MULTIFRACTAL BEHAVIOR OF CRYPTOCURRENCIES DURING PERIODS OF ECONOMIC UNCERTAINTY

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ABSTRACT

Background: In recent years, investors’ interest in cryptocurrencies has increased due to their notable price volatility and rapid price increases. These investors view cryptocurrencies as suitable financial assets for portfolio rebalancing strategies.

Purpose: The main objective of this study is to examine the multifractality of the cryptocurrencies Bitcoin (BTC), Lisk (LSK), Quantum (QUA), Litecoin (LTC), Ripple (XRP), Augur (REP), Darkcoin (DASH), EOS, IOTA (MIOTA).

Methods: The Detrended Fluctuation Analysis (DFA) econophysics model supports the methodology.

Results: The results suggest that during the 2020 pandemic period, the digital currencies LSK, QUA, MIOTA, XRP, REP, BTC, ETH, LTC and DASH showed very significant persistence, indicating that price formation is not random. However, validating that cryptocurrency prices are predictable based on historical time series was impossible. On the other hand, the digital currency EOS proved to be in equilibrium; in other words, price formation follows the random walk pattern, suggesting that prices are not autocorrelated over time. During the 2022 geopolitical conflict, long-term memory patterns shifted significantly towards short-term memories, i.e. anti-persistence. The digital currencies ETH, MIOTA, EOS, LTC, REP, LSK and DASH showed anti-persistence slopes, indicating that prices were less influenced by past events and more by recent events. On the other hand, the cryptocurrencies BTC (0.50), QUA (0.50), and XRP (0.50) demonstrate that prices contain a significant random component and that the residuals are independent and identically distributed (i.i.d.), supporting the idea that white noise might be present.

Conclusion: From a risk management perspective, these findings are highly relevant to investors, traders and market participants.

Keywords: White Noise, Persistence, DFA, Risk Management, Long Memories.

COMPORTAMENTO MULTIFRACTAL DAS CRIPTOMOEDAS EM PERÍODOS DE INCERTEZA ECONÔMICA

RESUMO

Contexto: Nos últimos anos, o interesse dos investidores pelas criptomoedas aumentou devido à sua notável volatilidade e ao rápido aumento dos preços. Estes investidores consideram as criptomoedas como activos financeiros adequados para estratégias de reequilíbrio de carteiras.

Objetivo: O principal objetivo deste estudo é examinar a multifractalidade das criptomoedas Bitcoin (BTC), Lisk (LSK), Quantum (QUA), Litecoin (LTC), Ripple (XRP), Augur (REP), Darkcoin (DASH), EOS, IOTA (MIOTA).

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Métodos: O modelo econofísico Detrended Fluctuation Analysis (DFA) suporta a metodologia.

Resultados: Os resultados sugerem que, durante o período pandêmico de 2020, as moedas digitais LSK, QUA, MIOTA, XRP, REP, BTC, ETH, LTC e DASH apresentaram uma persistência muito significativa, indicando que a formação dos preços não é aleatória. No entanto, foi impossível validar que os preços das criptomonedas são previsíveis com base em séries cronológicas históricas. Por outro lado, a moeda digital EOS provou estar em equilíbrio; por outras palavras, a formação de preços segue o padrão de passeio aleatório, sugerindo que os preços não estão autocorrelacionados ao longo do tempo. Durante o conflito geopolítico de 2022, os padrões de memória de longo prazo mudaram significativamente para memórias de curto prazo, ou seja, anti-persistência. As moedas digitais ETH, MIOTA, EOS, LTC, REP, LSK e DASH apresentaram declives anti-persistência, indicando que os preços foram menos influenciados por eventos passados e mais por eventos recentes. Por outro lado, as criptomonedas BTC (0,50), QUA (0,50) e XRP (0,50) demonstam que os preços contêm um componente aleatório significativo e que os resíduos são independentes e identicamente distribuídos (i.i.d.), apoiando a ideia de que o ruído branco pode estar presente.

Conclusão: De ponto de vista da gestão de riscos, estas conclusões são altamente relevantes para os investidores, comerciantes e participantes no mercado.

Palavras-chave: Ruído Branco, Persistência, DFA, Gestão de Risco, Memórias Longas.

