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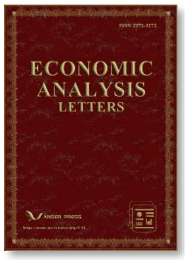

Asymmetric efficiency of cryptocurrencies during the 2020 and 2022 events

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ABSTRACT

In this study, we examined the efficiency of cryptocurrencies Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Ripple (XRP), DASH, EOS, and MONERO from March 1, 2018, to March 1, 2023. We separated the sample into four subperiods for this purpose: a Tranquil period that includes the period from March 1, 2018, to December 31, 2019; a First Wave that includes the year 2020; a Second Wave that includes the year 2021; and a fourth subperiod that includes Russia's invasion of Ukraine in 2022-2023. The results are mixed, with some cryptocurrencies exhibiting equilibrium and others exhibiting autocorrelation and predictability in their pricing. When the sample is divided into subperiods, most digital currencies have long memories in their returns during the Tranquil period, BTC, LTC, and XRP exhibit efficiency during the First Wave of the pandemic, while BTC, ETH, and MONERO indicate efficiency during the Second Wave. Most assessed digital currencies showed equilibrium by 2022, with the exception of ETH and MONERO, which exhibit long memories, and LTC, which demonstrates anti-persistence. These results hold significance for investors in these alternative markets, as they suggest that some cryptocurrencies may be more predictable and therefore potentially profitable, whereas others may require greater caution and risk management strategies.

KEYWORDS

Cryptocurrencies; autocorrelation; detrended fluctuation analysis; efficiency

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1. Introduction

Since cryptocurrencies have emerged as an alternative to government-backed currency and as a new vehicle for digital investment, the emergence of digital currencies has significant implications for market participants as well as policymakers. Whether the market is efficient is one of the most contentious arguments in finance and economics. An efficient market assumes that the information that reaches the market is fully and immediately reflected in the price of each asset. This theory is predicated on the notion that no investor is capable of identifying undervalued assets and making abnormal returns (Fama, 1970, 1991).

Several studies about the efficiency, in its weak form, of cryptocurrency markets have been conducted in recent years. The literature revealed mixed results in certain aspects. First, and based on the literature consulted, we confirmed the existence of mixed results about the efficiency of the main digital currency (Bitcoin), namely the authors Urquhart (2016), Zargar and Kumar (2019) have emphasized conclusive results on (in) efficiency. In addition, the authors Kristoufek (2018) and Chu et al. (2019) have highlighted efficiency over certain periods of time without precisely demonstrating this phenomenon. Second, the rise of alternative digital currencies (altcoins) such as Ethereum, Ripple, and Litecoin has increased the challenge of explaining efficiency clearly. However, authors (Drożdż et al. 2018) and Chu et al. (2019) show that some of the leading digital currencies exhibit signs of some efficiency over time. The authors Drożdż et al. (2018), in particular, underline that the Bitcoin market, and possibly other cryptocurrencies, have a clear potential to soon become an alternative regulated market to the exchange market. Third, according to the authors Tran and Leirvik (2020), the efficiency of digital currency markets is unstable due to the impact of various events.

In this study, we will examine the impact of 2020 and 2022 events on the efficiency of digital currencies, including Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Ripple (XRP), DASH, EOS, and MONERO, over the period from March 1, 2018, to March 1, 2023. This essay extends and contributes to earlier research. First, this study covers six of the most significant cryptocurrencies, unlike the majority of articles that have concentrated on the study of Bitcoin. Second, our work fills a gap in the literature by demonstrating the efficiency of cryptocurrency markets during the four subperiods, each of which was characterized by a period of market stability, a period of high uncertainty and complexity driven by the first wave of COVID-19, a period of uncertainty about the second wave's development, and finally the most recent event of 2022, the arm conflict between Russia and Ukraine.

Our main results show hybrid results in relation to the efficiency of these digital currency markets. When we analyze the results Lo and MacKinlay (1988), applied to the entire sample, we realize that BTC and ETH cryptocurrencies show signs of a trend toward equilibrium, but the rest of the cryptocurrencies show negative autocorrelation. In other words, the findings indicate the presence of autocorrelation, implying some predictability in the prices of the cryptocurrencies under consideration. Nevertheless, when we divide the sample into four subperiods and use the Detrended Fluctuation Analysis (DFA) methodology, the results are mixed.

