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Middle East Conflict Impact on Cryptocurrencies' Volatility: A Comparative Analysis

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ABSTRACT

The main objective of this study is to compare the efficiency levels, in their weak form, between sustainable cryptocurrencies such as Avalanche (AVAX), Cardano (ADA), Solana (SOL), Toncoin (TON) and Ethereum (ETH) (after 'The Merge'), which use efficient mechanisms such as proof-of-stake (PoS), and Binance Coin (BNB), Litecoin (LTC), Monero (XMR), Ripple (XRP), and Bitcoin (BTC) classified as unsustainable cryptocurrencies due to their excessive energy consumption based on proof-of-work (PoW). The analysed period was from 1 January 2023 to 10 December 2024. The Detrended Fluctuation Analysis (DFA) slopes reveal a significant impact of the 2023 Conflict on cryptocurrency dynamics, with distinct effects per asset. Sustainable cryptocurrencies (AVAX, ADA, SOL) demonstrated greater resilience, maintaining persistence with a brief reduction in long memory, reflecting their relative stability and attractiveness in uncertainty scenarios. In contrast, non-sustainable cryptocurrencies (LTC, XMR) transitioned from persistence to anti-persistence, indicating greater instability and speculation, associated with lower investor confidence. Assets such as TON (white noise) and XRP (consistent persistence) were less affected, suggesting intrinsic characteristics that confer resilience. Distinguishing between sustainability and other market factors is crucial to understand behaviours and build resilient portfolios, providing valuable insights for investors and researchers.

Keywords: Sustainable cryptocurrencies, speculative bubbles, trends, efficiency, long memories, arbitrage

JEL Classification: G10; G14; G15.

INTRODUCTION

The recent conflict between Israel and Hamas had significant repercussions on the financial markets and global economy. Armed conflicts cause extreme volatility in financial markets, which affects asset prices, investor confidence and global supply chains. Additionally, the media influences public perception and market reactions, thereby amplifying the economic effects (Du, 2024). Yulivan et al. (2024) demonstrate that the conflict between Hamas and Israel could lead to increases in global oil prices, given their geographical proximity to oil-producing countries. According to them, disruptions in the oil supply could create market shocks, affecting commodities and financial markets in general.

Oil shocks generate volatility in financial markets, increasing energy costs and inflation and causing shocks in the main currencies used in international trade. Investors seek hedge assets, while energy-dependent sectors experience structural breakdowns, leading to currency devaluation in oil-importing countries, while oil-exporting countries benefit from these shocks. However, oil price shocks cause shocks in other financial markets (Afshan et al., 2024; Ben Salem et al., 2024).

The rapid growth of cryptocurrencies has increased demand, but it has also raised concerns, especially with 'dirty' cryptocurrencies that use the Proof of Work (PoW) consensus mechanism. This method consumes a large amount of energy, resulting in significant ecological damage and public concern. At the same time, altcoins have emerged as alternatives to Bitcoin and traditional currencies, offering distinct features, but have not yet reached Bitcoin's market size. Although risky due to high volatility, cryptocurrencies attract investors because of their potential for high returns (Kubar & Toprak, 2021; Ghorbel et al., 2022)

The efficient market hypothesis (EMH) argues that security prices reflect all available information and investors cannot obtain abnormal returns by trading on that information. The EMH is an essential concept for financial institutions, individual and institutional investors, and government regulators. Market efficiency greatly influences investors' investment strategies. Market efficiency also determines the regulatory measures to be developed to ensure the development and organised management of a country's markets (Fama, 1965, 1970).

Bitcoin (BTC) has established itself as an alternative store of value due to its decentralisation, scarcity and widespread adoption. Its most significant market capitalisation among cryptocurrencies attracts investors as a hedge against inflation and instability. Its acceptance by financial institutions and governments reinforces its position as a trusted digital asset and benchmark in the cryptocurrency market (Rudolf et al., 2021).

The main objective of this study is to compare the efficiency levels, in their weak form, between sustainable cryptocurrencies such as Avalanche (AVAX), Cardano (ADA), Solana (SOL), Toncoin (TON) and Ethereum (ETH) (after 'The Merge'), which use efficient mechanisms such as proof-of-stake (PoS). On the other hand, Binance Coin (BNB), Litecoin (LTC), Monero (XMR), Ripple (XRP), and Bitcoin (BTC) are classified as unsustainable cryptocurrencies owing to their excessive energy consumption based on proof-of-work (PoW) from 1 January, 2023, to 10 December, 2024.

This study is groundbreaking in its analysis of the impact of the Israel-Hamas conflict on the efficiency of sustainable cryptocurrencies, introducing a perspective that is unprecedented in the literature. Furthermore, it contributes by explicitly distinguishing between sustainable cryptocurrencies, based on proof-of-stake (PoS), and non-sustainable ones, based on proof-of-work (PoW), highlighting the environmental impact of blockchain technologies. Practically, it broadens the debate on efficiency in financial markets by applying the concept of efficiency, in its weak form, to cryptocurrencies, with a focus on sustainable currencies, a topic that has yet to be fully explored. It also addresses the impact of technological events, such as 'The Merge' on Ethereum, allowing for an assessment of how structural changes affect market efficiency and behaviour. This study analyses a recent period (2023-2024), incorporating the most current dynamics in cryptocurrency markets and the impact of macroeconomic, regulatory and geopolitical events. The comparison between sustainable and unsustainable cryptocurrencies in terms of efficiency and the presence of long memories brings an innovative perspective, treating cryptocurrencies differently, in contrast to the prevailing homogeneous approach. Ultimately, this research has significant implications for investors, regulators, and policymakers, as it explores the intersection between market efficiency, sustainability, and the impact of geopolitical events.

The remainder of this paper is organised as follows. Section 2 presents the literature review, and Section 3 describes the data and methodology used in the analysis. Section 4 presents the empirical results, and Section 5 concludes and discusses the implications of the study.

LITERATURE REVIEW

The Israel-Hamas conflict, which began on 7 October 2023, involved coordinated attacks by militant Palestinian groups, including Hamas, against military and civilian targets in Israel. These attacks triggered Israel's retaliation in the so-called' Operation Iron Swords', with bombings and military incursions into Gaza. The conflict was described by some as a Third Intifada and supported by Iran (Du, 2024; Yulivan et al., 2024).

According to Yulivan et al. (2024), one of the main threats arising from the intensified conflict between Hamas and Israel is the global increase in crude oil prices. The geographical proximity of the Middle East to oil-producing countries makes this issue even more relevant. If there is an interruption in the supply or distribution of oil in the region, prices could rise significantly in a short period, severely impacting the market. This increase in commodity prices is likely reflected in the international economy.

Kristoufek and Vosvrda (2019), Hawaldar et al. (2019), and Kristjanpoller and Bouri (2019) analysed the efficiency and behaviour of cryptocurrencies using different approaches, contributing to a broader understanding of the market. Kristoufek and Vosvrda (2019) investigated market efficiency using the Efficiency Index, which combines long-range dependence, fractal dimension, and entropy. The authors concluded that historical cryptocurrencies, such as Bitcoin, Litecoin, and Monero, were inefficient during the analysis period. Dash was considered the most efficient, whereas Ethereum and Litecoin were the least efficient. Hawaldar et al. (2019) evaluated the random walk hypothesis of the cryptocurrencies Bitcoin and Litecoin from 2013 to 2017, showing that both follow random walk behaviour, which differs partially from the conclusions of Kristoufek and Vosvrda (2019) on inefficiency. Complementarily, Kristjanpoller and Bouri (2019) examined the asymmetric multifractal correlations between cryptocurrencies and fiat currencies, such as the Euro and the Australian dollar, from 2014 to 2018. The authors argue that Bitcoin and Litecoin exhibited the most multifractal behaviour, whereas Monero and Ripple exhibited less multifractality, suggesting greater complexity in the behaviour of the former two.

Avatrade (2021), Ghazani and Jafari (2021), and Kakinaka and Umeno (2022) analysed the market efficiency of cryptocurrencies from different perspectives, converging on the point that this efficiency is dynamic and depends on factors such as the time horizon, market context, and economic events. Avatrade (2021) investigated the efficiency in its weak form in five major cryptocurrencies. The results indicated that daily returns validate the weak form of the efficient market hypothesis, suggesting that time scales influence efficiency, with markets being more efficient at higher frequencies (daily) and less efficient at lower frequencies (weekly). Ghazani and Jafari (2021) applied the adaptive market hypothesis (AMH) to cryptocurrencies, such as Bitcoin, Ethereum, and Ripple, as well as other assets, including oil and gold. The authors concluded that market efficiency evolves, being influenced by market conditions and adapting to new information and structures. The AMH suggests that markets are not static, but rather move between periods of efficiency and inefficiency, depending on the economic environment. Kakinaka and Umeno (2022) explored the multifractality and efficiency of the main cryptocurrencies during the COVID-19 pandemic. They showed that the outbreak intensified multifractality in the short term, indicating a greater complexity and inefficiency during this period. However, in the long term, the multifractality was lower, suggesting greater efficiency. This behaviour reflects the impact of global events on the market structure, where short-term memory and complexity make the market less efficient, while long-term stability favours efficiency.