RESUMEN

Antecedentes: En los últimos años ha aumentado el interés de los inversores por las criptomonedas debido a su notable volatilidad y a la rápida subida de sus precios. Estos inversores consideran las criptodivisas como activos financieros adecuados para estrategias de reequilibrio de carteras.

Objetivo: El objetivo principal de este estudio es examinar la multifractalidad de las criptodivisas Bitcoin (BTC), Lisk (LSK), Quantum (QUA), Litecoin (LTC), Ripple (XRP), Augur (REP), Darkcoin (DASH), EOS, IOTA (MIOTA).

Métodos: El modelo econofísico Detrended Fluctuation Analysis (DFA) sustenta la metodología.

RESULTADO: Los resultados sugieren que, durante el período pandémico de 2020, las monedas digitales LSK, QUA, MIOTA, XRP, REP, BTC, ETH, LTC y DASH mostraron una persistencia muy significativa, lo que indica que la formación de precios no es aleatoria. Sin embargo, fue imposible validar que los precios de las criptodivisas sean predecibles basándose en series temporales históricas. Por otra parte, la moneda digital EOS demostró estar en equilibrio; en otras palabras, la formación de precios sigue el patrón del paseo aleatorio, lo que sugiere que los precios no están autocorrelacionados a lo largo del tiempo. Durante el conflicto geopolítico de 2022, los patrones de memoria a largo plazo se desplazaron significativamente hacia la memoria a corto plazo, es decir, hacia la antipersistencia. Las monedas digitales ETH, MIOTA, EOS, LTC, REP, LSK y DASH mostraron pendientes antipersistencia, lo que indica que los precios se vieron menos influidos por acontecimientos pasados y más por acontecimientos recientes. Por otro lado, las criptomonedas BTC (0,50), QUA (0,50) y XRP (0,50) muestran que los precios contienen un componente aleatorio significativo y que los resíduos son independientes e identicamente distribuidos (i.i.d.), lo que apoya la idea de que pueden haber ruido blanco.

Conclusión: Desde el punto de vista de la gestión del riesgo, estos resultados son muy pertinentes para los inversores, operadores y participantes en el mercado.

Palabras clave: Ruido Blanco, Persistencia, DFA, Gestión del Riesgo, Memorias Largas.

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1 INTRODUCTION

In recent years, cryptocurrencies have seen increased media attention due to the significant price volatility and rampant price increases, calling the attention of an increasing number of investors who see them as an appropriate financial asset for portfolio rebalancing strategy. Therefore, the main purpose of this study is to measure the persistence and presence of long memories in the digital currencies Bitcoin (BTC), Lisk (LSK), Quantum (QUA), Litecoin (LTC), Ripple (XRP), Augur (REP), Darkcoin (DASH), EOS and IOTA (MIOTA), in the pre-Covid 19 period, during the 2020 pandemic, and more recently the geopolitical conflict in 2022, to understand whether there are significant differences.

Understanding long memories is also crucial for assessing the stability and efficiency of cryptocurrency markets, which can help regulators develop policies that promote market integrity and transparency. In addition, the study could stimulate financial innovation, resulting in new financial products and instruments adapted to the specific characteristics of cryptocurrencies. Given the relevance of these digital assets in financial markets, this study offers new perspectives to the existing literature, especially in analysing how digital currency markets respond during extreme events in international financial markets. The analysis period comprises three range dates: the Tranquil period covers the years from January 2018 to 31 December 2019; the Covid-19 sub-period begins on 1 January 2020 and ends on 23 February 2022; and the 2022 geopolitical conflict sub-period covers the period from 24 February 2022 to 23 November 2023. To summarise, this cryptocurrency research aims to understand the dynamics of these digital markets and promote a more transparent and stable financial environment.

This paper is organised as follows: section one refers to the introduction, followed by the literature review in section two. Section three explains the methodology and data used. Section four is dedicated to the discussion of results, and section five presents the conclusion.

2 LITERATURE REVIEW

The Efficient Market Hypothesis (EMH) is a fundamental theory in economics and finance that suggests that the prices of financial assets reflect all the information available on the market. This implies that it is difficult for investors to achieve anomalous returns based on public analyses alone. HME is grounded in the arbitrage principle, where investors seek returns from price differences between similar assets in different markets. However, evidence has emerged on whether all investors act rationally at all times, which can affect asset prices. So,
while HME highlights market efficiency, it also recognises the possibility of irrational investor behaviour, which helps us to understand better how financial markets work (Bondt & Thaler, 1987; Choi & Jayaraman, 2009; Michel, 2017; Dias et al., 2023).