- During the quiet period, we can see that most digital currencies show long memories in their returns. The only one that does not is LTC crypto, where there was no rejection of the random walk hypothesis.
- In the year 2021, which we have designated as the 2nd Wave of the pandemic, we have seen that the digital currencies DASH, XRP, LTC, and EOS have long memories as compared to the cryptocurrencies BTC, ETH, and MONERO, which exhibit signs of efficiency in their markets.
- In the year 2022, which includes Russia's invasion of Ukraine, we noticed that the analyzed cryptocurrencies are efficient, except for the digital currencies ETH and MONERO, which exhibit long memories, while LTC shows anti-persistence.

In general, cryptocurrency markets show some predictability in their returns, challenging the notion of Market efficiency. Nevertheless, there have been signs of efficiency in some cryptocurrencies in certain periods, and in the most recent event of 2022, a trend towards greater efficiency on the cryptocurrency markets has been observed.

This finding has significant practical implications for cryptocurrency market investors. Arbitrage trading opportunities diminish as markets get more efficient since future price movements can only be the consequence of fresh information being accessible. This conclusion means that the investment selection cannot guarantee profit levels above average.

These insights are particularly crucial for regulators and policymakers to create a regulatory framework that is effective when "externalities" happen, like the events of 2020 (the COVID-19 pandemic) and 2022 (the military and political conflict between Russia and Ukraine), in order to correct potential financial market failures. A robust regulatory structure might enhance the global financial system's efficiency, safety, and stability.

The remainder of the article is structured as follows: The data and methodology used are described in Section 2. The empirical results are shown and discussed in Section 3. Section 4 has concluded.

2. Methodology

2.1. Data

The data analyzed is the price index for Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Ripple (XRP), DASH, EOS, MONERO, from March 1, 2018, to March 1, 2023. In order to give robustness to the results, the sample was divided into four subperiods, namely: a Tranquil period that spans from March 1, 2018, to December 31, 2019; the 1st Wave that incorporates the year 2020; the 2nd Wave, which includes the year 2021; and, finally, the fourth subperiod, which considers Russia's invasion of Ukraine in 2022-2023. The quotations are daily and were obtained from the Thomson Reuters platform.

Table 1. The name and indexes of the cryptocurrencies used in this study.

Cryptocurrencies	Index
Bitcoin	BTC
Ethereum	ETH
Litecoin	LTC
Ripple	XRP
DASH	DASH
EOS	EOS
MONERO	MONERO

Source: Own Elaboration.

2.2. Methodology

The research will be conducted in several phases. To estimate the evolution of the analyzed cryptocurrency markets, market charts in terms of levels and returns were created. Using descriptive statistics, the sample shall be characterized in order to confirm that the data follows a normal distribution. To determine whether the time series follow a white noise process (average = 0; constant variance), the Levin et al. (2002), and Im et al. (2003)tests will be used, and for the validation of the results, we will use the Dickey and Fuller (1981), Phillips and Perron (1988) tests with Fisher Chi-square transformation. To answer the research question, we will apply the variance ratio method proposed by Lo and MacKinlay (1988) to assess the autocorrelation between the return series. This is classified as a parametric test. The efficient market hypothesis, in its weak form, establishes that it is not possible to predict future prices based on historical prices. Rosenthal (1983) argues that if a market is efficient in its weak form, then there should be no linear dependence between lagged returns, both in the statistical sense (absence of autocorrelation) and in the economic sense (absence of positive returns after considering transaction costs). The

Lo and MacKinlay (1988) model defines P_t as the price of an asset at t and X_t is 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 feature of the random walk process is that the variance of increases grows linearly according to the observation range. That is, the variance of $X_t - X_{t-2}$ is twice as much as the variation of $X_t - X_{t-1}$. Therefore, the validity of a random walk model can be evaluated by comparing variance estimators of returns at different frequencies. For example, the variance of the series of weekly returns should be five times greater than the variation of the daily returns. The model consists of testing whether the ratio of variance for different ranges weighed by the duration of these is equal to one. The results will be evaluated using Detrended Fluctuation Analysis (DFA). DFA is an analysis method that examines time dependence in non-stationary serial data. By assuming that time series are non-stationary, this method prevents spurious results when the analysis focuses on the long-term relations between data series. The following interpretation is provided through Detrended Fluctuation Analysis (DFA):

Table 2. Detrended Fluctuation Analysis (DFA).

