence of unit roots). In order to strengthen the results, the Dickey and Fuller (1981) and Phillips and Perron (1988) tests with Fisher's chi-square transformation and Choi's (2001) unit root tests will also be estimated.

In order to answer the main objective of the study, the econometric model of Lo and Mackinlay (1988) will be used to assess the existence of autocorrelation between the series of cryptocurrency returns. This method is classified as a parametric test. The weak form of the efficient market hypothesis states that it is not possible to predict future prices based on historical prices. As argued by Rosenthal (1983), if a market is efficient in its weak form, there should be no linear dependence between lagged returns, both from a statistical point of view (no autocorrelation) and from an economic point of view (no abnormal returns after taking transaction costs into account). The Lo and Mackinlay (1988) model defines P_t as the price of an asset at *t* and X_t as the natural logarithm of P_t, the random walk hypothesis is given by:

$$X_t = \mu + X_{t-1} + \epsilon_t \quad [1]$$

Where μ is an arbitrary movement parameter and ϵ_t is the random error term. The authors point out that an important characteristic of the random walk process is that the variance of the increments grows linearly according to the observation interval. In other words, the variance o $X_t - X_{t-2}$ is double the variance of $X_t - X_{t-1}$. Thus, the validity of a random walk model can be tested by comparing estimators of the variance of returns at different frequencies. For example, the variance of the weekly returns series should be five times greater than the variance of the daily returns. The model tests whether the variance ratio for different intervals weighted by their duration is equal to one.

The variance of a *q*-differentiated series ($X_t - X_{t-q}$) will be *q* times the variance of the series from the first differentiation ($X_t - X_{t-1}$). The variance ratio test is carried out according to the heteroscedasticity-consistent estimator defined by Lo and Mackinlay (1988). In a sample with *nq + 1* observations, where *q* is an integer greater than 1, the following estimators are defined:

$$\hat{\mu} \equiv \frac{1}{nq}\sum_{k=1}^{nq}(X_k - X_{k-1}) = \frac{1}{nq}\left(X_{nq} - X_0\right) \quad [2]$$

$$\bar{\sigma}_a^2 \equiv \frac{1}{nq}\sum_{k=1}^{nq}(X_k - X_{k-1} - \hat{\mu})^2 \quad [3]$$

$$\bar{\sigma}_c^2(q) \equiv \frac{1}{m}\sum_{k=1}^{n}\left(X_{qk} - X_{qk-q} - q\hat{\mu}\right)^2 \quad [4]$$

Where:

$$m = q(nq - q + 1)\left(1 - \frac{q}{nq}\right) \quad [5]$$

The variance ratio is given by:

$$\widehat{VR}(q) = \frac{\bar{\sigma}_c^2(q)}{\bar{\sigma}_a^2} \quad [6]$$

The test statistic robust to heteroscedasticity is defined by:

$$z^*(q) = \frac{\sqrt{nq}(\widehat{VR}(q) - 1)}{\sqrt{\hat{\phi}(q)}} \quad [7]$$

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Onde:

$$\hat{\phi}(q) = \sum_{j=1}^{q-1} \left[\frac{2(q-j)}{q}\right]^2 \hat{\delta}(j) \qquad [8]$$

$$\hat{\delta}(j) = \frac{\sum_{t=j+1}^{nq} (X_k - X_{k-1} - \hat{\mu})^2 \left(X_{k-j} - X_{k-j-1} - \hat{\mu}\right)^2}{\sum_{t=j+1}^{nq} (X_k - X_{k-1} - \hat{\mu})^2} \qquad [9]$$

The Detrended Fluctuation Analysis (DFA) econophysics model will be used to make the results more robust. DFA is an analysis method that examines time dependence in non-stationary data series. By assuming that the time series are non-stationary, this technique avoids spurious results when analysing the long-term relationships of the data series. The DFA has the following interpretation: $0 < \alpha < 0{,}5$: anti persistent series; $\alpha = 0{,}5$ random walk; $0{,}5 < \alpha < 1$ persistent series. The function of this technique is to examine the relationship between the values x_k and x_{k+t} at different times. For a better understanding, see the authors' articles Guedes et al. (2022), Santana et al. (2023), Dias et al. (2024), Dias, Galvão, Irfan, Alexandre, Gonçalves, et al. (2024).

Results

Figure 1 shows the levels of the digital currencies Bitcoin (BTC), Lisk (LISK), Metaverse (METAVERSE), Quantum (QTUM), Ethereum (ETH), Litecoin (LTC), Ripple (XRP), Augur (REP), Cardano (ADA), Dash (DASH), EOS (EOS), IOTA (IOTA), Monero (XMR), Neo (NEO), Omisego (OMG), Stellar (XLM) and Zcash (ZEC), from 1 January 2018 to 23 November 2023. Based on the graphical analysis, we can see that the digital currency markets are experiencing extreme volatility marked by extreme fluctuations, reflecting both macroeconomic factors and events specific to the crypto sector. In 2018, the collapse of Bitcoin (BTC), which fell from $20,000 to $3,000, signalled the start of a difficult period for the market, the "crypto winter", characterised by a generalised correction in cryptocurrency prices. In 2019, a partial recovery took place, with Bitcoin reaching $13,000, while the emergence of new technologies, such as Decentralised Finance (DeFi) and the announcement of the Libra cryptocurrency by Facebook, boosted interest in the sector. The 2020 pandemic also had an impact, with Bitcoin reaching $29,000, driven by growing institutional adoption, while other digital assets such as Ethereum (ETH) and Litecoin (LTC) also saw an increase in value, reflecting the sector's growth. In 2021, volatility peaked, with Bitcoin reaching $69,000 and Ethereum hitting $4,800 against a backdrop of great euphoria and market expansion. The 'crypto winter' returned in 2022 with significant losses, including Bitcoin's fall to $16,000, the collapse of the FTX exchange and the collapse of tokens such as Terra/LUNA. Finally, in 2023, the market saw a moderate recovery, with Bitcoin rising again to $35,000, but still far from the historic highs of 2021. This period reflects a series of oscillations influenced by internal and external factors such as regulation, institutional interest and global economic uncertainty.