The financial industry has seen an increase in the use of cryptocurrencies. Numerous reports, news, opinions, and critiques on cryptocurrencies are available and must be considered in their context. For example, Kristoufek and Vosvrda (2019) studied the cryptocurrency market in relation to the efficient market hypothesis, namely Bitcoin, DASH, Litecoin, Monero, Ripple, and Stellar. The authors found that all historical currencies were inefficient during the period analysed.

In 2021, the authors Naeem et al. (2021) examined the asymmetric efficiency of the Bitcoin, Ethereum, Litecoin and Ripple cryptocurrencies and showed that the COVID-19 outbreak negatively impacted the efficiency of the cryptocurrencies studied, given a substantial increase in inefficiency levels during the COVID-19 period. Complementarily, the authors Palamalai et al. (2021) investigated the efficiency, in its weak form, of the ten leading cryptocurrencies. The findings do not confirm the random walk hypothesis, thus validating inefficiency in its weak form for the daily returns of cryptocurrencies.

Later on, the authors Chambino et al. (2023) examined returns persistence of the cryptocurrencies Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), Ripple (XRP), DASH, EOS and MONERO during the events of 2020 and 2022, finding contradictory outcomes. Some cryptocurrencies exhibit equilibrium, and others show autocorrelation and predictability in their returns. Additionally, the authors Dias et al. (2023) examined persistence in the stock markets of Austria (ATX), Poland (WIG), the Czech Republic (PX Prague), Hungary (BUX), Croatia (CROBEX), Serbia (BELEX 15), Romania (BET) and Slovenia (SBI TOP) in the period from 16 February 2018 to 15 February 2023. The research results revealed that the persistence of returns increased significantly during the first wave of COVID-19 and the geopolitical conflict of 2022. Complementarily, Dias, Horta, et al. (2023) examined the multifractal scaling behaviour and efficiency of green financial markets, and traditional markets such as gold, crude oil and natural gas, during the events of 2020 and 2022. The findings demonstrated no noteworthy differences between sustainable and traditional since the return data series indicated (in)efficiency.

The persistence of clean energy stock indices and cryptocurrencies labelled as "dirty" because of their high energy usage, such as Bitcoin (BTC), Ethereum (ETH), Ethereum Classic (ETH Classic) and Litecoin (LTC), was investigated by Galvão and Dias (2024), in 2024. The authors found that both clean energy indices and dirty digital currencies showed that prices are
not independent and identically distributed (i.i.d), meaning autocorrelation in their returns. Therefore, evidence suggests that during the 2020 and 2022 events, there are no distinctions between sustainable assets and assets classified as "dirty" in the context of the persistence phenomena. Complementing, Akbar et al. (2024) examined the persistence of nine indices in the Islamic market and their equivalent conventional indices at Morgan Stanley. They examined the non-predictability of returns over time, that is, the martingale hypothesis. They assessed the adaptive market hypothesis under several market scenarios, demonstrating no distinctions between Islamic and conventional stock indices during the two events analysed: the 2007-08 financial crisis and the COVID-19 pandemic.

Summarising, this research aims to contribute to the information available to investors and portfolio managers in the cryptocurrency markets seeking diversification benefits. Therefore, the purpose of this study is to understand the predictability of the markets being analysed and determine whether the events of 2020 and 2022 caused different reactions in the prices of digital currencies.

3 DATA AND METHODS

3.1 DATA

The research was based on the daily index prices of the cryptocurrencies Bitcoin (BTC), Lisk (LSK), Quantum (QUA), Litecoin (LTC), Ripple (XRP), Augur (REP), Darkcoin (DASH), EOS, IOTA (MIOTA), from 1 January 2018 to 23 November 2023. The sample period was partitioned into three range dates to ensure the research robustness: the Tranquil period from January 2018 to 31 December 2019; the Covid-19 pandemic sub-period begins on 1 January 2020 and ends on 23 February 2022; and the period that includes the 2022 geopolitical conflict from 24 February 2022 to 23 November 2023. The data was extracted from the Thomson Reuters Eikon platform. All index prices are in US dollars. Cryptocurrencies are divided into ecological and polluting ones.