Exponent	Type of signal
$\alpha_{DFA} < 0.5$	long-range anti-persistent
$\alpha_{DFA} \simeq 0.5$	uncorrelated, white noise
$\alpha_{DFA} > 0.5$	long-range persistent

Source: Own Elaboration.

For a better analysis of this methodology see Guedes et al. (2022), Revez et al. (2022), Zebende et al. (2022) and Santana et al. (2023).

3. Results

3.1. Descriptive Statistics

In Figure 1, we can see the evolution, in levels, of the cryptocurrencies under analysis, namely BTC, DASH, EOS, ETH, LTC, MONERO, and XRP, in the period from January 23, 2017, to February 28, 2021. In order to give robustness to the results, the sample was divided into four subperiods: the first period, referred to as Tranquil, which considers the time span from 1 March 2018 to 31 December 2019; a second subperiod, referring to the year 2020 and designated as the 1st Wave; a third subperiod, which includes the year 2021 and, finally, the fourth subperiod, which focuses on the Russian invasion of Ukraine and incorporates the years 2022 and 2023. This price fluctuation is also explained by the authors R. T. Dias et al. (2021), Vasco et al. (2021), Teixeira et al. (2022), Horta et al. (2022), which highlight shocks in price indexes resulting from significant events in the global economy.

The graph depicted in Figure 2 shows the evolution, in daily returns, of the cryptocurrencies under study. By its interpretation, considering the full period of the sample, the average return suggests some dispersion, but with values approaching zero. However, it is in the subperiod of Stress that a greater dispersion compared to the average of returns is evident, with highlighting for the digital currencies EOS, DASH, and XRP, which exhibit sharper volatility, mainly in the first half of 2021. This volatility is also explained by the authors Revez et al. (2022), Pardal, P., Dias, R., Teixeira, N. and Horta (2022), R. Dias et al. (2022), who demonstrated that the events of 2020 and 2022 impacted financial markets in general as a result of the global economic uncertainty.