Souza and Carvalho (2023), Dias et al. (2023), and Abdullah et al. (2023) analysed the market efficiency of cryptocurrencies from different perspectives, converging on the concept that the market exhibits characteristics that oscillate between efficiency and inefficiency. Souza and Carvalho (2023) demonstrated that Bitcoin and Ethereum are efficient, in their weak form, in individual markets; however, the connectivity between exchanges compromises overall efficiency. However, Dias et al. (2023) identified autocorrelations and persistence in the returns of various cryptocurrencies, demonstrating a tendency towards inefficiency in the long term. Abdullah et al. (2023) compared cryptocurrencies with other assets, concluding that gold is more efficient and halal tourism stocks outperform cryptocurrencies in efficiency. Overall, the studies by Souza and Carvalho (2023), Dias et al. (2023), and Abdullah et al. (2023) reinforce that the cryptocurrency market has not yet reached full maturity, and it is necessary to consider factors such as connectivity between platforms and temporal patterns in order to understand its dynamics and risks.

The studies by Galvão and Dias (2024) and Alexakis et al. (2024) presented complementary perspectives on the dynamics of cryptocurrencies, highlighting different factors that affect their efficiency and commercial activity. Galvão and Dias (2024) analysed weak-form efficiency in cryptocurrencies classified as "dirty" and clean energy indices, concluding that both exhibit autocorrelation in returns, indicating that prices do not follow random movement behaviour. This result implies that the cryptocurrencies analysed, such as Bitcoin, Ethereum, Ethereum Classic and Litecoin, have predictable patterns that compromise their market efficiency. Alexakis et al. (2024) investigated the impact of geopolitical crises on cryptocurrency trading activity, highlighting that trading increases in the context of instability due to the dual functionality of cryptocurrencies as both speculative assets and payment methods. In times of crisis, such as EU sanctions against Russia in 2022, cryptocurrency trading was significantly impacted by specific restrictions, demonstrating that external factors, including financial sanctions, can substantially shape cryptocurrency markets. The relationship between these two studies arises from the interaction between efficiency and external events. While Galvão and Dias (2024) highlighted the intrinsic inefficiencies of cryptocurrencies, Alexakis et al. (2024) suggested that geopolitical events amplify or attenuate these characteristics. Increased trading during geopolitical crises can intensify autocorrelation and further compromise efficiency. However, regulations such as financial sanctions can help moderate these dynamics. In summary, these two studies offer an integrated view of how internal (efficiency) and external (crises and regulations) factors affect cryptocurrency market behaviour.

METHODOLOGY

Data

The study data consists of daily quotes for sustainable currencies due to their lower environmental impact and use of more efficient consensus mechanisms, such as proof-of-stake (PoS), namely: Avalanche (AVAX), Cardano (ADA), Solana (SOL), Toncoin (TON) and Ethereum (ETH) after 'The Merge' update. On the other hand, cryptocurrencies considered unsustainable are Binance Coin (BNB), Litecoin (LTC), Monero (XMR), Ripple (XRP) and Bitcoin (BTC), due to their higher energy consumption, especially in the case of Bitcoin and Litecoin, which use PoW for transaction validation, requiring high levels of computation and, consequently, energy, from 1 January 2023 to 10 December 2024.

To add robustness to the results, the sample was divided into two sub-periods: the first, designated as Pre-Conflict, covers the period from 1 January 2023 to 6 October 2023; the second sub-period, which was defined as Conflict, covers the period from 7 October 2023 to 10 December 2024. The data were extracted from the Thomson Reuters database, and cryptocurrencies were denominated in US dollars to eliminate exchange rate distortions.

Table 1: Summary table of the classification of sustainable and unsustainable cryptocurrencies, from 1 January 2023 to 10 December 2024

Name	Acronym	Sustainability	Description
Avalanche	AVAX	Sustaibable	Efficient, low-energy PoS cryptocurrency focused on dApps and smart contracts.
Cardano	ADA	Sustaibable	Highly scalable and sustainable PoS blockchain designed for smart contracts.
Solana	SOL	Sustaibable	High-speed network for dApps and NFTs, optimised for energy efficiency.
Toncoin	TON	Sustaibable	Sustainable cryptocurrency, designed for fast and economical transfers.
Ethereum	ETH	Sustaibable	After "The Merge", it uses PoS, with a reduction in energy consumption of over 99%.
Binance Coin	BNB	Not Sustainable	Cryptocurrency used on Binance with a PoW model has significant energy consumption.
Litecoin	LTC	Not Sustainable	One of the first altcoins, based on PoW, has high energy consumption.
Monero	XMR	Not Sustainable	It is a privacy-focused cryptocurrency uses PoW with high energy consumption.
Ripple	XRP	Not Sustainable	Focused on global payments, it has significant energy consumption.
Bitcoin	BTC	Not Sustainable	The first cryptocurrency and market benchmark has significant energy consumption due to PoW.

Source: Prepared by the authors

Methods

The sample will be characterised using descriptive statistics to verify that the data follows a normal distribution, as well as graphs. To ensure that the time series follow white noise (mean = 0; constant variance), the panel unit root tests by Breitung (2000), Levin, Lin, and Chu (2002), and Im et al. (2003), which postulate the same null hypotheses (unit roots), are used. To enhance the robustness of the results, the Dickey and Fuller (1981) and Phillips and Perron (1988) tests will be estimated using Fisher's chi-square transformation, as well as Choi's (2001) unit root tests. To assess whether cryptocurrencies were subject to speculative bubbles during the review period, the Rolling Augmented Dickey-Fuller (RADF) test will be employed. This is an extension of the Augmented Dickey–Fuller test (ADF) that identifies speculative bubbles in financial time series by analysing explosive behaviour in asset prices. In practical terms, it employs a rolling window approach, enabling the monitoring of dynamic changes over time and allowing significant deviations from the fundamental value to be detected. The test checks for the presence of explosive roots, which indicate speculative bubbles, by comparing the statistical values with critical limits (Phillips et al., 2013, 2015).

To validate trends and assess the existence of consistent patterns of change over time in time series, the trend t-stat and Squared-trend F-stat were applied. In addition, the Mann-Kendall test will also be estimated, a non-parametric test developed by Henry Mann in 1945 and later refined by Maurice Kendall in 1975, a widely used test to detect monotonic trends in time series without requiring the data to follow a specific distribution (Mann, 1945; Kendall, 1975; Gilbert, 1988). The simple non-parametric test to identify trends in the time series, as proposed by Cox and Stuart (1955), was also applied. Finally, the WAVK (Weighted Average Variance of Kendall's Tau) test was used (Cabilio et al., 2013; Lyubchich et al., 2013).

To validate the results, change point tests will be used to analyse structural changes in the time series, such as changes in the mean or median, which are important tools for identifying significant events over time. The Quandt-Andrews test, developed to detect breakpoints in the mean or variance, presents three statistics: maximum (Max), average (Avg) and exponential (Exp). It is widely used in econometrics to identify structural changes and was developed by Andrews (1993). The Buishand test, developed by Buishand (1984) and focused on changes in the mean, has variations U, based on the cumulative sum, and Range, which measures the maximum difference between data blocks, and is being applied to both environmental and financial series. Finally, the Pettitt Ranks test, developed by Pettitt (1979), is a non-parametric test that identifies changes in the median or distribution. It is particularly useful due to its robustness in situations where data distributions are unknown. These methods are widely used to detect breakpoints in time series, such as critical changes in financial asset prices, to help understand the dynamics of relevant events.

To answer the research question of whether sustainable cryptocurrencies such as Avalanche (AVAX), Cardano (ADA), Solana (SOL), Toncoin (TON) and Ethereum (ETH) (after 'The Merge') are more efficient, in their weak form, when compared to unsustainable cryptocurrencies such as Binance Coin (BNB), Litecoin (LTC), Monero (XMR), Ripple (XRP), and Bitcoin (BTC) during the Conflict (Israel-Hamas), the variance ratio methodology proposed by Lo and Mackinlay (1988), to assess the autocorrelation between the series of returns, was employed.