3.2 METHODOLOGY

The research will be developed in different stages. First, the sample will be characterised using descriptive statistics to check that the data follow a normal distribution as well as the graphs. Secondly, the panel unit root tests of Levin, Lin, and Chu (2002) and Im et al. (2003),
which postulate the same null hypotheses (unit roots), will be used to ensure that the time series follow white noise (mean = 0; constant variance). For robustness, Dickey and Fuller (1981) and Phillips and Perron (1988) tests with Fisher's chi-square transformation and Choi's (2001) unit root tests will be used. Then, the Cusum (cumulative sum) test will be used to validate the results and detect significant changes or deviations in the time series (Caporale & Pittis, 2004).

The Detrended Fluctuation Analysis (DFA) is the model used to investigate the research question. This analysis technique examines temporal dependency dependence in non-stationary data series. When examining the long-term relationships of the data series, this technique prevents spurious results by assuming that the time series are non-stationary. The DFA results interpretation is: 0 < α < 0.5: non-persistent series; α = 0.5 random walk series; 0.5 < α < 1 persistent series. The function of this technique is to examine the relationship between values at different times. For a better understanding, see the following research, Horta et al. (2022), Dias, Pardal et al. (2022), Guedes et al. (2022), Santana et al. (2023), Dias, Horta, and Chambino (2023a).

4 RESULTS AND DISCUSSION

Figure 1 shows the evolution of the cryptocurrencies Bitcoin (BTC), Lisk (LSK), Quantum (QUA), Litecoin (LTC), Ripple (XRP), Augur (REP), Darkcoin (DASH), EOS, IOTA (MIO-TA), from 1 January 2018 to 23 November 2023. The observation reveals a large dispersion in relation to the mean, which shows that these markets were under tremendous pressure during the period analysed. In 2021, the cryptocurrency market experienced a period of great activity and interest from investors. BTC reached new price records, surpassing US$60,000 in April 2021, which led to a sharp rise in other digital currencies. However, there have also been regulatory challenges and volatility, especially with certain currencies facing legal issues and regulatory uncertainties.
Figure 1

Graph of the evolution, in returns, of cryptocurrencies from 1 January 2018 to 23 November 2023

Source: Own elaboration

Figure 2 shows the mean returns of the cryptocurrencies Bitcoin (BTC), Lisk (LSK), Quantum (QUA), Litecoin (LTC), Ripple (XRP), Augur (REP), Darkcoin (DASH), EOS, IOTA (MIOTA) over the period from 1 January 2018 to 23 November 2023. Graphical observation shows that the majority of digital currencies have negative mean returns, namely DASH (-0.00231), EOS (-0.00158), LSK (-0.00196), LTC (-0.00076), MIOTA (-0.00205), QUA (-0.00188), REP (-0.00309), XRP (-0.00078), the exception being the cryptos BTC (0.00066), ETH (0.00065). These results indicate that, on average, most of the cryptocurrencies studied performed negatively regarding returns during the period analysed, thus allowing investors to assess return trends and make informed decisions regarding their investments.

Figure 2

The evolution of mean returns for cryptocurrencies from 1 January 2018 to 23 November 2023

Source: Own elaboration
Figure 3 shows the standard deviations of the cryptocurrencies Bitcoin (BTC), Lisk (LSK), Quantum (QUA), Litecoin (LTC), Ripple (XRP), Augur (REP), Darkcoin (DASH), EOS, IOTA (MIOTA) over the period from 1 January 2018 to 23 November 2023. The digital currencies REP (0.07635), MIOTA (0.07491), LSK (0.07389) and QUA (0.07214) show the highest dispersion concerning the mean, showing that these markets exhibit increased risk. To a lesser extent, the cryptocurrencies XRP (0.06725), EOS (0.06574), DASH (0.06275), LTC (0.05894), ETH (0.05812), BTC (0.04472) have lower values, i.e. less volatility and associated risk.