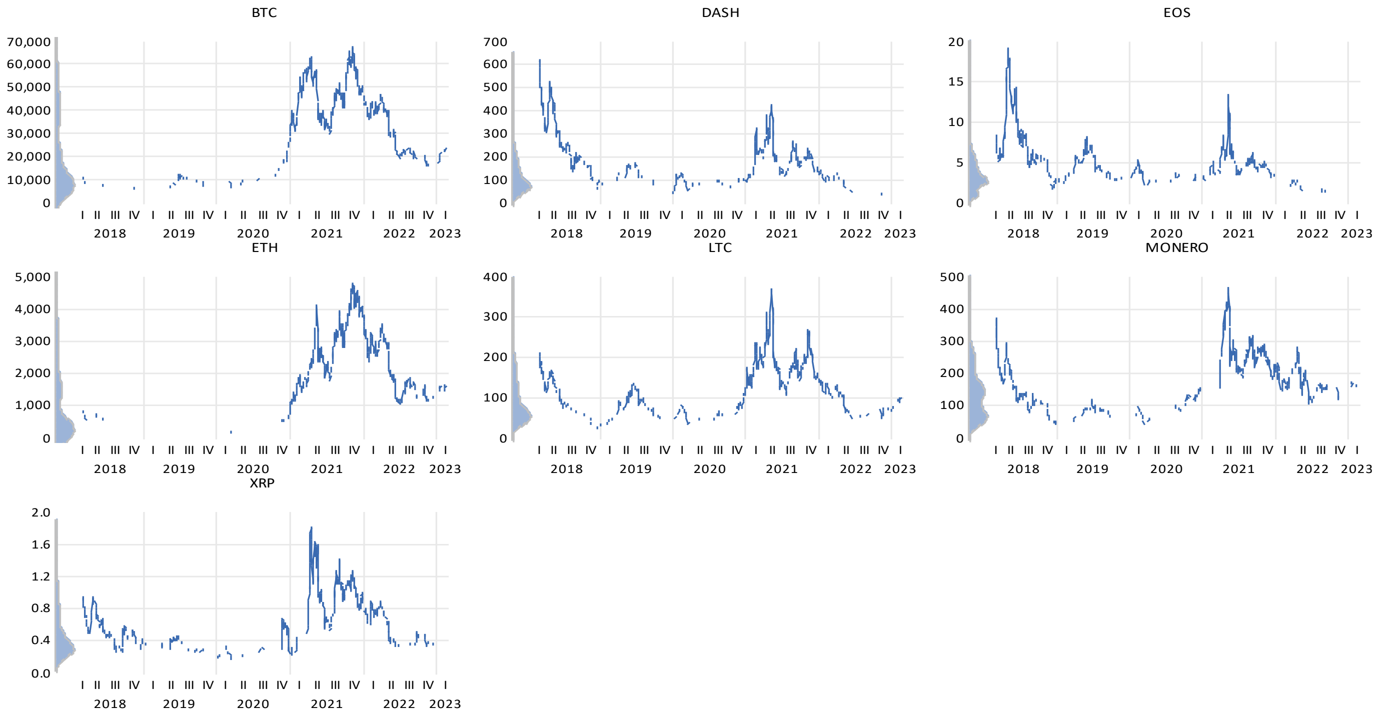

Figure 1. Evolution, in levels, of the cryptocurrencies under analysis, from March 1, 2018, to March 1, 2023.

Source: Own Elaboration. Notes: Software DataStream, 1305 observations.

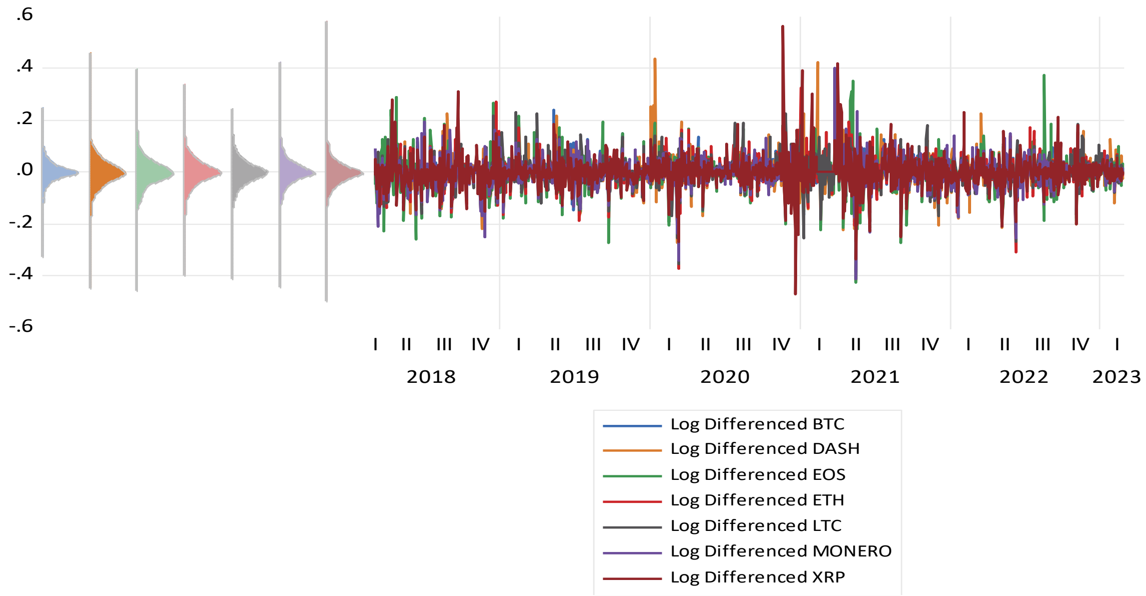

Figure 2. Evolution, in returns, of the cryptocurrencies under analysis, from March 1, 2018, to March 1, 2023.

Source: Own Elaboration. Notes: Software DataStream, 1305 observations.