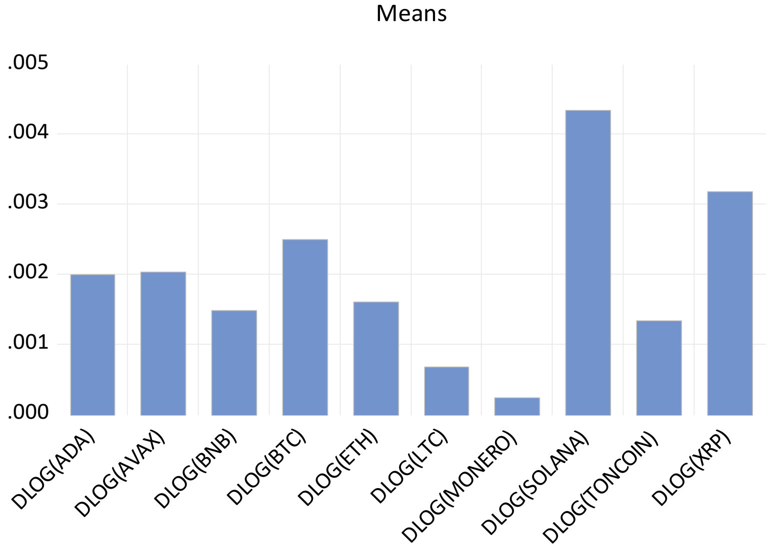
To determine whether the geopolitical event (Israel-Hamas Conflict) has caused long-term effects on sustainable and unsustainable cryptocurrencies, the Detrended Fluctuation Analysis (DFA) model was used. DFA is an analysis method that examines temporal dependence in non-stationary data series. By assuming that the time series are non-stationary, this technique avoids spurious results when analysing the relationships between data series in the long term. DFA has the following interpretation: $0 < \alpha < 0{,}5$: anti-persistent series; $\alpha = 0{,}5$: series presents a random walk; $0{,}5 < \alpha < 1$: persistent series. The purpose of this technique is to examine the relationship between values. x_k and x_{k+t} at different moments. For a better understanding, see the articles by the authors Guedes et al. (2022), Santana et al. (2023), Santana et al. (2023), and Namila da Costa et al. (2024).

RESULTS

Figure 1 illustrates the mean returns of the analysed cryptocurrencies, revealing significant differences in performance. The cryptocurrencies with the most significant mean returns were Solana (0.0043), XRP (0.0032) and Bitcoin (0.0024), indicating that they performed better during this period. In contrast, Monero (0.0002) and Litecoin (0.0007) recorded the lowest mean returns, suggesting weaker performance.

Among the most relevant cryptocurrencies, Bitcoin stood out with a solid mean return (0.0024), higher than that of Ethereum (0.0016), thus reinforcing its position as the leading cryptocurrency on the market. Although Ethereum is the second-largest cryptocurrency in terms of capitalisation, its average performance is below that of Bitcoin and other cryptocurrencies, such as XRP and Solana. Emerging cryptocurrencies such as ADA (0.0019), AVAX (0.0020), BNB (0.0015), and Toncoin (0.0013) recorded moderate mean returns, closely in performance but below assets such as Solana and XRP.

Figure 1: Evolution of mean returns for sustainable and non-sustainable cryptocurrencies, analysed from 1 January 2023 to 10 December 2024.



Source: Prepared by the authors

Figure 2 presents the analysis of the standard deviations of cryptocurrencies during the studied period, revealing important information about the dispersion of returns in relation to the average, risk, and volatility of each asset. Solana has the highest standard deviation (0.0469), indicating the greatest dispersion and, consequently, the highest level of risk and volatility. This is followed by AVAX (0.0460) and XRP (0.0443), which also show high variability in returns, reflecting a higher risk profile.

Meanwhile, Bitcoin has the lowest standard deviation (0.0253), followed by BNB (0.0269), showing lower return dispersion, lower risk, and greater stability, and is considered a more traditional asset for investors. The Monero (0.0330), Ethereum (0.0292) and Toncoin (0.0380) are at intermediate levels of volatility, presenting moderate risk.

The relationship between return and risk in certain cryptocurrencies is remarkable. Solana has the highest mean return (0.0043) and also exhibits the highest volatility, indicating a high-risk investment profile with high potential returns. In contrast, Bitcoin, with a solid mean return (0.0024) and a lower standard deviation, confirms its position as a more stable and less risky option.

In practice, it can be seen that cryptocurrencies such as Solana, AVAX, and XRP are more suitable for investors willing to take greater risks and, as a result, obtain above-average returns, while Bitcoin and BNB are more suitable for investors who prefer greater stability and lower risk. Standard deviation, as a measure of volatility, is key to understanding the balance between risk and return in digital asset investments.

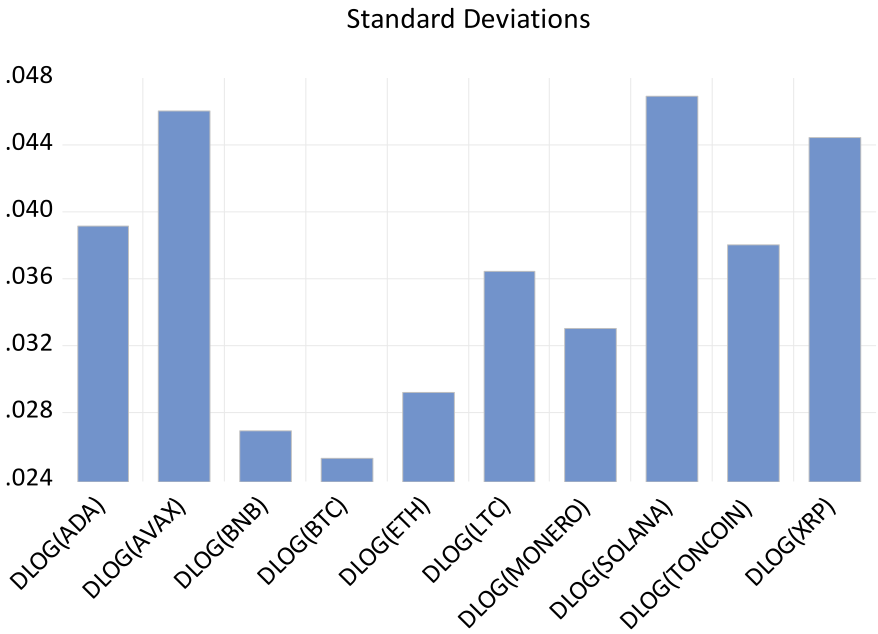


Figure 2: Evolution of standard deviations for sustainable and non-sustainable cryptocurrencies analysed, from 1 January 2023 to 10 December 2024.

Source: Prepared by the authors

In Figure 3, it is possible to analyse the skewness of cryptocurrencies, which provides crucial information about the behaviour of their returns, especially in relation to risk, probability of extreme events, and significant losses. Skewness measures the symmetry of the distribution of returns, where positive values indicate a longer right tail (potential for extreme gains) and negative values indicate a longer left tail (greater risk of significant losses).

The cryptocurrencies ADA (0.6266), AVAX (0.3935), BNB (0.3315), BTC (0.4747), and ETH (0.4886) exhibit positive asymmetry, indicating a higher probability of extreme gains than significant losses. These cryptocurrencies have distributions with longer right tails, making them less susceptible to extreme loss events, while maintaining some potential for upward movements. By contrast, Monero (-3.7780) shows strong negative asymmetry, indicating a high probability of extreme loss events. This feature makes it particularly risky, as the tails of the distribution point toward significant downward movements. This asymmetry suggests that investors should be aware that, despite possible moderate gains, there is a high risk of substantial losses. XRP (3.933) exhibits extremely positive asymmetry, indicating a distribution with strong potential for significant gains. Such behaviour may attract investors seeking speculative opportunities for high returns, although it may involve extreme volatility.

In conclusion, the moderate positive asymmetry in most cryptocurrencies (ADA, AVAX, BNB, BTC, and ETH) suggests a lower risk of extreme losses and higher potential for gains. However, Monero has a high-risk profile due to its significant negative asymmetry, whereas XRP, with extremely positive asymmetry, offers a high probability of extreme gains, albeit with potentially greater volatility. This analysis is essential for investors assessing risk exposure and tolerance to extreme events in the cryptocurrency market.

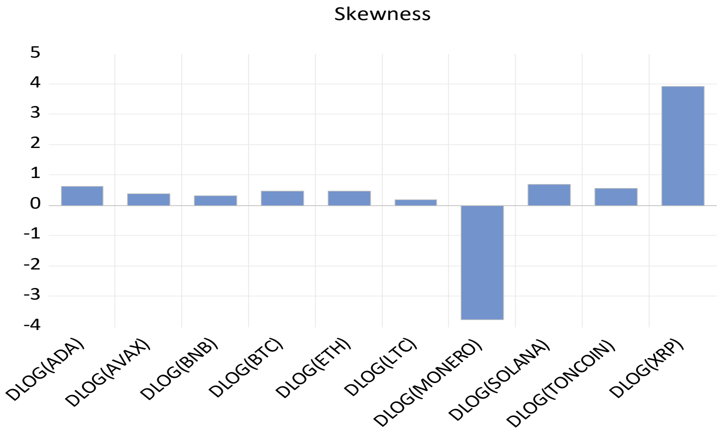


Figure 3: The evolution of asymmetries between sustainable and unsustainable cryptocurrencies analysed from 1 January 2023 to 10 December 2024.
Source: Prepared by the authors

Figure 4 shows the kurtosis of the cryptocurrencies, indicating the degree of concentration of returns around the mean and the presence of heavier tails than a normal distribution. Kurtosis values above three suggest leptokurtic distributions, which have a higher probability of extreme events (values in the tails), increasing the risk of large gains or losses. Cryptocurrencies with very high kurtosis are AVAX (62.4812) and ETH (43.5832), which have extremely high kurtosis values, indicating a significant risk of extreme events, including gains and losses. These distributions have very heavy tails, which indicates a high probability of unexpected movements, making them particularly volatile and risky. These values suggest that the returns on these cryptocurrencies are highly concentrated at extreme values, deviating significantly from the normal distribution. The cryptocurrencies ADA (9.3522), BTC (6.8446), and BNB (5.7126) also had kurtosis values above 3, but at more moderate levels compared to AVAX and ETH. These values indicate that, although the risk of extreme events is present, it is lower than in cryptocurrencies with higher kurtosis. Even so, these cryptocurrencies exhibit distributions that do not follow a normal pattern and have a higher concentration of returns at the extremes, which may be a factor to consider for more risk-averse investors.