**Figure 3**

*Evolution of standard deviations, in returns, of cryptocurrencies, from 1 January 2018 to 23 November 2023*

![Graph of standard deviations](source: Own elaboration)

Figure 4 shows the asymmetries for the cryptocurrencies Bitcoin (BTC), Lisk (LSK), Quantum (QUA), Litecoin (LTC), Ripple (XRP), Augur (REP), Darkcoin (DASH), EOS, IOTA (MIOTA), for the period from 1 January 2018 to 23 November 2023. When analysing the results, it becomes clear that the values differ from zero, showing that the distributions are non-Gaussian. The digital currencies BTC (-1.1533), DASH (-0.1460), EOS (-0.3076), ETH (-0.7871), LTC (-0.59156), REP (-0.1220) show negative values, indicating a negative asymmetry. In this case, the longest tails are on the left-hand side of the chart, suggesting a
propensity to extreme events or lower returns. On the other hand, the cryptocurrencies MIOTA (7.0709), LSK (4.9188), MIO-TA (7.0709), QUA (2.9719), and XRP (0.58309) show positive asymmetries. These results indicate a tendency towards extremely high values in the price data, which may be relevant for investors looking for return opportunities in volatile markets. However, it is important to note that positive asymmetry does not guarantee future price movements but provides insights into the distribution of historical price data.

**Figure 4**
*Evolution of asymmetries in returns for cryptocurrencies over the period from 1 January 2018 to 23 November 2023*

[Figure showing skewness of different cryptocurrencies]

Source: Own elaboration

Figure 5 shows the kurtosis of the cryptocurrencies Bitcoin (BTC), Lisk (LSK), Quantum (QUA), Litecoin (LTC), Ripple (XRP), Augur (REP), Darkcoin (DASH), EOS, IOTA (MIO-TA), from 1 January 2018 to 23 November 2023. The digital currencies MI-OTA (168.1328), LSK (112.9539), have the most significant values, and to a lesser extent, the cryptos QUA (69.1165), REP (22.4161), XRP (17.8407), BTC (15.6343), ETH (12.8717), DASH (9.74065), LTC (9.8127), EOS (8.96971). When examining the results, it is noticeable that the values differ from 3, indicating that the distributions do not follow a Gaussian pattern, i.e. they are not normal distributions.
Figure 5

Evolution of kurtoses, in returns, for cryptocurrencies, from 1 January 2018 to 23 November 2023

Figure 6 shows the cumulative CUSUM graphs used to analyse the trends of the cryptocurrencies Bitcoin (BTC), Lisk (LSK), Quantum (QUA), Litecoin (LTC), Ripple (XRP), Augur (REP), Darkcoin (DASH), EOS, IOTA (MIOTA), from 1 January 2018 to 23 November 2023. Through graphical observation, the results are hybrid, i.e. CUSUM lines are moving above the upper control line, suggesting that the observed values are consistently above expectations or the mean. On the other hand, there are also movements below the lower control line, indicating that the observed values are consistently below what is expected or the mean.
Figure 6

Cusum of Squares graphs, in returns, for the cryptocurrencies from 1 January 2018 to 23 November 2023.
Multifractal Behavior of Cryptocurrencies During Periods of Economic Uncertainty

![Graph of LSK and LTC CUSUM of Squares with 5% Significance](image)
Table 1 shows the panel unit root tests of Levin, Lin, and Chu (2002) and Im et al. (2003), which postulate the same null hypotheses (unit roots). The Dickey and Fuller (1981) and Phillips and Perron (1988) tests with Fisher's chi-square transformation and Choi's (2001) unit root tests are used to robust the results. The results show that when applying the unit root tests to the prices of the cryptocurrencies Bitcoin (BTC), Lisk (LSK), Quantum (QUA), Litecoin (LTC), Ripple (XRP), Augur (REP), Darkcoin (DASH), EOS, IOTA (MIOTA), there are unit roots. First differences are applied to all the time series to solve for stationarity, and the null hypothesis is rejected at a significance level of 1%, i.e. there is white noise (mean = 0; constant variance).
Table 1

Summary table of the unit root tests, in first differences, concerning digital currencies, for the period from 1 January 2018 to 23 November 2023

<table>
<thead>
<tr>
<th>Method</th>
<th>Statistic</th>
<th>Prob. **</th>
<th>Cross-sections</th>
<th>Obs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Levin, Lin &amp; Chu t*</td>
<td>-56.249</td>
<td>0.0000</td>
<td>10</td>
<td>15340</td>
</tr>
<tr>
<td>Im, Pesaran and Shin W-stat</td>
<td>-56.633</td>
<td>0.0000</td>
<td>10</td>
<td>15340</td>
</tr>
<tr>
<td>ADF - Fisher Chi-square</td>
<td>1757.778</td>
<td>0.0000</td>
<td>10</td>
<td>15340</td>
</tr>
<tr>
<td>PP - Fisher Chi-square</td>
<td>535.298</td>
<td>0.0000</td>
<td>10</td>
<td>15380</td>
</tr>
</tbody>
</table>