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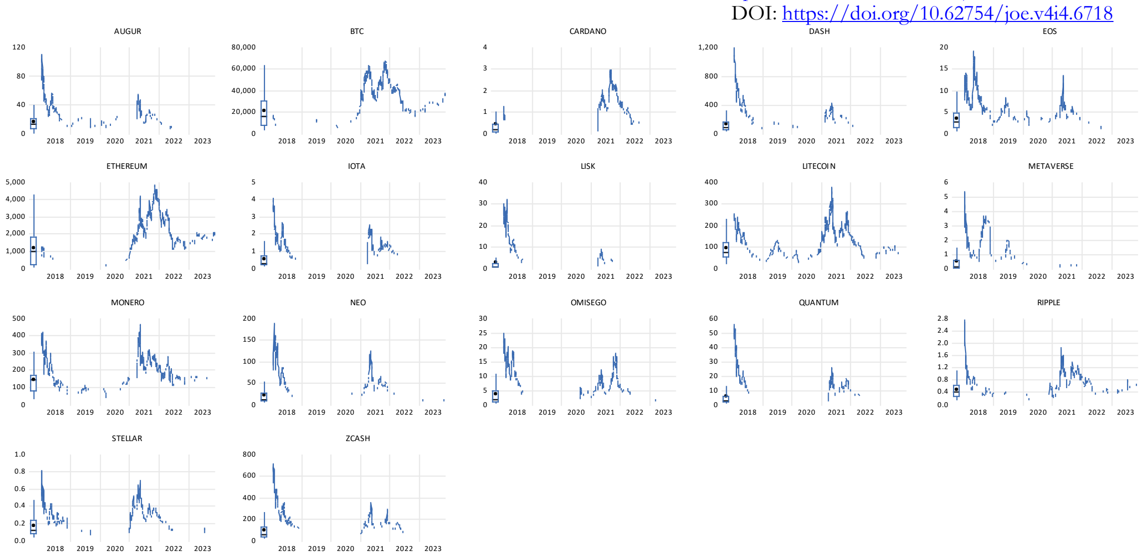

Figure 1. Evolution, in levels, of the cryptocurrencies analysed from 1 January 2018 to 23 November 2023.

The results presented in Table 2 describe the statistical characteristics of the returns of the cryptocurrencies AUGUR (-0.00301), CARDANO (-0.00037), DASH (-0.0023) and EOS (-0.00158), BTC (0.00066), over the period from 1 January 2018 to 23 November 2023. The digital currencies AUGUR, CARDANO, EOS and DASH had negative averages, while BTC had relatively positive average returns. Regarding the standard deviation, which measures volatility, the digital currency CARDANO (0.07964) had the highest volatility, while BTC (0.04472) proved the most stable. The other cryptocurrencies exhibited intermediate volatility, with AUGUR (0.07635), DASH (0.06275) and REOS (0.06574). As far as asymmetry is concerned, the cryptocurrencies AUGUR (-0.12202), BTC (-1.15332), DASH (-0.14603) and REOS (-0.30763) show negative values, indicating a higher probability of extreme negative returns. In contrast, the digital currency CARDANO (12.60112) shows a highly positive asymmetry, reflecting a long tail with high returns. The kurtosis, which measures the frequency of extreme values, is much higher than 3 in all cryptocurrencies, characterising leptokurtic distributions. The values range from 8.9697 (EOS) to 346.0407 (CARDANO), with AUGUR (22.41609), BTC (15.6343) and DASH (9.74065) being at intermediate levels. The digital currency CARDANO, particularly, had exceptionally high kurtosis, indicating a high frequency of extreme returns. The Jarque-Bera test confirms that cryptocurrency returns do not follow a normal distribution, with very high statistics (AUGUR: 24177.955, BTC: 10577.33, CARDANO: 7586765.18, DASH: 2919.07 and EOS: 2309.53) and associated probabilities of (0.0000) in all digital currencies, thus rejecting the hypothesis of normality.

Table 2. Summary table of the main statistics, in returns, of the cryptocurrencies analysed from 1 January 2018 to 23 November 2023.

	AUGUR	BTC	CARDANO	DASH	EOS
Mean	-0.00301	0.00066	-0.00037	-0.0023	-0.00158
Std. Dev.	0.07635	0.04472	0.07964	0.06275	0.06574
Skewness	-0.12202	-1.15332	12.60112	-0.14603	-0.30763
Kurtosis	22.41609	15.6343	346.0407	9.74065	8.9697
Jarque-Bera	24177.955	10577.33	7586765.18	2919.07	2309.53
Probability	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	1539	1539	1539	1539	1539

The results in Table 3 describe the statistical characteristics of the returns of the cryptocurrencies ETHEREUM (0.00065), IOTA (-0.00202), LISK (-0.00196), LITECOIN (-0.00078) and METAVERSE (-0.00367) over the period from 1 January 2018 to 23 November 2023. The average returns are close to zero, being positive for the digital currency ETHEREUM (0.00065) and negative for the other cryptocurrencies, with METAVERSE showing the greatest average loss (-0.00367). The standard deviation, which measures

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volatility, reveals that METAVERSE had the highest volatility (0.0867), while ETHEREUM (0.0581) and LITECOIN (0.0589) were the least volatile. The asymmetry of the returns shows that ETHEREUM (-0.7871) and LITECOIN (-0.5915) have longer tails to the left, indicating a greater likelihood of extreme negative returns. In contrast, the digital currencies IOTA (7.0709), LISK (4.9188) and METAVERSE (3.2538) exhibit significant positive asymmetries, suggesting a higher frequency of extreme positive returns. As for kurtosis, all cryptocurrencies have leptokurtic distributions (kurtosis > 3), reflecting the presence of heavier tails and a greater occurrence of extreme events. The digital currencies IOTA (168.1328) and LISK (112.9533) stand out for their exceptionally high values, followed by METAVERSE (69.0642), while ETHEREUM (12.8717) and LITECOIN (9.8127) exhibit high but less extreme levels. The Jarque-Bera test confirms that none of the cryptocurrencies follows a normal distribution, with very high statistics (ETHEREUM: 6407.93, IOTA: 1761439.31, LISK: 781458.58, LITECOIN: 3066.01, METAVERSE: 282587.96) and associated probabilities of 0.0000. These results indicate that cryptocurrency returns are highly volatile, non-normal and characterised by extreme events such as large positive and negative shocks.