Concluding, all cryptocurrencies analysed have kurtosis values above 3, deviating from a normal distribution and indicating high risk. AVAX and ETH stand out for their extremely high kurtosis values, indicating high volatility and strong exposure to extreme events. In contrast, ADA, BTC, and BNB, although carrying considerable risk, have more moderate kurtosis values. This type of analysis is crucial for evaluating the suitability of assets to investors' risk profiles, particularly in highly volatile markets such as cryptocurrencies.

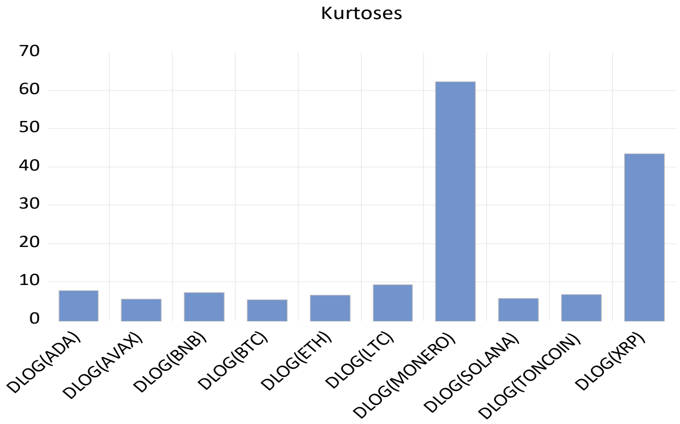


Figure 4: Evolution of the kurtosis of sustainable and non-sustainable cryptocurrencies under analysis, from 1 January 2023 to 10 December 2024**.**

Source: Prepared by the authors

Breitung (2000), Levin, Lin, and Chu (2002), and Im et al. (2003) tests were applied, which postulate the same null hypotheses (unit roots). Dickey and Fuller (1981) and Phillips and Perron (1988) tests using Fisher's chi-square transformation and Choi's (2001) unit root tests were employed to strengthen the results.

The results indicate that the time series has unit roots when estimating the original price series. Therefore, a logarithmic transformation of first differences was performed to achieve stationarity (Table 2).

Table 2: Summary table of unit root tests applied to sustainable and non-sustainable cryptocurrencies analysed from 1 January 2023 to 10 December 2024.

Group unit root test: Summary				
Method	**Statistic**	**Prob.****	**Cross-sections**	**Obs**
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-146.11	0.0000	10	7067
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-93.89	0.0000	10	7067
ADF - Fisher Chi-square	2370.52	0.0000	10	7067
PP - Fisher Chi-square	2540.41	0.0000	10	7080

Source: Prepared by the authors

Table 3 presents the results of speculative bubbles detected in cryptocurrencies using the Rolling ADF (RADF) test, which reveals the presence of unsustainable price dynamics in several cryptocurrencies from 1 January 2023 to 10 December 2024. The test rejects the null hypothesis that there is no bubble when the probability value (p-value) is less than 0.05, indicating a high probability of speculative bubbles.

Solana presented one of the most significant speculative bubbles, identified on 15 November 2023, with a statistic of 3.8583 and a p-value of 0.0021. These values exhibit strong speculative dynamics, with a high probability of unsustainable price movements, potentially triggered by events such as partnership announcements or technological advancements.

Litecoin experienced a speculative bubble on 12 February 2024, with a statistic of 2.6740 and a p-value of 0.0484. Although the value is close to the threshold, it is sufficient to reject the null hypothesis, indicating that prices exhibited speculative dynamics. The Bitcoin test revealed possible speculative behaviour on 4 March 2024, with a statistic of 2.700 and a p-value of 0.0590. Although close to the significance threshold, the result does not provide sufficient statistical robustness to confirm the existence of a speculative bubble. Nevertheless, this value suggests that BTC prices were in a phase of high volatility and close to bubble dynamics.

Ethereum also showed results close to the significance threshold, with a statistic of 2.7181 and a p-value of 0.0502 on 6 March 2024. This result points to possible speculative dynamics, but without robust statistical confirmation. The behaviour may reflect ETH's sensitivity to external factors, such as technological developments or speculative movements. Toncoin recorded a speculative bubble on 12 March 2024, with a statistic of 2.7220 and a p-value of 0.0459. These results confirm that the price exhibited speculative behaviour during this period, albeit with less intensity than other cryptocurrencies.

The BNB speculative bubble was identified on 15 March 2024, with a statistic of 3.8579 and a p-value of 0.0033. This result confirms the existence of significant speculative dynamics, characterised by a sharp increase in prices beyond levels supported by economic fundamentals. Monero experienced a speculative bubble on 10 June

2024, with a statistic of 3.1651 and a p-value of 0.0170. This result confirms the presence of speculative behaviour, possibly related to the nature of this asset, which is often associated with privacy and speculative flows.

The ADA cryptocurrency experienced a speculative bubble on 15 November 2024 (statistic of 3.3646 and a p-value of 0.0114). These values indicate that prices were significantly above sustainable levels, confirming the existence of a speculative bubble with strong statistical support. Such behaviour can be associated with a period of high speculative enthusiasm in the market. AVAX experienced a speculative bubble on 17 November 2023, as evidenced by a statistic of 3.9497 and an extremely low p-value of 0.0020.

XRP identified a speculative bubble on 21 November 2024, with a statistic of 3.5547 and a p-value of 0.0238. This result confirms that the cryptocurrency was subject to strong speculative dynamics, with prices significantly above sustainable levels.

The analysis of Rolling ADF (RADF) tests showed that several cryptocurrencies were subject to speculative bubbles during the reviewed period, with AVAX, Solana, and XRP showing the strongest evidence of extreme speculative behaviour. Although not statistically confirming bubbles, cryptocurrencies such as BTC and ETH exhibit price dynamics close to unsustainable levels, suggesting high volatility. These dynamics reflect the speculative and highly volatile nature of the cryptocurrency market, requiring prudential attention from investors.

Table 3: Summary table of speculative bubble detection using the Rolling ADF (RADF) Bubble test, applied to sustainable and non-sustainable cryptocurrencies under analysis, from 1 January 2023 to 10 December 2024.

Rolling ADF (RADF) Bubble Test for ADA Null Hypothesis: Series does not contain a bubble			
Test	Location	Statistic	Prob.
Rolling ADF (RADF)	15/11/2024	3.3646	0.0114
Rolling ADF (RADF) Bubble Test for AVAX Null Hypothesis: Series does not contain a bubble			
Test	Location	Statistic	Prob.
Rolling ADF (RADF)	17/11/2023	3.9497	0.0020
Rolling ADF (RADF) Bubble Test for BNB Null Hypothesis: Series does not contain a bubble			
Test	Location	Statistic	Prob.
Rolling ADF (RADF)	15/03/2024	3.8579	0.0033
Rolling ADF (RADF) Bubble Test for BTC Null Hypothesis: Series does not contain a bubble			
Test	Location	Statistic	Prob.
Rolling ADF (RADF)	04/03/2024	2.700	0.0590
Rolling ADF (RADF) Bubble Test for ETH Null Hypothesis: Series does not contain a bubble			
Test	Location	Statistic	Prob.
Rolling ADF (RADF)	06/03/2024	2.7181	0.0502
Rolling ADF (RADF) Bubble Test for LTC Null Hypothesis: Series does not contain a bubble			
Test	Location	Statistic	Prob.
Rolling ADF (RADF)	12/02/2024	2.6740	0.0484
Rolling ADF (RADF) Bubble Test for MONERO Null Hypothesis: Series does not contain a bubble			
Test	Location	Statistic	Prob.
Rolling ADF (RADF)	10/06/2024	3.1651	0.0170
Rolling ADF (RADF) Bubble Test for SOLANA Null Hypothesis: Series does not contain a bubble			

Test	Location	Statistic	Prob.
Rolling ADF (RADF)	15/11/2023	3.8583	0.0021
Rolling ADF (RADF) Bubble Test for TONCOIN Null Hypothesis: Series does not contain a bubble			
Test	Location	Statistic	Prob.
Rolling ADF (RADF)	12/03/2024	2.7220	0.0459
Rolling ADF (RADF) Bubble Test for XRP Null Hypothesis: Series does not contain a bubble			
Test	Location	Statistic	Prob.
Rolling ADF (RADF)	21/11/2024	3.5547	0.0238

Note: The ADF (RADF) Bubble test identifies the presence of bubbles in time series by assessing explosive behaviour in prices. It uses the Augmented Dickey-Fuller (ADF) model with a sliding window approach to detect unsustainable deviations from economic fundamentals.