In Table 3, for the full sample period, we can see the summary of the main descriptive statistics, in returns, of the 7 cryptocurrencies under study, as well as the results of the Jarque and Bera (1980) adherence test. In terms of average returns, all digital currencies show negative values, with the exception of BTC (0.000571) and ETH. (0.000467). We see that the standard deviation of the EOS cryptocurrency (0.066729) shows the less pronounced degree of dispersion, as opposed to BTC (0.042613), which has the less significant standard deviation, then less volatile. In order to see if we are facing a normal distribution, we estimated the skewness and kurtoses values, where the results suggest for all cryptocurrencies in the study different values of 0 and 3, respectively. Additionally, to corroborate the previous evidence, we conducted the (Jarque & Bera, 1980) test and realized that there is rejection of H_0 at a level of significance of 1%, that is, the daily returns of the time series do not present values corresponding to a normal distribution.

Table 3. Summary table of descriptive statistics, in returns, in respect of the cryptocurrencies under analysis, from March 1, 2018, to March 1, 2023.

	BTC	DASH	EOS	ETH	LTC	MONERO	XRP
Mean	0.000571	-0.001657	-0.001529	0.000467	-0.000624	-0.000562	-0.000684
Std. Dev.	0.042613	0.064197	0.066729	0.056324	0.058194	0.055398	0.062772
Skewness	-0.474092	-0.002465	-0.146585	-0.359280	-0.536404	-0.504036	0.674267
Kurtosis	7.963501	9.467086	8.249220	7.468006	7.605415	10.21548	15.81223
Jarque-Bera	1388.487	2274.138	1502.939	1113.568	1215.867	2886.192	9024.711
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	1305	1305	1305	1305	1305	1305	1305

Source: Own Elaboration.

3.2. Stationarity Time Series Analysis

In order to validate the assumption of stationarity of the time series of cryptocurrencies BTC, DASH, EOS, ETH, LTC, MONERO, and XRP, we resorted to the summary frame of the panel unit root tests, namely the tests of Levin et al. (2002), Im et al. (2003), and, for the validation of the results, we used the tests of Dickey and Fuller (1981), Phillips and Perron (1988), with Fisher Chi-square transformation. For the purpose of obtaining stationarity, we chose to perform the logarithmic transformation, in first differences, to align the time series so that the characteristics of white noise can be achieved, thus validating the assumption of stationarity with the rejection of H_0 at a level of significance of 1% (see Table 4).

Table 4. Summary table of panel unit root tests, in returns, concerning the cryptocurrencies under analysis, from March 1, 2018, to March 1, 2023.

Group unit root test: Summary				
Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-107.317	0.0000	7	9106
Breitung t-stat	-25.5369	0.0000	7	9099
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-75.7370	0.0000	7	9106
ADF - Fisher Chi-square	1595.85	0.0000	7	9106
PP - Fisher Chi-square	1843.74	0.0000	7	9121

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

3.3. Rank Variation Ratio Test

In order to assess the autocorrelation between the return series, we used the parametric test of Lo and MacKinlay (1988), which includes the variance test of Ranking. Statistics were calculated, in all cases, for time deviations between 2 and 16 days, for cryptocurrencies BTC, DASH, EOS, ETH, LTC, MONERO, and XRP, taking into account the entire period of the sample. In Figure 3, the results suggest the rejection of the random walk hypothesis for all the digital currencies under study.

Because all four cryptocurrencies— DASH, EOS, LTC, and MONERO—show values below the unit, we may infer from the variance ratio values that the returns on these cryptocurrencies are negatively autocorrelated over time. The variance ratios for BTC and LTC are larger than those for the unit, so their returns have a positive temporal autocorrelation.

News can push prices outside of the support and resistance bands as a result of irrational responses to fear or optimistic expectations. Price increases may result from good news and markets with positive serial autocorrelation as investors become more optimistic about these markets' future prospects. On the other side, markets that offer bad news and negative serial autocorrelation could lead to a sell as investors become more pessimistic about the future prospects of these markets.

The findings draw attention to the presence of autocorrelation, which suggests some degree of predictability in the pricing of the cryptocurrencies under investigation. These results are validated by the authors' research in the financial markets arising from the global pandemic of 2020 (R. Dias and Santos, 2020a; R. Dias and Carvalho, 2020; R. Dias et al., 2020; R. Dias & Santos, 2020b).