Table 3. Summary table of the main return statistics for the cryptocurrencies under analysis from 1 January 2018 to 23 November 2023.

	ETHEREUM	IOTA	LISK	LITECOIN	METAVERSE
Mean	0.00065	-0.00202	-0.00196	-0.00078	-0.00367
Std. Dev.	0.0581	0.07491	0.0738	0.0589	0.0867
Skewness	-0.7871	7.0709	4.9188	-0.5915	3.2538
Kurtosis	12.8717	168.1328	112.9533	9.8127	69.0642
Jarque-Bera	6407.93	1761439.31	781458.58	3066.01	282587.96
Probability	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	1539	1539	1539	1539	1539

The results in Table 4 reveal the statistical properties of the returns of the MONERO (-0.00047), NEO (-0.00136), OMISEGO (-0.00225), QUANTUM (-0.00189), RIPPLE (-0.00075), STELLAR (-0.00089) and ZCASH (-0.00191) cryptocurrencies over the period from 1 January 2018 to 23 November 2023. Based on the results, we can see that all digital currencies show negative average returns, reflecting a general downward trend over the period, with the OMISEGO digital currency showing the most significant average loss (-0.00225) and MONERO the smallest (-0.00047). The standard deviation, an indicator of volatility, ranges from 0.05415 (MONERO, the least volatile) to 0.07317 (OMISEGO, the most volatile), with the remaining cryptocurrencies showing intermediate levels, such as digital currencies like QUANTUM (0.07214), RIPPLE (0.06484) and STELLAR (0.06369). Analysing the asymmetry reveals distinct patterns between the cryptocurrencies. MONERO (-0.6622), NEO (-0.0636), STELLAR (-0.4559) and ZCASH (-0.3167) show negative asymmetry, suggesting a greater propensity to negative extreme returns. On the other hand, OMISEGO (0.0482) and RIPPLE (0.71646) exhibit moderate positive skewness, while QUANTUM (2.9719) stands out due to its high positive skewness, indicating a higher concentration of positive extreme events. Concerning kurtosis, all cryptocurrencies have leptokurtic distributions characterised by heavy and high tails with strong probabilities of extreme events. QUANTUM (69.1165) has an exceptionally high kurtosis, followed by STELLAR (23.5696) and RIPPLE (17.5486). The digital currencies OMISEGO (7.3619) and ZCASH (6.3276) have high but less extreme values. The Jarque-Bera test rejects the hypothesis of normality for all cryptocurrencies, with high statistics (MONERO: 4328.83, NEO: 2649.52, OMISEGO: 1220.69, QUANTUM: 282581.56, RIPPLE: 13704.48, STELLAR: 27185.31, ZCASH: 735.80) and associated probabilities of 0.0000, i.e. significant at 1%. These results indicate that cryptocurrency returns are highly volatile, non-normal and marked by extreme events, with heavy tail characteristics and significant asymmetries. In particular, the QUANTUM digital currency stands out for its instability, with significantly high positive kurtosis and asymmetry, showing a significant frequency of extreme positive shocks.

Table 4. Summary table of the main statistics, in returns, of the cryptocurrencies analysed from 1 January 2018 to 23 November 2023

	MONERO	NEO	OMISEGO	QUANTUM	RIPPLE	STELLAR	ZCASH
Mean	-0.00047	-0.00136	-0.00225	-0.00189	-0.00075	-0.00089	-0.00191

Journal of Ecohumanism
2025
Volume: 4, No: 4, pp. 142 – 159
ISSN: 2752-6798 (Print) | ISSN 2752-6801 (Online)
https://ecohumanism.co.uk/joe/ecohumanism
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Std. Dev.	0.05415	0.06761	0.07317	0.07214	0.06484	0.06369	0.06339
Skewness	-0.6622	-0.0636	0.0482	2.9719	0.71646	-0.4559	-0.3167
Kurtosis	11.1087	9.4266	7.3619	69.1165	17.5486	23.5696	6.3276
Jarque-Bera	4328.83	2649.52	1220.69	282581.56	13704.48	27185.31	735.80
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	1539	1539	1539	1539	1539	1539	1539

Table 5 shows the results of the unit root tests carried out on cryptocurrency returns from 1 January 2018 to 23 November 2023, indicating that the series is stationary. The Levin et al. (2002) test shows a statistical value of -162.32, with an associated probability significant at 1%. This result rejects the null hypothesis of a standard unit root, indicating stationarity at the level of returns. Similarly, Breitung (2000) shows a statistical value of -10.32, with p=0.0000. Again, the null hypothesis is rejected, confirming that the returns are stationary, while the test by Im et al. (2003) To provide robustness, we also estimated the ADF - Fisher Chi-square test, which is based on the Dickey and Fuller (1981) test combined for each series, the chi-square value was 3473.54, with a significance level of 1%. Similar to the ADF test, but using the Perron and Phillips (1988) est, the chi-squared value was 4477.64, with a probability of (0.0000). This test reinforces the previous conclusions that the series is stationary.

Table 5. Summary table of the unit root tests, in returns, of the cryptocurrencies under analysis from 1 January 2018 to 23 November 2023.

Group unit root test: Summary				
Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-162.32	0.0000	17	26019
Breitung t-stat	-10.32	0.0000	17	26002
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-116.01	0.0000	17	26019
ADF - Fisher Chi-square	3473.54	0.0000	17	26019
PP - Fisher Chi-square	4477.64	0.0000	17	26129

Note:** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Figure 2 shows an analysis of the serial autocorrelation of the time series of the cryptocurrencies studied using the econometric model of Lo and MacKinlay (1988). This model, widely recognised for its application in market efficiency analysis, is suitable for investigating the presence of time dependence in financial returns, a characteristic that can indicate inefficiencies or predictability in prices.

The results show different behaviours among the cryptocurrencies analysed: Augur (REP) shows dynamic patterns, with negative autocorrelation between days 16 and 6, suggesting mean reversion, and positive autocorrelation between days 5 and 2, indicating the persistence of returns over short horizons. Bitcoin (BTC) shows a predominance of positive autocorrelation throughout the period, reflecting the possible presence of time dependence and market inefficiency, except for the 5 to 2-day interval, where autocorrelation becomes negative, suggesting short-term price corrections.