Source: Prepared by the authors

Table 4 shows the results of the trend detection tests applied to cryptocurrencies between 1 January 2023 and 10 December 2024, revealing important information about the presence of price behaviour patterns and the practical implications for forecasting and risk management. The tests address different forms of trends (linear, quadratic, monotonic, etc.) and use analytical and bootstrap methods to assess the robustness of the results.

ADA indicates the presence of significant trends in all forms, with p-values equal to 0.0000. However, bootstrap probabilities show inconsistent results, especially for linear (0.3837), quadratic (0.8907) and monotonic (0.5577 in the Mann-Kendall test) trends. This suggests that, although there is analytical evidence of trends in ADA prices, these may be sensitive to market conditions and less robust when subjected to bootstrap replications. In summary, ADA may exhibit temporary trend patterns, but caution is needed when predicting price movements based solely on apparent trends. On the other hand, the AVAX cryptocurrency indicates significant analytical and bootstrap trends, with bootstrap p-values below 0.05 in all tests. The quadratic trend is particularly strong, with a statistic of 196.20 and a bootstrap p-value of 0.0318. This behaviour suggests a consistent price trajectory with predictable patterns. AVAX exhibits more stable and predictable price behaviour, making it a potential choice for trend-based strategies.

BNB shows that all tests, analytical and bootstrap, confirm the presence of highly significant trends in all forms, with p-values of 0.0000 for all approaches. The WAVK test statistic (47527.23) reinforces the robustness of the trends. BNB is one of the most consistent cryptocurrencies in terms of trend patterns, providing opportunities for investors who employ trend analysis-based strategies. Bitcoin has the highest statistics among the cryptocurrencies analysed, particularly in the quadratic trend test (2120.91). Both analytical and bootstrap tests confirmed clear and robust trends. In practical terms, BTC, due to its strong consistency in trend patterns, can serve as a benchmark for the cryptocurrency market and is a reliable option for long-term strategies.

Ethereum follows patterns similar to BTC, with highly significant results for all forms of trend. The WAVK statistic (23603.21) highlights the robustness of the trends in any form. ETH demonstrates consistent predictability, making it a viable option for investors seeking to capitalise on market trends.

Regarding LTC, although analytical tests indicated significant trends, bootstrap probabilities showed mixed results. Only the Cox-Stuart and WAVK tests show significant bootstrap support. LTC exhibits less consistent trend patterns, making it difficult to use strategies based on linear or quadratic forecasts.

Monero did not show significant trends in most tests, with analytical and bootstrap p-values greater than 0.05. Only the WAVK test suggests some analytical evidence of a trend, but without bootstrap confirmation. In practical terms, Monero appears to have more random and less predictable price behaviour, making it less suitable for strategies based on trend analysis.

Solana showed highly significant results in all tests, with analytical and bootstrap p-values of 0.0000. The WAVK statistic (53401.61) shows strong evidence of trends. In practical terms, Solana presents clear opportunities for trend-based strategies, as it is one of the most consistent and predictable cryptocurrencies. Similar to Solana, Toncoin showed robust results in all forms of trends, with clear analytical and bootstrap support. The WAVK statistic (45884.48) reinforces the predictability of prices. Toncoin is a cryptocurrency suitable for strategies based on long-term forecasts and trends.

XRP exhibits analytical results with significant trends; however, bootstrap support is weaker, with p-values above 0.05 in several tests. This behaviour suggests that trend patterns may not be sufficiently robust for reliable predictions. Practically, XRP may exhibit temporary trend patterns; however, investors should exercise caution when basing their decisions on such signals.

Cryptocurrencies such as BTC, ETH, Solana, AVAX, Toncoin, and BNB show clear and robust trends, making them ideal investment strategies based on predictability and trend analysis. On the other hand, cryptocurrencies such as ADA, XRP, LTC, and Monero exhibit more inconsistent patterns, requiring greater attention to external factors and market context. This analysis reinforces the importance of combining analytical and bootstrap approaches to validate the robustness of trends before making investment decisions.

Table 4: Summary table of trend detection tests applied to sustainable and unsustainable cryptocurrencies under analysis, from 1 January 2023 to 10 December 2024.

Trend Tests for ADA				
Null Hypothesis: Series does not contain a trend				
Test	Alternative	Statistic	Analytic Prob.	Bootstrap Prob.
Trend t-stat	Linear	12.45	0.0000	0.3837
Squared-trend F-stat	Quadratic	80.98	0.0000	0.8907
Mann-Kendall	Monotonic	0.196	0.0000	0.5577
Cox-Stuart	Monotonic	8.79	0.0000	0.2512
WAVK	Any Form	8299.85	0.0000	0.3446
Trend Tests for AVAX				
Null Hypothesis: Series does not contain a trend				
Test	Alternative	Statistic	Analytic Prob.	Bootstrap Prob.
Trend t-stat	Linear	19.29	0.0000	0.0062
Squared-trend F-stat	Quadratic	196.20	0.0000	0.0318
Mann-Kendall	Monotonic	0.30	0.0000	0.0448
Cox-Stuart	Monotonic	15.42	0.0000	0.0000
WAVK	Any Form	20384.24	0.0000	0.0000
Trend Tests for BNB				
Null Hypothesis: Series does not contain a trend				
Test	Alternative	Statistic	Analytic Prob.	Bootstrap Prob.
Trend t-stat	Linear	36.13	0.0000	0.0000
Squared-trend F-stat	Quadratic	1066.24	0.0000	0.0000
Mann-Kendall	Monotonic	0.45	0.0000	0.0000
Cox-Stuart	Monotonic	15.42	0.0000	0.0000
WAVK	Any Form	47527.23	0.0000	0.0000
Trend Tests for BTC				
Null Hypothesis: Series does not contain a trend				
Test	Alternative	Statistic	Analytic Prob.	Bootstrap Prob.
Trend t-stat	Linear	61.56	0.0000	0.0000
Squared-trend F-stat	Quadratic	2120.91	0.0000	0.0000
Mann-Kendall	Monotonic	0.72	0.0000	0.0000
Cox-Stuart	Monotonic	15.42	0.0000	0.0000
WAVK	Any Form	56086.93	0.0000	0.0000
Trend Tests for ETH				
Null Hypothesis: Series does not contain a trend				
Test	Alternative	Statistic	Analytic Prob.	Bootstrap Prob.
Trend t-stat	Linear	32.65	0.0000	0.0000
Squared-trend F-stat	Quadratic	550.01	0.0000	0.0000
Mann-Kendall	Monotonic	0.58	0.0000	0.0000
Cox-Stuart	Monotonic	15.42	0.0000	0.0000
WAVK	Any Form	23603.21	0.0000	0.0000
Trend Tests for LTC				
Null Hypothesis: Series does not contain a trend				

Test	Alternative	Statistic	Analytic Prob.	Bootstrap Prob.
Trend t-stat	Linear	-7.90	0.0000	0.1973
Squared-trend F-stat	Quadratic	79.31	0.0000	0.1398
Mann-Kendall	Monotonic	-0.24	0.0000	0.0455
Cox-Stuart	Monotonic	10.87	0.0000	0.0025
WAVK	Any Form	2980.84	0.0000	0.0000

Trend Tests for MONERO

Null Hypothesis: Series does not contain a trend

Test	Alternative	Statistic	Analytic Prob.	Bootstrap Prob.
Trend t-stat	Linear	-0.77	0.43792	0.9733
Squared-trend F-stat	Quadratic	48.66	0.0000	0.5280
Mann-Kendall	Monotonic	0.03	0.8982	0.9820
Cox-Stuart	Monotonic	0.47	0.6335	0.8978
WAVK	Any Form	1653.46	0.0000	0.0000

Trend Tests for SOLANA

Null Hypothesis: Series does not contain a trend

Test	Alternative	Statistic	Analytic Prob.	Bootstrap Prob.
Trend t-stat	Linear	59.19	0.0000	0.0000
Squared-trend F-stat	Quadratic	1962.30	0.0000	0.0000
Mann-Kendall	Monotonic	0.67	0.0000	0.0000
Cox-Stuart	Monotonic	15.42	0.0000	0.0000
WAVK	Any Form	53401.61	0.0000	0.0000

Trend Tests for TONCOIN

Null Hypothesis: Series does not contain a trend

Test	Alternative	Statistic	Analytic Prob.	Bootstrap Prob.
Trend t-stat	Linear	34.89	0.0000	0.0000
Squared-trend F-stat	Quadratic	764.24	0.0000	0.0000
Mann-Kendall	Monotonic	0.45	0.0000	0.0000
Cox-Stuart	Monotonic	15.42	0.0000	0.0000
WAVK	Any Form	45884.48	0.0000	0.0000

Trend Tests for XRP

Null Hypothesis: Series does not contain a trend

Test	Alternative	Statistic	Analytic Prob.	Bootstrap Prob.
Trend t-stat	Linear	11.94	0.0000	0.3675
Squared-trend F-stat	Quadratic	94.79	0.0000	0.6993
Mann-Kendall	Monotonic	0.36	0.0000	0.1199
Cox-Stuart	Monotonic	12.69	0.0000	0.0592
WAVK	Any Form	619.54	0.0000	0.9075

Note: Bootstrap probabilities use 9,999 replications. Replications are based on Hall and Van Keilegom (HVK) estimates of an AR(1) process.
Source: Prepared by the authors

Table 5 presents a detailed analysis of the Change Point tests applied to cryptocurrencies between 1 January 2023 and 10 December 2024, which identifies significant structural changes in the means of the price time series. These tests assess the occurrence of substantial changes in the series patterns, indicating potential changes in price behaviour. These approaches include analytical and bootstrap methods to validate the results.