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

Source: Own elaboration

Table 2 shows the results of the Detrended Fluctuation Analysis (DFA) exponent for the cryptocurrencies Bitcoin (BTC), Lisk (LSK), Quantum (QUA), Litecoin (LTC), Ripple (XRP), Augur (REP), Darkcoin (DASH), EOS, IOTA (MIOTA), for the period from 1 January 2018 to 23 November 2023. The DFA slopes were estimated to strengthen the analysis for the Full, Tranquil period (1 January 2018 to 31 December 2019), the Covid-19 pandemic (1 January 2020 to 23 February 2022) and the geopolitical conflict between Russia and Ukraine (24 February 2022 to 23 November 2023).

The results show that during the entire sample period, most cryptocurrencies are persistent, i.e. they have long-term memories, except for REP (0.48), which shows slopes of anti-persistence (short-term memories) and XRP (0.50), which shows signs of equilibrium. When analysing the DFA exponents for the Tranquil period, the trend of persistence is maintained, i.e. all cryptocurrencies show long-term memories, except for LSK (0.50), which does not reject the hypothesis of white noise. These results show that cryptocurrency prices do not follow a purely random process, but this does not necessarily imply predictability in returns.

Table 2

DFA exponent for return. The values of the linear adjustments for $\alpha_{DFA}$ always had $R^2 > 0.99$

<table>
<thead>
<tr>
<th>Cryptocurrencies</th>
<th>$\alpha_{DFA}$ (Full)</th>
<th>Results</th>
<th>$\alpha_{DFA}$ (Tranquil)</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>BTC</td>
<td>0.55** $\equiv 0.0075$</td>
<td>Persistent</td>
<td>0.54** $\equiv 0.0086$</td>
<td>Persistent</td>
</tr>
<tr>
<td>LSK</td>
<td>0.53** $\equiv 0.0064$</td>
<td>Persistent</td>
<td>0.50 $\equiv 0.0081$</td>
<td>White noise</td>
</tr>
<tr>
<td>QUA</td>
<td>0.56** $\equiv 0.0065$</td>
<td>Persistent</td>
<td>0.53** $\equiv 0.0012$</td>
<td>Persistent</td>
</tr>
<tr>
<td>ETH</td>
<td>0.53** $\equiv 0.0057$</td>
<td>Persistent</td>
<td>0.59** $\equiv 0.0013$</td>
<td>Persistent</td>
</tr>
<tr>
<td>LTC</td>
<td>0.53** $\equiv 0.0069$</td>
<td>Persistent</td>
<td>0.52** $\equiv 0.0072$</td>
<td>Persistent</td>
</tr>
<tr>
<td>XRP</td>
<td>0.50 $\equiv 0.0091$</td>
<td>White noise</td>
<td>0.55** $\equiv 0.0063$</td>
<td>Persistent</td>
</tr>
</tbody>
</table>
Table 3 shows the DFA slopes for the cryptocurrencies analysed during the 2020 global pandemic and during the conflict between Russia and Ukraine. In the Covid-19 pandemic period, the digital currencies LSK (0.62), QUA (0.62), MIOTA (0.61), XRP (0.58), REP (0.57), BTC (0.55), ETH (0.54), LTC (0.53), DASH (0.54), show very significant persistence, showing that price formation is not random. Still, it is not possible to say that cryptocurrency prices are predictable based on historical time series. Also, during this period, the digital currency EOS (0.50) is in equilibrium; in other words, price formation follows the random walk pattern, suggesting that prices are not autocorrelated over time. In practical terms, for traders looking for short-term returns, identifying long-memory patterns can be useful when making decisions about buying and selling digital currencies, as it provides a pattern for the volatility of the cryptocurrency markets.