Cardano (ADA) shows no autocorrelation between days 16 and 11 and negative autocorrelation between days 10 and 2, which may signal mean-reversion patterns or price adjustments. Dash (DASH) shows no autocorrelation between days 16 and 12, followed by positive autocorrelation between days 11 and 5, reflecting short-term trends, and then autocorrelation turns negative on days 4 to 2, suggesting corrections.

Journal of Ecohumanism
2025
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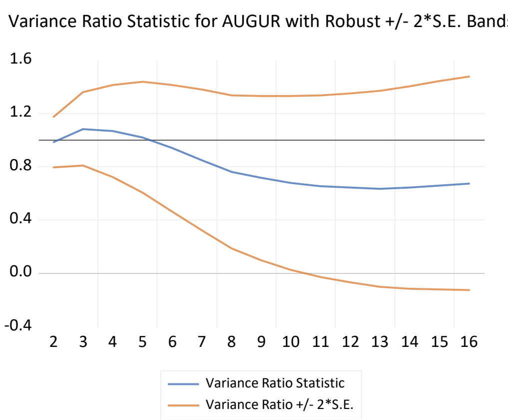
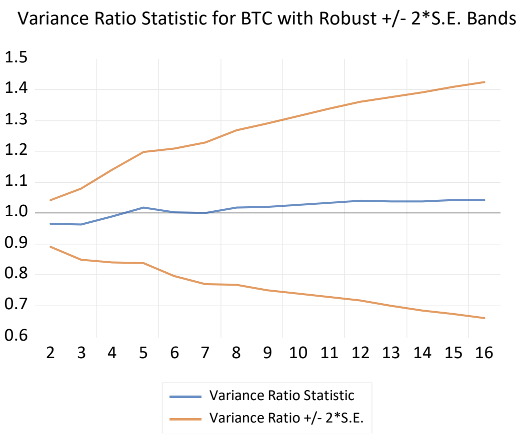
EOS (EOS) shows no autocorrelation between days 16 and 11, with positive autocorrelation between days 10 and 4, indicating persistence in medium-term returns. Litecoin (LTC) shows no autocorrelation between days 11 and 5, alternating between negative and positive autocorrelation at the extremes of the period analysed.

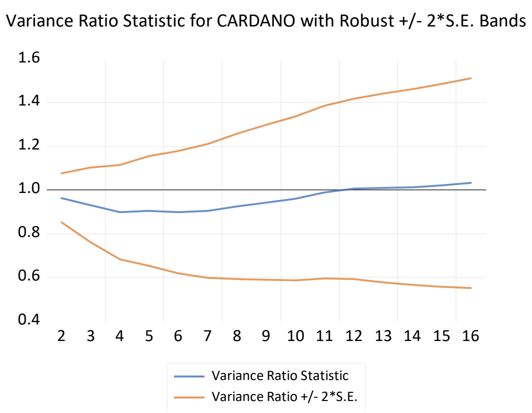
The cryptocurrencies Ethereum (ETH), Ripple (XRP), IOTA (IOTA), Lisk (LISK), Metaverse (METAVERSE), Monero (XMR), Neo (NEO), Omisego (OMG), Stellar (XLM) and Zcash (ZEC) exhibit negative serial autocorrelation during all 16 lag days analysed, which characterises consistent mean reversion over the period, suggesting that returns tend to adjust after deviations. The serial autocorrelation in the time series indicates that cryptocurrency returns do not follow a purely random process, as expected in efficient markets in their weak form.

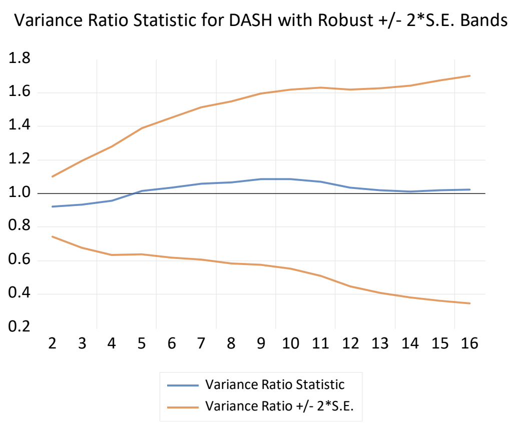
Positive autocorrelation reflects persistence in returns, which indicates that positive (or negative) shocks tend to be followed by returns of the same sign, suggesting trends or momentum in the markets. In contrast, negative autocorrelation suggests mean reversion, where positive returns are followed by negative ones and vice versa, which is common in markets with frequent price corrections.

These results have important implications for the study of efficiency and predictability in the cryptocurrency market, as the presence of negative serial autocorrelation in several coins, such as ETH, XRP and IOTA, may indicate that these cryptocurrencies are subject to mean-reversion behaviour, potentially exploitable by arbitrage strategies. On the other hand, the predominance of positive autocorrelation in BTC and DASH suggests that they may be more susceptible to momentum strategies. This evidence challenges the Efficient Markets Hypothesis in its weak form for the cryptocurrency market, indicating that, despite its growing maturity, there are still inefficiencies that sophisticated investors can exploit. In addition, the autocorrelation patterns may reflect specific characteristics of each cryptocurrency, such as its liquidity, technological adoption or sensitivity to macroeconomic events, justifying further analyses to identify the determinants of these dynamics.









Journal of Ecohumanism
2025
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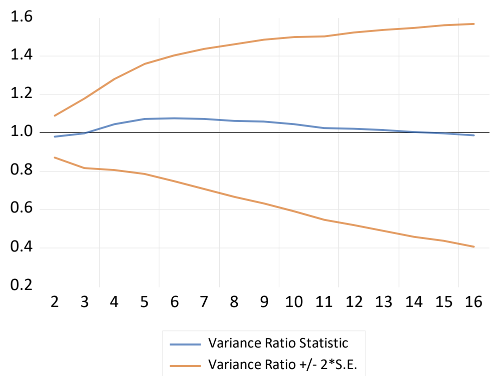
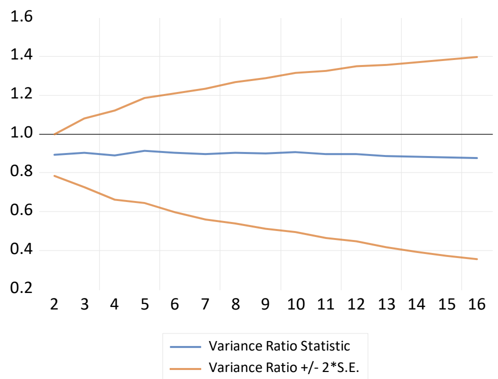
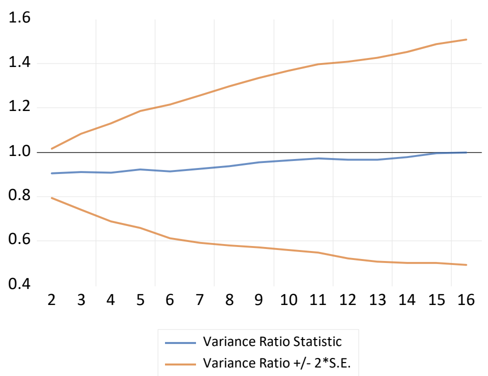
Variance Ratio Statistic for EOS with Robust +/- 2*S.E. Bands