Regarding ADA, Quandt-Andrews Max., Exp., and Avg. tests identified a significant change point on 5 December 2023, with highly significant analytical values (p = 0.0000). However, the bootstrap values do not corroborate the results, except for Pettitt Ranks (p = 0.0388), which suggests a relevant change on 22 November 2023. ADA shows signs of structural changes in prices, but the lack of robust support in the bootstrap indicates that these changes may be less consistent.

AVAX shows well-defined structural changes, suggesting moments of volatility or changes in price patterns that may reflect market events or fundamental changes. BNB exhibits this evidence, and according to the Quandt-

Andrews tests, a significant structural change is identified on 6 March 2024, while the Pettitt Ranks indicate a change on 8 February 2024. Both analytical and bootstrap methods support these conclusions.

BNB has consistent and robust structural changes, indicating that investors should focus on events during this period that may justify these changes. On BTC, significant changes were identified on 2 December 2024 in all methods. Pettitt Ranks detected an additional change on 12 May 2023. Both analytical and bootstrap analyses corroborate the results. BTC exhibits relevant and reliable structural changes that may be associated with macroeconomic events or relevant news in the cryptocurrency market. Tests performed on the ETH cryptocurrency identified a significant change on 2 September 2024 and another on 12 May 2023 by Pettitt Ranks. The analytical and bootstrap results reinforce the robustness of the changes detected. Therefore, ETH shows consistent structural changes, indicating that investors should monitor events during these periods to understand the underlying factors.

The LTC recorded changes on 15 August 2023, supported by the Quandt-Andrews and Pettitt Ranks tests. The bootstrap values also corroborate this, although the significance in the Buishand U test ($p = 0.0754$) is marginal. In practical terms, the changes in the LTC are moderately robust, suggesting structural volatility during this period. Regarding Monero, analytical tests suggest a possible change on 6 April 2024, but bootstrap values do not confirm these results, except for the Buishand Range test ($p = 0.0002$). In terms of practical implications, Monero shows less consistent changes, reflecting greater randomness in prices or less pronounced local changes.

For Solana, the tests detected significant structural changes on 21 December 2023, supported by all analytical and bootstrap methods. An additional change was identified on 11 December 2024 by the Buishand Range. So, Solana exhibits clear and robust structural changes, indicating potential moments of price revaluation. Regarding Toncoin, tests indicate a significant change on 20 March 2024, supported by analytical and bootstrap analyses. Additionally, a change was detected through the Pettitt Ranks test on 28 February 2024. Toncoin exhibits strong and reliable structural changes, suggesting periods of greater instability or reconfiguration in its price behaviour.

For XRP, the analytical tests indicate changes on 26 August 2024; however, bootstrap values do not corroborate these changes, except in Pettitt Ranks, which identifies a change on 13 July 2023 ($p = 0.0945$). Practically, changes in XRP are less robust and may reflect temporary fluctuations in price patterns, with a lesser structural impact.

Cryptocurrencies with robust structural changes, such as AVAX, BNB, BTC, ETH, Solana, and Toncoin, exhibited significant and consistent changes in all analyses. These cryptocurrencies are more predictable in terms of structural changes, allowing investment strategies to be adjusted based on identified patterns. Regarding cryptocurrencies with less consistent changes, cryptocurrencies such as ADA, Monero, XRP, and, to a lesser extent, LTC, exhibit more moderate changes or inconsistent results between analytical and bootstrap methods. These cryptocurrencies may exhibit greater randomness and localised volatility. These results are crucial for investors seeking to identify moments of price revaluation, adjusting buying or selling strategies based on significant structural changes in cryptocurrency markets.

Table 5: Summary table of Change Point tests applied to sustainable and non-sustainable cryptocurrencies analysed, from 1 January 2023 to 10 December 2024.

Change Point Tests for ADA				
Null Hypothesis: Series does not contain a mean change point				
Test	Statistic	Change Location	Analytic Prob.	Bootstrap Prob.
Quandt-Andrews Max.	316.02	05/12/2023	0.0000	0.6998
Quandt-Andrews Exp.	153.53	05/12/2023	0.0000	0.6927
Quandt-Andrews Avg.	100.85	05/12/2023	0.0000	0.2210
Buishand U	14.52	05/12/2023	---	0.2994
Buishand Range	7.38	11/11/2024	---	0.0367
Pettitt Ranks	95385	22/11/2023	0.0000	0.0388
Change Point Tests for AVAX				
Null Hypothesis: Series does not contain a mean change point				
Test	Statistic	Change Location	Analytic Prob.	Bootstrap Prob.
Quandt-Andrews Max.	1390.70	06/12/2023	0.0000	0.0000
Quandt-Andrews Exp.	689.95	06/12/2023	0.0000	0.0000
Quandt-Andrews Avg.	354.14	06/12/2023	0.0000	0.0000
Buishand U	30.81	06/12/2023	---	0.0000
Buishand Range	10.83	11/12/2024	---	0.0000
Pettitt Ranks	124997	04/12/2023	0.0000	0.0000

Change Point Tests for BNB				
Null Hypothesis: Series does not contain a mean change point				
Test	Statistic	Change Location	Analytic Prob.	Bootstrap Prob.
Quandt-Andrews Max.	6842.88	06/3/2024	0.0000	0.0000
Quandt-Andrews Exp.	3415.66	06/3/2024	0.0000	0.0000
Quandt-Andrews Avg.	1259.78	06/3/2024	0.0000	0.0000
Buishand U	52.74	06/3/2024	---	0.0000
Buishand Range	12.40	11/12/2024	---	0.0000
Pettitt Ranks	123281	08/2/2024	0.0000	0.0000

Change Point Tests for BTC				
Null Hypothesis: Series does not contain a mean change point				
Test	Statistic	Change Location	Analytic Prob.	Bootstrap Prob.
Quandt-Andrews Max.	2969.45	2/12/2024	0.0000	0.0000
Quandt-Andrews Exp.	1478.99	2/12/2024	0.0000	0.0000
Quandt-Andrews Avg.	1106.27	2/12/2024	0.0000	0.0000
Buishand U	61.27	2/12/2024	---	0.0000
Buishand Range	11.84	12/11/2024	---	0.0000
Pettitt Ranks	125702	12/05/2023	0.0000	0.0000

Change Point Tests for ETH				
Null Hypothesis: Series does not contain a mean change point				
Test	Statistic	Change Location	Analytic Prob.	Bootstrap Prob.
Quandt-Andrews Max.	1946.67	2/09/2024	0.0000	0.0000
Quandt-Andrews Exp.	967.94	2/09/2024	0.0000	0.0000
Quandt-Andrews Avg.	707.35	2/09/2024	0.0000	0.0000
Buishand U	47.69	2/09/2024	---	0.0000
Buishand Range	11.29	12/11/2024	---	0.0000
Pettitt Ranks	125700	12/05/2023	0.0000	0.0000

Change Point Tests for LTC				
Null Hypothesis: Series does not contain a mean change point				
Test	Statistic	Change Location	Analytic Prob.	Bootstrap Prob.
Quandt-Andrews Max.	262.59	15/8/2023	0.0000	0.0078
Quandt-Andrews Exp.	127.02	15/8/2023	0.0000	0.0074
Quandt-Andrews Avg.	70.96	15/8/2023	0.0000	0.0423
Buishand U	9.09	15/8/2023	---	0.0754
Buishand Range	8.495	16/8/2023	---	0.0000
Pettitt Ranks	81118	16/8/2023	0.0000	0.0015

Change Point Tests for MONERO				
Null Hypothesis: Series does not contain a mean change point				
Test	Statistic	Change Location	Analytic Prob.	Bootstrap Prob.
Quandt-Andrews Max.	82.32	6/04/2024	0.0000	0.4884
Quandt-Andrews Exp.	36.76	6/04/2024	0.0000	0.4833
Quandt-Andrews Avg.	24.40	6/04/2024	0.0000	0.4344
Buishand U	3.71	6/04/2024	---	0.5693
Buishand Range	7.34	2/06/2024	---	0.0002
Pettitt Ranks	39095	6/04/2024	0.0000	0.4103

Change Point Tests for SOLANA				
Null Hypothesis: Series does not contain a mean change point				
Test	Statistic	Change Location	Analytic Prob.	Bootstrap Prob.
Quandt-Andrews Max.	3533.12	21/12/2023	0.0000	0.0000
Quandt-Andrews Exp.	1760.36	21/12/2023	0.0000	0.0000