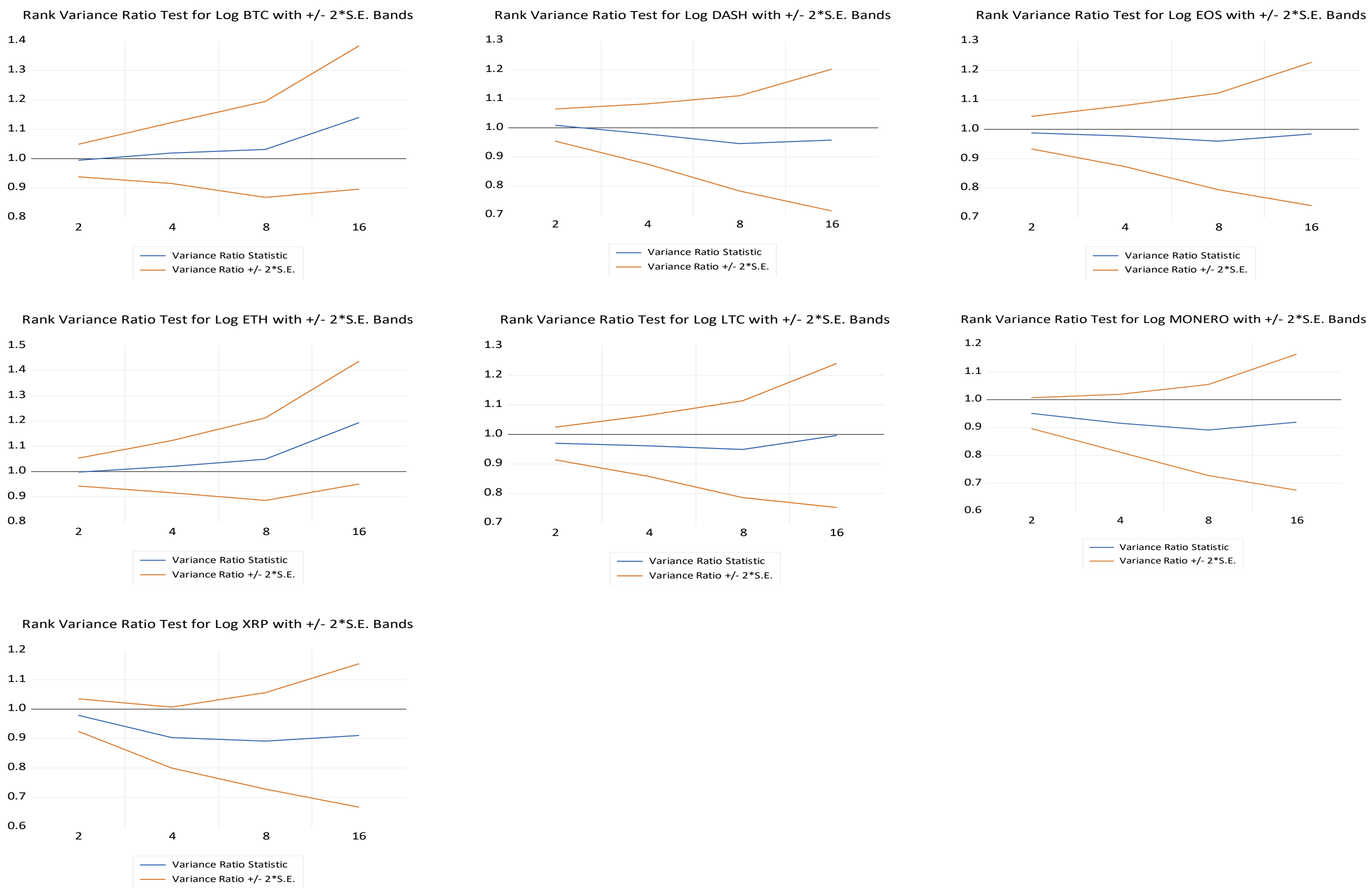

Figure 3. The Lo and MacKinlay (1988) Variation Rates test, in returns, for the cryptocurrencies under consideration from March 1, 2018, to March 1, 2023.