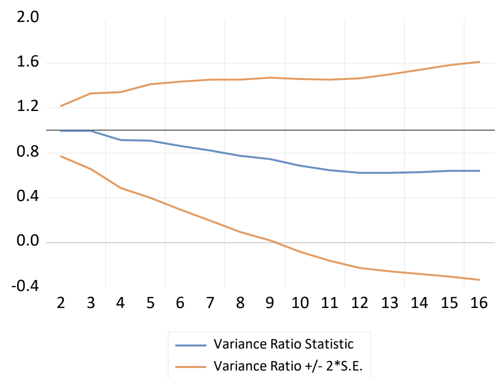
Variance Ratio Statistic for ETHEREUM with Robust +/- 2*S.E. Bands



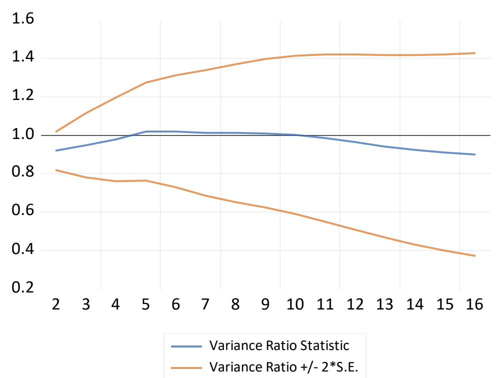
Variance Ratio Statistic for IOTA with Robust +/- 2*S.E. Bands



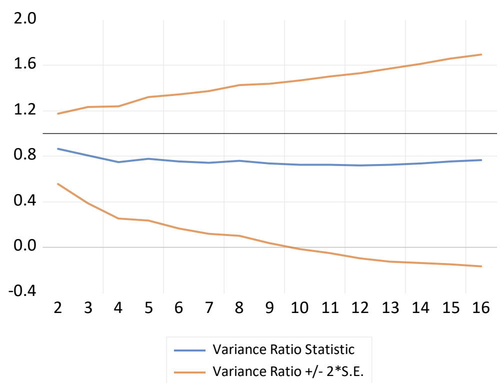
Variance Ratio Statistic for LISK with Robust +/- 2*S.E. Bands



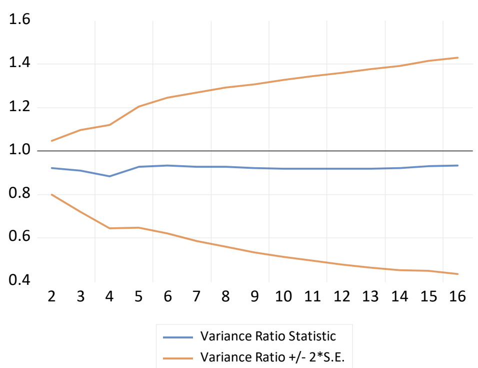
Variance Ratio Statistic for LITECOIN with Robust +/- 2*S.E. Bands



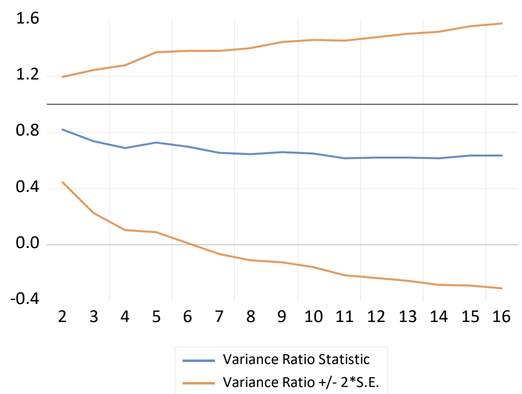
Variance Ratio Statistic for METAVERSE with Robust +/- 2*S.E. Bands