Quandt-Andrews Avg.	1294.57	21/12/2023	0.0000	0.0000
Buishand U	62.31	21/12/2023	---	0.0000
Buishand Range	12.15	11/12/2024	---	0.0000
Pettitt Ranks	126024	21/12/2023	0.0000	0.0000
Change Point Tests for TONCOIN				
Null Hypothesis: Series does not contain a mean change point				
Test	Statistic	Change Location	Analytic Prob.	Bootstrap Prob.
Quandt-Andrews Max.	6215.54	20/03/2024	0.0000	0.0000
Quandt-Andrews Exp.	3101.56	20/03/2024	0.0000	0.0000
Quandt-Andrews Avg.	1178.65	20/03/2024	0.0000	0.0000
Buishand U	51.98	20/03/2024	---	0.0000
Buishand Range	12.260	11/12/2024	---	0.0000
Pettitt Ranks	121373	28/02/2024	0.0000	0.0000
Change Point Tests for XRP				
Null Hypothesis: Series does not contain a mean change point				
Test	Statistic	Change Location	Analytic Prob.	Bootstrap Prob.
Quandt-Andrews Max.	165.54	26/8/2024	0.0000	0.7488
Quandt-Andrews Exp.	77.29	26/8/2024	0.0000	0.7502
Quandt-Andrews Avg.	63.78	26/8/2024	0.0000	0.5605
Buishand U	10.82	26/8/2024	---	0.5308
Buishand Range	4.42	11/12/2024	---	0.9620
Pettitt Ranks	87924	13/07/2023	0.0000	0.0945

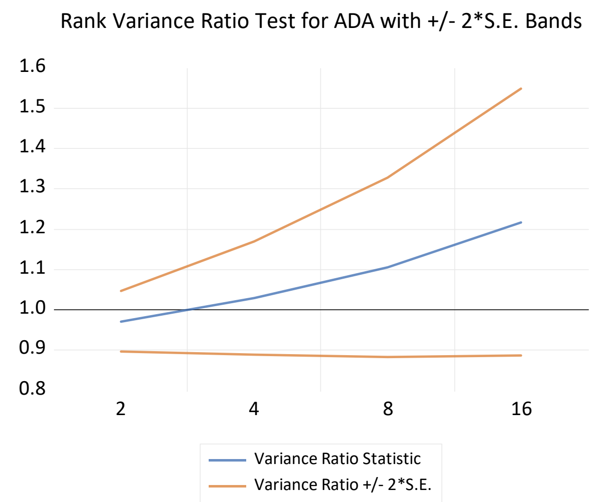
Note: Bootstrap probabilities use 9,999 replications. Replications are based on Hall and Van Keilegom (HVK) estimates of an AR(1) process.
Source: Prepared by the authors

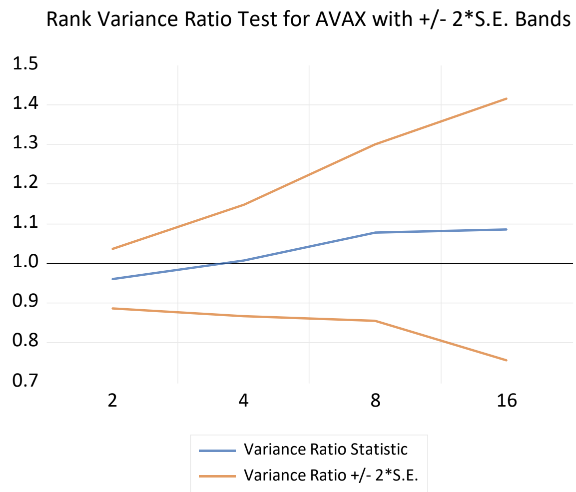
The analysis of serial autocorrelation in cryptocurrencies (figure 5), based on the model developed by Lo and Mackinlay (1988), reveals distinct patterns between sustainable and non-sustainable cryptocurrencies, with relevant practical implications for investors, regulators, and other financial market participants.

The presence of positive autocorrelation, as observed in the AVAX and ADA cryptocurrencies between the 16th and 4th, and predominantly in SOL, indicates that past returns directly influence future returns. In practice, this means that prices are predictable, creating opportunities for arbitrage and speculative gains. However, this predictability suggests less efficient markets, where prices do not fully reflect the available information, also increasing the risk of speculative bubble formation. In contrast, negative autocorrelation, identified in AVAX and ADA between days 4 and 2, and predominant in TON, ETH, and unsustainable cryptocurrencies (BTC, BNB, LTC, XMR, and XRP), suggests that extreme price movements tend to be corrected, creating opportunities for investment strategies based on mean reversion. This behaviour reflects more efficient markets, where prices adjust quickly to new information, reducing the predictability of future returns and making speculation based on historical patterns more difficult.

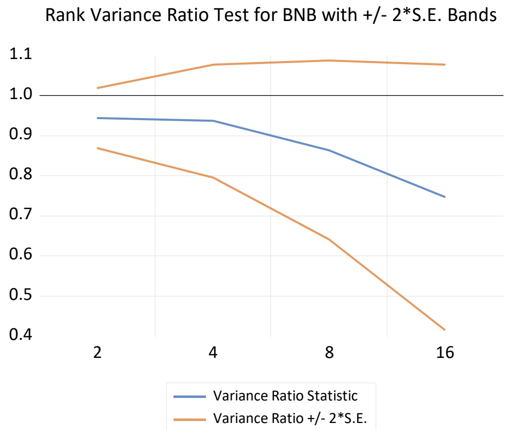
Summarising, positive autocorrelation presents opportunities for investors but also reflects market inefficiencies and potential risks of speculation. Conversely, negative autocorrelation is associated with more efficient and less predictable markets, requiring more sophisticated investment strategies. The analysis clearly distinguishes between the market dynamics of sustainable and unsustainable cryptocurrencies, demonstrating how their underlying mechanisms directly impact the efficiency and predictability of returns.

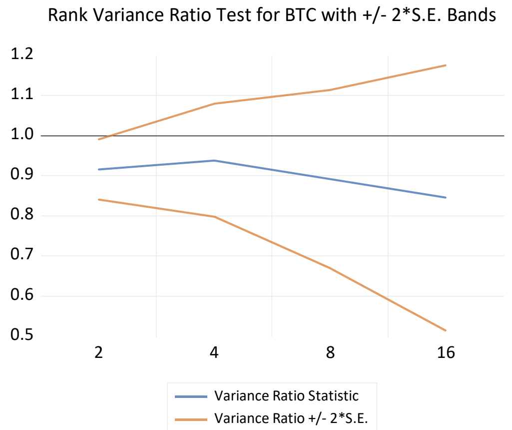
Figure 5: Summary table of Lo and Mackinlay (1988), Variance Ratio tests, applied to sustainable and non-sustainable cryptocurrencies under analysis, from 1 January 2023 to 10 December 2024.

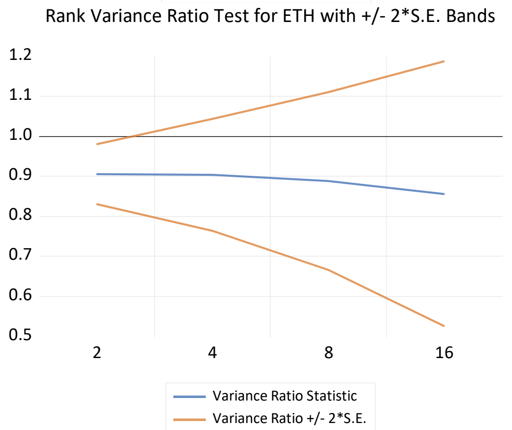


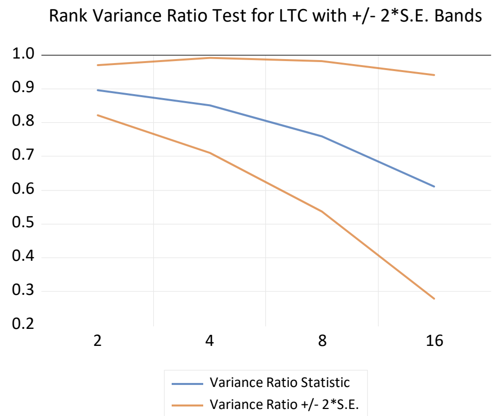


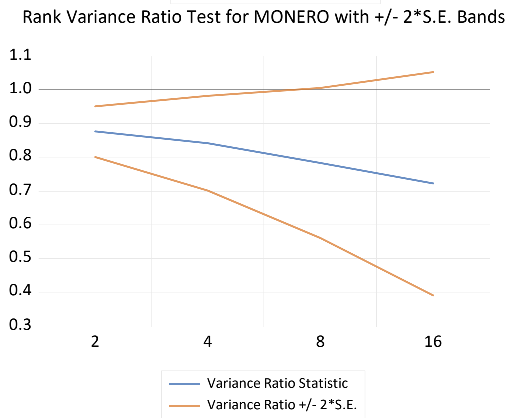
Fonte: Elaboração própria.