Source: Own Elaboration. Notes: Software DataStream.

3.4. Detrended Fluctuation Analysis

The Detrended Fluctuation Analysis method (DFA) was used to evaluate long-range autocorrelation of each cryptocurrency, including BTC, DASH, EOS, ETH, LTC, MONERO, and XRP. With the use of this approach, it is feasible to determine if the time series exhibit random behavior (efficiency) as would be predicted. In order to give robustness to the results the sample was divided into 4 subperiods, namely a Tranquil period, that spans from March 1, 2018, to December 31, 2019; 1st Wave that incorporates the year 2020; 2nd Wave which includes the year 2021 and, finally, the fourth subperiod which considers Russia's invasion of Ukraine in 2022-2023.

In the Tranquil subperiod (see table 5), we can observe that digital currencies show long memories in their returns, with the exception of LTC, where the random walk hypothesis was not rejected, showing some equilibrium (0.52 ≅ 0.0120).

Already in relation to the period that incorporates the first wave of the global pandemic of 2020 (see table 5), we have seen that the digital currencies BTC (0.52 ≅ 0.0633) LTC (0.52 ≅ 0.0552) and XRP (0.49 ≅ 0.0366) show evidence of equilibrium since the random walk hypothesis has not been rejected, but the currencies DASH (0.62 ≅ 0.0025), MONERO (0.58 ≅ 0.0054), ETH (0.57 ≅ 0.0042), and EOS (0.53 ≅ 0.0057) show long memories in their returns.

In the period of the 2nd Wave of the global pandemic (see table 6), we have seen that the digital currencies DASH (0.61 ≅ 0.0016), XRP (0.59 ≅ 0.0049), LTC (0.54 ≅ 0.024), and EOS (0.52 ≅ 0.0017) show signs of long memories during the year 2021, as compared to the cryptocurrencies BTC (0.52 ≅ 0.0178), ETH (0.51 ≅ 0.0277), and MONERO (0.51 ≅ 0.0834) that show efficiency in their markets.

When we analyze the period that covers the Russian invasion of Ukraine (see table 6), we see that the studied cryptocurrencies are predominantly in equilibrium. Yet, ETH (0.54 ≅ 0.0034) and MONERO (0.56 ≅ 0.0022) exhibit long memories, but LTC (0.47 ≅ 0.0022) indicates anti-persistency.

Table 5. Detrended Fluctuation Analysis (DFA), in the Tranquil subperiod and in the 1st Wave.

Cryptocurrency	DFA exponent (Tranquil)	DFA exponent (1st Wave: 2020)
BTC	0.55*** ≅ 0.0066 (R^2 = 0.99)	0.52 ≅ 0.0633 (R^2 = 0.94)
DASH	0.57*** ≅ 0.0092 (R^2 = 0.99)	0.62*** ≅ 0.0025 (R^2 = 0.93)
EOS	0.60*** ≅ 0.0079 (R^2 = 0.98)	0.53*** ≅ 0.0057 (R^2 = 0.94)
ETH	0.62*** ≅ 0.0171 (R^2 = 0.98)	0.57*** ≅ 0.0042 (R^2 = 0.94)
LTC	0.52 ≅ 0.0120 (R^2 = 0.99)	0.52 ≅ 0.0552 (R^2 = 0.95)
MONERO	0.54*** ≅ 0.0062 (R^2 = 0.98)	0.58*** ≅ 0.0054 (R^2 = 0.94)
XRP	0.58*** ≅ 0.0080 (R^2 = 0.98)	0.49 ≅ 0.0366 (R^2 = 0.95)

*Note: *** represent the rejection of the null hypothesis at a significance level of 1%.*
Source: Own Elaboration.

Table 6. Detrended Fluctuation Analysis (DFA), in the 2nd Wave subperiod, and in the Russian invasion of Ukraine in 2022-2023.