Variance Ratio Statistic for MONERO with Robust +/- 2*S.E. Bands



Variance Ratio Statistic for NEO with Robust +/- 2*S.E. Bands



Journal of Ecohumanism
2025
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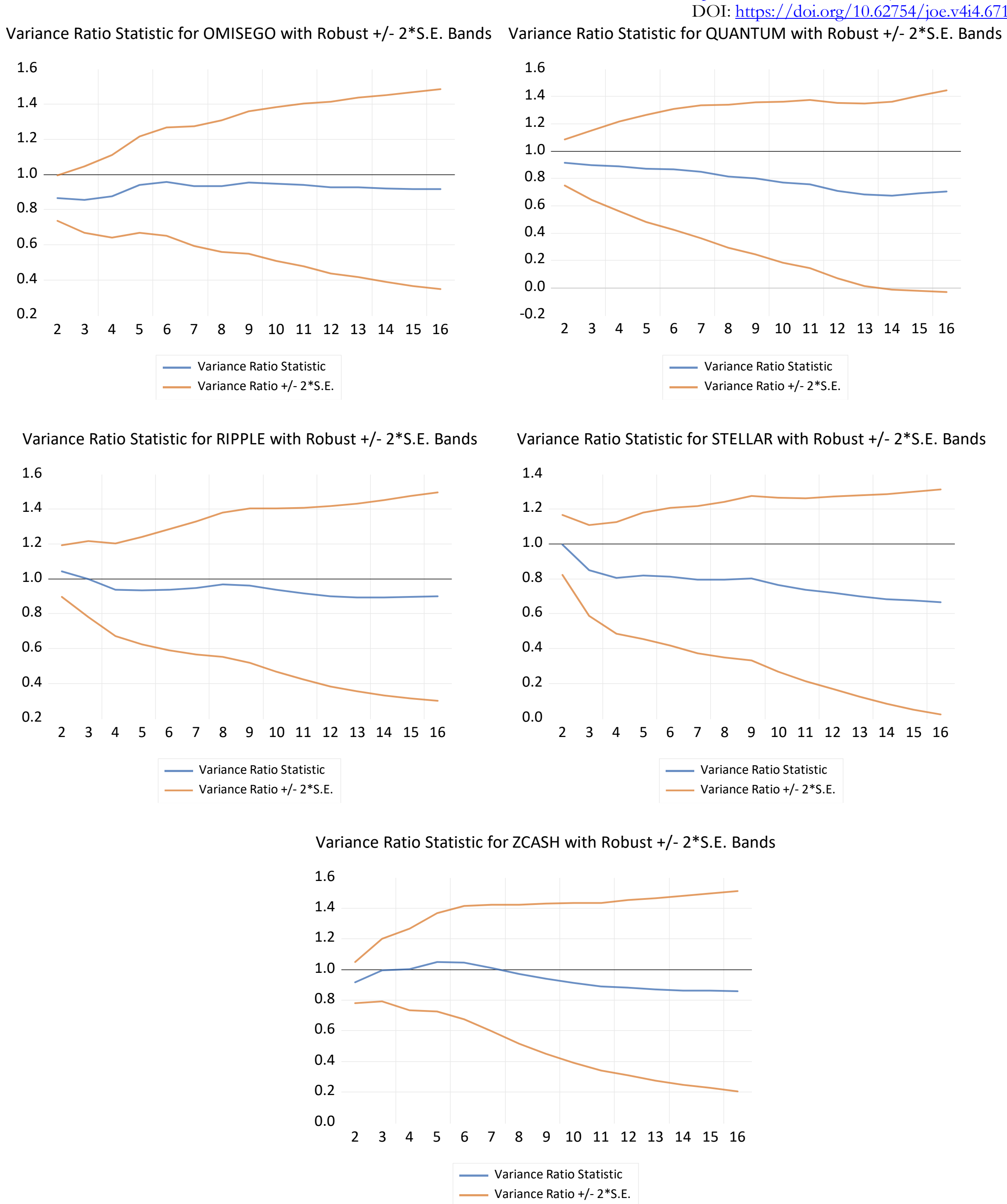

Figure 2. Evolution of autocorrelation in returns, measured using the Lo and MacKinlay test (1988), applied to the cryptocurrencies analysed from 1 January 2018 to 23 November 2023.

Figure 3 shows the evolution of the slopes obtained by the DFA methodology applied to the time series, in returns, of the digital currencies analysed between 1 January 2018 and 23 November 2023. The digital currencies included in the study are Bitcoin (BTC), Lisk (LISK), Metaverse (METAVERSE), Quantum (QTUM), Ethereum (ETH), Litecoin (LTC), Ripple (XRP), Augur (REP), Cardano (ADA), Dash (DASH), EOS (EOS), IOTA (IOTA), Monero (XMR), Neo (NEO), Omisego (OMG), Stellar (XLM) and Zcash (ZEC). Analysing the slopes allows us to identify the presence of long memories in the yield series, i.e. patterns of temporal dependence that extend over time. The results shown in the figure make it possible to observe variations in the dynamics of the memories of the different cryptocurrencies over the period analysed, reflecting possible changes in investor behaviour, liquidity levels or general market conditions. Bitcoin (BTC) and Ethereum (ETH), being the two largest cryptocurrencies in terms of market

Journal of Ecohumanism
2025
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capitalisation and transaction volume, show distinct patterns compared to smaller cryptocurrencies such as Augur (REP) or Omisego (OMG), which may be more sensitive to specific shocks or variations in the market structure.

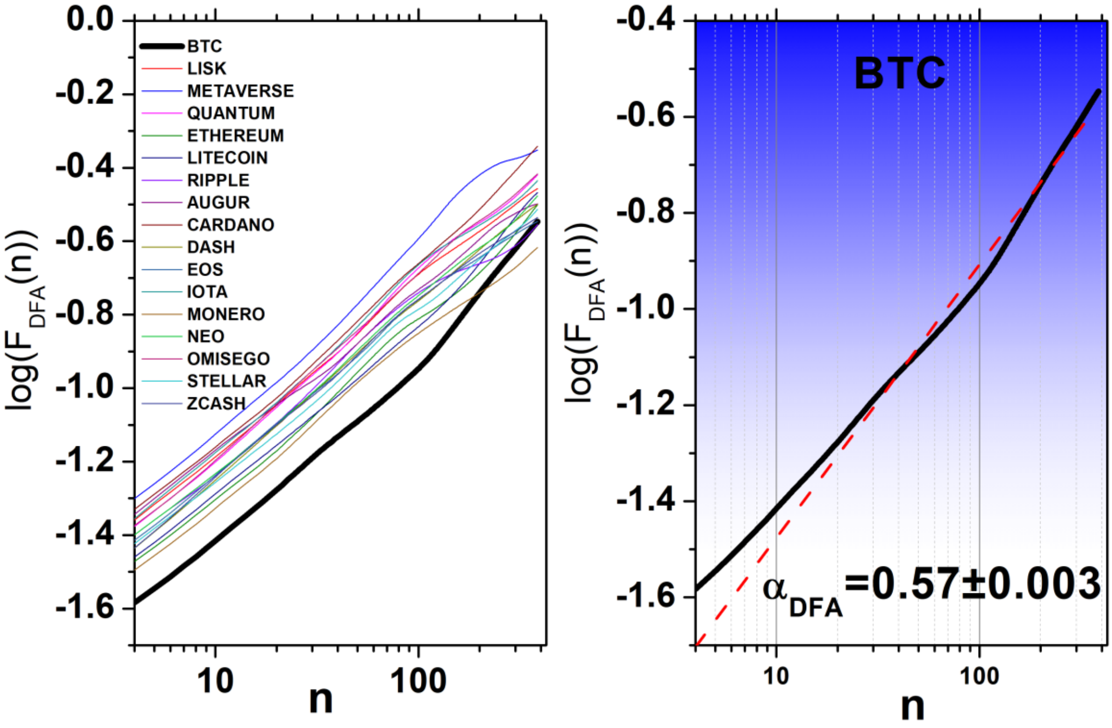

Figure 3. Evolution of autocorrelation, in returns, applied to the cryptocurrencies analysed, from 1 January 2018 to 23 November 2023.