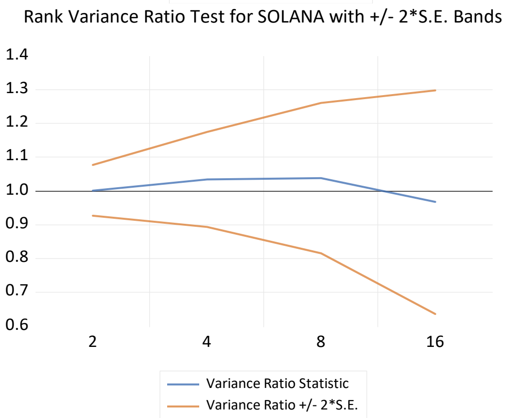


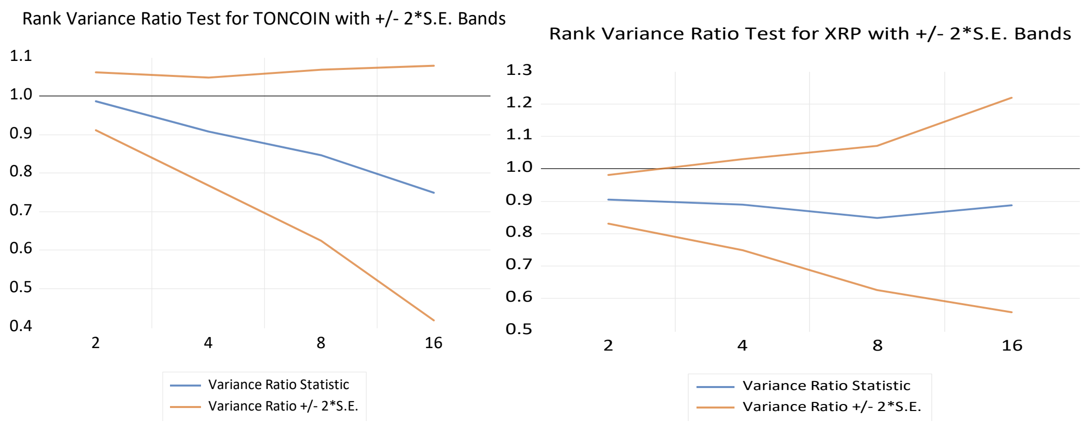












Source: Prepared by the authors

Table 6 shows the slopes of the DFAs for sustainable and unsustainable cryptocurrencies analysed from 1 January 2023 to 10 December 2024.

The results of the DFA slopes, divided between the Pre-Conflict and Conflict periods of 2023, revealed significant changes in the dynamics of the cryptocurrency time series. These changes provide insights into how different assets reacted to an environment of greater uncertainty and volatility, highlighting the differences between sustainable and unsustainable cryptocurrencies.

In the Pre-Conflict period, AVAX, ADA, and SOL had αDFA values of 0.59, 0.62, and 0.64, respectively, indicating persistent behaviour. These values reflect the existence of long memory in returns, where past trends (positive or negative) influence future price movements. During the Conflict, there was a slight reduction in αDFA slope values, which fell to 0.56, 0.57 and 0.53. Although they still show persistence in their returns, this decrease suggests that the impact of the Conflict reduced the strength of trends in returns, possibly due to greater volatility or uncertainty in the market. Despite the decline in values, the relative stability of these assets indicated that sustainable cryptocurrencies maintained some consistency in their price dynamics.

The TON cryptocurrency maintained an αDFA of 0.50 both in the Pre-Conflict period and during the Conflict, characterised as white noise (mean zero and constant variance). This random behaviour reflects the absence of predictable patterns in prices, suggesting that this cryptocurrency was less affected by external conditions and continued to behave as an efficient asset, with no memory in returns.

Meanwhile, ETH exhibited interesting behaviour. In the Pre-Conflict period, it had an αDFA of 0.50, indicating white noise; however, during the Conflict, this value increased to 0.56, indicating persistence. This means that price movements became reactive, with positive returns followed by negative ones (and vice versa). This change can be attributed to a combination of factors, including the recent 'The Merge' update, which brought greater attention and speculation to the asset, and the environment of uncertainty associated with the Conflict.

Among the non-sustainable cryptocurrencies, BTC and BNB exhibited persistent behaviour in the Pre-Conflict period, with αDFA of 0.65 and 0.62, respectively. During the Conflict, these values decreased to 0.53 and 0.52, indicating that persistence remained, but with less intensity. This change suggests that these assets still exhibited memory in returns, buhowever the impact of the Conflict reduced both predictability and trends.

The Cryptocurrencies LTC and XMR showed a more significant transformation. During the Pre-Conflict period, both groups exhibited values that indicated persistence (0.58 and 0.54, respectively). However, during the Conflict, αDFA values fell to 0.42, characterising anti-persistent behaviour. This phenomenon reflects an increase in instability, where positive movements tend to be followed by negative ones, a characteristic of highly speculative markets or situations of high uncertainty.

On the other hand, XRP remained relatively stable, with αDFA de 0.55 of 0.55 in the Pre-Conflict period and 0.54 during the Conflict period, maintaining its persistent behaviour. This result suggests that, despite the impact of the Conflict, this cryptocurrency has consistently maintained its long-term dynamics.

Table 6: DFA exponent for return. The values of the linear adjustments for $\boldsymbol{\alpha DFA}$ always had $\boldsymbol{R^2}$ > 0.99

Cryptocurrencies (Sustainable)	αDFA (Pre-Conflict)	Results	αDFA (Conflict in 2023)	Results
AVAX	0.59** ≅ 0.0031	Persistent	0.56** ≅ 0.0011	Persistent
ADA	0.62** ≅ 0.0023	Persistent	0.57** ≅ 0.0023	Persistent
SOL	0.64** ≅ 0.0025	Persistent	0.53** ≅ 0.0010	Persistent
TON	**0.50 ≅ 0.0040**	**White noise**	**0.50 ≅ 0.0018**	**White noise**

ETH (after "The Merge")	**0.50 ≅ 0.0207**	**White noise**	0.56** ≅ 0.0049	Anti-persistent
Cryptocurrencies (Not Sustainable)	αDFA (Pre-Conflict)	Results	αDFA (Conflict in 2023)	
BTC	0.65** ≅ 0.0011	Persistent	0.53** ≅ 0.0011	Persistent
BNB	0.62** ≅ 0.0052	Persistent	0.52** ≅ 0.0070	Persistent
LTC	0.58** ≅ 0.0012	Persistent	0.42** ≅ 0.0095	
XMR	0.54** ≅ 0.0046	Persistent	0.42** ≅ 0.0032	
XRP	0.55** ≅ 0.0035	Persistent	0.54** ≅ 0.0079	Persistent

*Note: The hypotheses are H_0: a = 0.5 and H_1: a ≠ 0.5. ** IC a 95%.*

Source: Prepared by the authors

CONCLUSION

This study aimed to compare the levels of efficiency, in its weak form, between sustainable cryptocurrencies, such as Avalanche (AVAX), Cardano (ADA), Solana (SOL), Toncoin (TON), and Ethereum (ETH) (after 'The Merge'), which use efficient mechanisms such as proof-of-stake (PoS). On the other hand, Binance Coin (BNB), Litecoin (LTC), Monero (XMR), Ripple (XRP), and Bitcoin (BTC) were classified as unsustainable cryptocurrencies due to their excessive energy consumption based on proof-of-work (PoW) from 1 January 2023 to 10 December 2024.

The analysis of serial autocorrelation and DFA slopes provides a deeper understanding of cryptocurrency market dynamics, highlighting how these time series react in scenarios of instability. Before the 2023 conflict, the αDFA slopes of sustainable cryptocurrencies (AVAX, ADA, SOL) indicated persistent behaviour, with values between 0.59 and 0.64, reflecting the presence of long memories and trends influenced by past returns. During the Conflict, these values decreased slightly to 0.56, 0.57, and 0.53, signalling that the environment of uncertainty reduced the strength of trends but did not eliminate persistence. This resilience highlights the greater stability of sustainable cryptocurrencies, possibly due to the perception of sustainability as a compelling factor in times of volatility.

Meanwhile, among unsustainable cryptocurrencies, BTC and BNB showed a reduction in persistence, with αDFA values decreasing from 0.65 and 0.62 in the Pre-Conflict period to 0.53 and 0.52 during the Conflict. This indicates that, despite maintaining memory in returns, the impact of the Conflict weakened trends, reducing predictability. On the other hand, LTC and XMR underwent more significant changes, moving from persistence (0.58 and 0.54) to anti-persistent behaviour (0.42). This phenomenon reflects instability and heightened speculation, suggesting that markets are more susceptible to external shocks.

In contrast, the TON cryptocurrency maintained an αDFA of 0.50 in both periods, characterising white noise (mean zero and constant variance). This behaviour demonstrates market efficiency and the absence of memory in returns, suggesting that the Conflict had less impact on it. ETH, however, showed a transition from white noise (0.50) in the Pre-Conflict period to moderate persistence (0.56) during the Conflict, indicating a change in its dynamics, possibly associated with increased speculative attention after 'The Merge' update.

The relationship between autocorrelation and DFA slopes corroborates that the presence of positive autocorrelation in previous periods, as observed in AVAX and ADA, coincides with higher αDFA values, signalling persistence and significant predictability. However, the transition to negative autocorrelation in some assets during the Conflict reflects the market's adaptation to conditions of high uncertainty, resulting in lower predictability or even instability.

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