Cryptocurrencies	DFA exponent (2nd Wave: 2021)	DFA exponent (Russian invasion: 2022-2023)
BTC	0.52 ≅ 0.0178 (R^2 = 0.94)	0.52 ≅ 0.0213 (R^2 = 0.95)
DASH	0.61*** ≅ 0.0016 (R^2 = 0.94)	0.50 ≅ 0.0218 (R^2 = 0.94)
EOS	0.52*** ≅ 0.0017 (R^2 = 0.94)	0.54 ≅ 0.0360 (R^2 = 0.95)
ETH	0.51 ≅ 0.0277 (R^2 = 0.94)	0.54*** ≅ 0.0034 (R^2 = 0.94)
LTC	0.54*** ≅ 0.024 (R^2 = 0.94)	0.47** ≅ 0.0022 (R^2 = 0.95)
MONERO	0.51 ≅ 0.0834 (R^2 = 0.94)	0.56*** ≅ 0.0022 (R^2 = 0.94)
XRP	0.59*** ≅ 0.0049 (R^2 = 0.95)	0.52 ≅ 0.0119 (R^2 = 0.94)

*Note: *** represent the rejection of the null hypothesis at a significance level of 1%.*
Source: Own Elaboration.

If a time series has a long memory (persistence), a high value in the series will probably be followed by another high value, and this impact will probably last for quite some time in the future. When the time series displays some antipersistence, it is more probable that the returns will oscillate between high and low values for a period.

When markets at certain times demonstrate persistent movements, it may mean that the information analyzed indicates long-term averages and therefore one of the investment decision-making techniques that can be used is fundamental analysis, since it has a long-term focus. Using primary data that has been made publicly available, investors can utilize fundamental analysis to determine if a firm is a lucrative investment or not. Fundamental analysis is a process, but it has limitations, main among them the fundamental analysis's focus on self-realization. When enough investors choose which stocks to buy based on the same signals and data, they might themselves trigger the anticipated movement. It will have a domino effect.

In contrast, the authors advise investors to use short-term tactics like technical analysis when series returns are anti-persistent, i.e., with reversal to average. Technical analysis proponents are more interested in predicting whether a stock's price will increase or decrease based on past trading activity in comparison to prior price movement patterns than in determining whether a stock is overvalued or undervalued. Technical analysis's disadvantage is that it is arbitrary and vulnerable to investor interpretation.

However, in general, it has been observed that in certain periods the cryptocurrency markets have become more efficient. This evidence call into question the application of investment strategy techniques (technical and fundamental), since market efficiency hypothesis contradicts these methods, since it postulates that market prices reflect past information and therefore there is no benefit in analyzing pattern-centric trends. In this sense, as a market becomes more efficient, arbitration strategies become diminished.

In addition to these implications in an investor's perspective, these evidence are important for regulators and policy makers to formulate a regulatory framework that is effective when "externalities" occur, such as the events of 2020 (COVID-19 pandemic) and 2022 (military and political conflict between Russia and Ukraine), in order to correct the financial anomalies observed in some cryptocurrencies markets.

4. Conclusions

Based on the results presented, it can be concluded that the efficiency of the digital currency markets is mixed, with some cryptocurrencies showing signs of equilibrium while others show autocorrelation and predictability in their prices. However, when the sample is divided into subperiods, it is observed that during the calm period, most digital currencies display long memories on their returns, except for the LTC, which follows an equilibrium trend. During the 1st Wave of the pandemic, BTC, LTC, and XRP cryptocurrencies showed signs of efficiency, while DASH, MONERO, ETH, and EOS exhibited long memories in their returns. In the 2nd Wave of the pandemic in 2021, BTC, ETH, and MONERO show signs of efficiency, while DASH, XRP, LTC, and EOS continue to exhibit long memories in their returns. Finally, during the years 2022-2023, which incorporate the Russian invasion of Ukraine, most of the analyzed digital currencies showed equilibrium, with the exception of ETH and MONERO, which displayed long memories, and LTC, which showed anti-persistence.

One conclusion that can be drawn from this study is that investors in digital currency markets should take into account the mixed efficiency of these markets and the different levels of predictability between the different digital currencies. Some cryptocurrencies may be more predictable and potentially more profitable, while others may require more caution and risk management strategies to mitigate potential losses. Lastly, investors should therefore carefully examine the results of studies such as this to make informed decisions about their investments in these alternative markets.

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Conflict of interest

All the authors claim that the manuscript is completely original. The authors also declare no conflict of interest.

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