Table 6 shows the slopes of the digital currencies analysed from 1 January 2018 to 23 November 2023. Bitcoin (BTC, 0.57) shows persistent behaviour, indicating long memory, with past shocks impacting the market over long periods. In practical terms, this pattern will favour long-term strategies and trend-following. Similarly, the digital currencies Metaverse (0.51), Litecoin (0.53) and Cardano (0.52) also show persistence, reflecting less efficient markets where investors can exploit trends over the long term. Regarding practical implications, long-term investment strategies may be more effective as trends tend to continue. Traders should consider the greater predictability in patterns, as the market is less efficient at correcting deviations quickly.

In contrast, the digital currencies Lisk (0.45), Quantum (0.48), Ethereum (0.49), Ripple (0.39 and 0.40), Augur (0.44), Dash (0.47), EOS (0.43), IOTA (0.45), Monero (0.43), Neo (0. 47), Omisego (0.48), Stellar (0.46) and Zcash (0.44) show anti-persistent behaviour, suggesting inefficient markets, but with rapid correction of deviations. This implies that price shocks are temporary, favouring short-term strategies such as arbitrage or scalping rather than investments based on long memory. Investors should focus on external events and volatility in markets with anti-persistent patterns to identify short-term opportunities.

The analysis reveals that while some cryptocurrencies, such as BTC, LTC and ADA, can be considered more predictable in the long term, the majority, such as ETH, XRP and DASH, reflect greater efficiency and less predictability, making them more suitable for short-term trading strategies. These dynamics reflect structural differences between the cryptocurrencies analysed, such as liquidity and market share. These results are similar to the evidence suggested by the authors Dias, Chambino, Galvão, Alexandre and Irfan (2024) and Dias, Galvão, Irfan, Alexandre and Teixeira (2024).

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Table 6. Summary table with the DFA slopes applied to the cryptocurrencies under analysis from 1 January 2018 to 23 November 2023.

Cryptocurrencies	DFA	Error_Slope	Results
BTC	0.57	0.003	Persistent
LISK	0.45	0.001	Anti-persistent
METAVERSE	0.51	0.003	Persistent
QUANTUM	0.48	0.002	Anti-persistent
ETHEREUM	0.49	0.002	Anti-persistent
LITECOIN	0.53	0.003	Persistent
RIPPLE	0.39	0.003	Anti-persistent
AUGUR	0.44	0.001	Anti-persistent
CARDANO	0.52	0.001	Persistent
DASH	0.47	0.001	Anti-persistent
EOS	0.43	0.002	Anti-persistent
IOTA	0.45	0.002	Anti-persistent
MONERO	0.43	0.002	Anti-persistent
NEO	0.47	0.001	Anti-persistent
OMISEGO	0.48	0.001	Anti-persistent
RIPPLE	0.4	0.003	Anti-persistent
STELLAR	0.46	0.001	Anti-persistent
ZCASH	0.44	0.002	Anti-persistent

Note: The DFA quantifies the long-range correlations in the time series, with DFA > 0.5 indicating persistence (long memory) and DFA < 0.5 reflecting anti-persistence (short-term memory).

Figure 4 shows the Detrended Fluctuation Analysis (DFA) slopes applied to cryptocurrencies from 1 January 2018 to 23 November 2023, which shows two distinct patterns in the behaviour of digital currencies, with practical implications for investment and trading strategies. The cryptocurrencies Bitcoin (0.57), Metaverse (0.51), Litecoin (0.53) and Cardano (0.52) have high DFA slopes, suggesting persistent behaviour, i.e. the presence of long memory in the market. Regarding time series modelling, this behaviour can be described as a "long memory series', in which deviations from the average take time to be corrected. The greater predictability observed in these markets favours long-term strategies, such as 'buy and hold', and the capture of sustained trends. Investors can exploit these prolonged trends, as the market tends to be less efficient at correcting deviations, which allows for a higher probability of a positive return by following the market's dominant direction.

On the other hand, the cryptocurrencies Lisk (0.45), Quantum (0.48), Ethereum (0.49), Ripple (0.39-0.40), Augur (0.44), Dash (0.47), EOS (0.43), IOTA (0. 45), Monero (0.43), Neo (0.47), Omisego (0.48), Stellar (0.46) and Zcash (0.44) have lower DFA values, indicating anti-persistent behaviour. In this context, price shocks tend to be short-lived, with a rapid correction of deviations from the average, characterising more efficient markets with a greater capacity to absorb shocks. In statistical terms, these markets have a 'short memory', where prices do not reflect long-term patterns but react quickly to changes, which favours short-term trading strategies such as arbitrage and scalping, where the aim is to take advantage of temporary, high-frequency fluctuations. The market efficiency observed in these assets indicates that price trends are more volatile and less predictable, which reduces the effectiveness of long-term strategies, requiring a more dynamic approach focused on identifying short-term events and volatility.

In conclusion, cryptocurrencies with persistent behaviour (such as BTC, LTC and ADA) may be more suitable for investors looking for long-term movements and benefit from price memory. These markets, which are less efficient at correcting deviations, allow investors to take advantage of trends, assuming that prices will continue to move in the same direction for an extended period. On the other hand, coins with

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anti-persistent behaviour (such as ETH, XRP and DASH) require a more tactical approach, focusing on identifying quick corrections and arbitrage opportunities in a shorter time. Investors should be alert to external events that could generate volatility and adapt their strategies according to the efficiency and memory profile of the market in question.

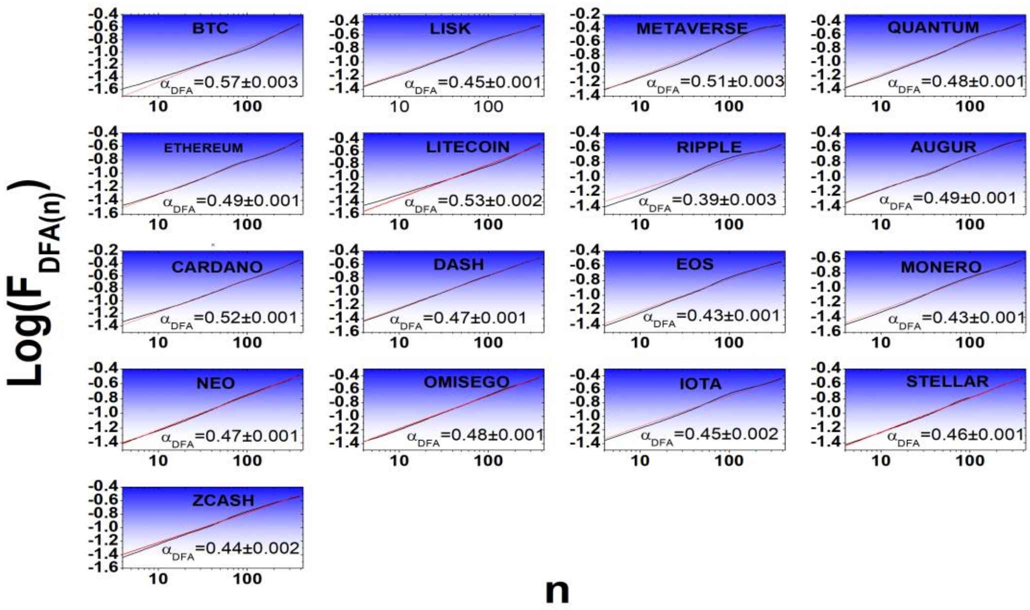

Figure 4. Summary of the DFA slopes applied to the cryptocurrencies analysed from 1 January 2018 to 23 November 2023.

Conclusions

The main objective of this research was to evaluate the efficiency, in its weak form, of digital currencies classified as "dirty" such as Bitcoin (BTC), Ethereum (ETH), and the green ones, namely Lisk (LISK), Metaverse (METAVERSE), Quantum (QTUM), Litecoin (LTC), Ripple (XRP), Augur (REP), Cardano (ADA), Dash (DASH), EOS (EOS), IOTA (IOTA), Monero (XMR), Neo (NEO), Omisego (OMG), Stellar (XLM) and Zcash (ZEC), in the period from 1 January 2018 to 23 November 2023.

This research has revealed two distinct behavioural patterns in the cryptocurrencies analysed from 1 January 2018 to 23 November 2023, with practical implications for investment and trading strategies. The cryptocurrencies Bitcoin, Metaverse, Litecoin and Cardano, with high DFA slopes (0.51 to 0.57), demonstrate persistent behaviour and the presence of long memory. This pattern implies that deviations from the mean are corrected more slowly, suggesting that these coins are less efficient in market terms. For investors, this presents an opportunity for long-term strategies such as buy-and-hold and sustained trend following, where it is possible to capitalise on prolonged price movements. The inherent predictability of these markets allows robust time series modelling, such as ARFIMA, to identify and exploit these trends.

On the other hand, cryptocurrencies such as Lisk, Quantum, Ethereum, Ripple, Augur, Dash, EOS, IOTA, Monero, Neo, Omisego, Stellar and Zcash, with lower DFA values (0.39 to 0.49) exhibit anti-persistent behaviour, characterised by rapid correction of deviations and short memory. This pattern reflects greater market efficiency, where prices react quickly to new shocks, making long-term forecasts difficult. For traders, these characteristics make these cryptocurrencies ideal for short-term strategies such as arbitrage, scalping and day trading, taking advantage of volatility and momentary fluctuations. The rapid correction

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2025
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of deviations requires a more dynamic approach, with advanced technological tools and continuous market monitoring to identify high-frequency opportunities.

These patterns have significant practical implications. Conservative investors interested in stable returns over time can opt for long-memory assets, which offer greater predictability and the potential for sustained gains. On the other hand, more risk-tolerant investors and traders who prefer quick gains can focus on cryptocurrencies with a short memory, optimising their strategy to capture short-term movements. From an institutional point of view, portfolio managers can diversify their portfolios based on these structural differences, balancing long- and short-term assets to mitigate risks and maximise returns.

Finally, these findings highlight the importance of understanding the underlying dynamics of cryptocurrency markets, allowing the development of more effective strategies and the improvement of predictive models for these assets. Future research could explore how exogenous factors such as regulations, technological innovations or geopolitical events affect the efficiency and persistence of these currencies, providing a more comprehensive view in line with the ongoing evolution of digital markets.

These behavioural differences have significant practical implications for investors and portfolio managers. Cryptocurrencies with long memory, lower efficiency, and greater predictability provide opportunities for strategic investments based on trend analyses and long-term econometric models. On the other hand, assets with anti-persistent behaviour offer greater efficiency for rapid operations, requiring constant monitoring and advanced technologies to identify momentary profit opportunities. Thus, the choice of strategy depends on the investor's profile, risk tolerance and investment time horizon.

Among the limitations of this study is the absence of external variables, such as macroeconomic events, regulatory changes or technological advances, which can directly influence the cryptocurrency markets. For example, stricter regulations or unexpected events, such as financial crises or advances in blockchain technology, can alter market efficiency and price dynamics. Another limitation is the static analysis of a specific period, which may not capture structural changes in the cryptocurrency markets, especially considering their rapid evolution and volatility. In addition, the study focused exclusively on historical series, disregarding the integration of market sentiment metrics such as news, social media or other behavioural indicators that can affect prices.

For future research, it is recommended to extend the analysis to a more diverse set of cryptocurrencies, including emerging assets that may present new efficiency characteristics. Integrating macroeconomic factors, such as interest rates, inflation, or global uncertainty indices, can help better understand the external forces that impact market behaviour. In addition, adopting hybrid approaches, combining traditional econometric models with artificial intelligence techniques such as machine learning and deep learning, can provide more robust forecasts and identify complex patterns in the cryptocurrency markets. Another promising field for future studies is assessing the environmental impact of green and dirty cryptocurrencies, considering the growing interest in sustainable investments and their implications for investor behaviour.

In practical terms, these additional studies could help institutional and individual investors align their strategies with the specific characteristics of each asset class. Regulators and policymakers could also use these results to create more transparent and efficient environments, while technology developers could explore ways to mitigate volatility and improve the stability of cryptocurrencies.

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