During the geopolitical conflict, the patterns of long memories changed significantly to short-term memories, i.e. anti-persistence. The digital currencies ETH (0.48), MIOTA (0.48), EOS (0.47), LTC (0.44), REP (0.46), LSK (0.45), and DASH (0.44) have anti-persistence slopes. In practical terms, these results mean that, during this period, the price of digital currencies was less influenced by past events and more influenced by recent events, suggesting that these digital currencies are more likely to change direction during geopolitical conflict. On the other hand, the cryptocurrencies BTC (0.50), QUA (0.50), and XRP (0.50) do not reject the hypothesis of white noise, showing that the prices have a strong random component and that the residuals are independent and identically distributed (i.i.d).

Table 3

<table>
<thead>
<tr>
<th>Cryptocurrencies</th>
<th>aDFA (2020 Pandemic)</th>
<th>Results</th>
<th>aDFA (2022 Geopolitical conflict)</th>
<th>Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>BTC</td>
<td>0.55** ± 0.0013</td>
<td>Persistent</td>
<td>0.50 ± 0.0016</td>
<td>White noise</td>
</tr>
<tr>
<td>LSK</td>
<td>0.62** ± 0.0033</td>
<td>Persistent</td>
<td>0.45** ± 0.0020</td>
<td>Anti-Persistent</td>
</tr>
<tr>
<td>QUA</td>
<td>0.62** ± 0.0036</td>
<td>Persistent</td>
<td>0.50 ± 0.0024</td>
<td>White noise</td>
</tr>
<tr>
<td>ETH</td>
<td>0.54** ± 0.0016</td>
<td>Persistent</td>
<td>0.48** ± 0.0038</td>
<td>Anti-Persistent</td>
</tr>
<tr>
<td>LTC</td>
<td>0.53** ± 0.0012</td>
<td>Persistent</td>
<td>0.44** ± 0.0031</td>
<td>Anti-Persistent</td>
</tr>
<tr>
<td>XRP</td>
<td>0.58** ± 0.0010</td>
<td>Persistent</td>
<td>0.50 ± 0.0033</td>
<td>White noise</td>
</tr>
<tr>
<td>REP</td>
<td>0.57** ± 0.0023</td>
<td>Persistent</td>
<td>0.46** ± 0.0025</td>
<td>Anti-Persistent</td>
</tr>
</tbody>
</table>

Note: The hypotheses are $H_0: \alpha = 0.5$ and $H_1: \alpha \neq 0.5$. ** Confidence interval 95%.

Source: Own elaboration
5 CONCLUSION

The main purpose of this study was to understand whether the cryptocurrencies Bitcoin (BTC), Lisk (LSK), Quantum (QUA), Litecoin (LTC), Ripple (XRP), Augur (REP), Darkcoin (DASH), EOS, IOTA (MIOTA) react in the same way to the phenomenon of persistence during extreme events on the international financial markets.

The results show that during the full sample period, most cryptocurrencies have long memories, i.e. they are persistent, except for REP (0.48), which shows slopes of anti-persistence (short-term memories) and XRP (0.50), which shows signs of equilibrium. When analysing the DFA exponents for the Tranquil period, it was found that the persistence trend continues, i.e. all cryptocurrencies show long-term memories, the exception being LSK (0.50), which does not reject the white noise hypothesis. These results show that cryptocurrency prices do not follow a purely random process, but this does not necessarily imply predictability in returns.

When analysing the period of the 2020 pandemic, the digital currencies LSK, QUA, MIOTA, XRP, REP, BTC, ETH, LTC and DASH showed significant persistence, indicating that price formation is not random. However, validating that cryptocurrency prices are predictable based on historical time series was impossible. On the other hand, the digital currency EOS proved to be in equilibrium; in other words, price formation follows the random walk pattern, suggesting that prices are not autocorrelated over time. On the other hand, during the geopolitical conflict in 2022, long-term memory patterns shifted significantly towards short-term memories, i.e. anti-persistence. The digital currencies ETH, MIOTA, EOS, LTC, REP, LSK and DASH showed anti-persistence slopes, indicating that prices were less influenced by past events and more by recent events. Meanwhile, the cryptocurrencies BTC (0.50), QUA (0.50), and XRP (0.50) do not reject the hypothesis of white noise, showing that prices have a strong random component and that the residuals are independent and identically distributed (i.i.d).

The main conclusion of this study is that the long-term memory patterns of digital currencies changed significantly during the geopolitical conflict. This means that digital currencies are more likely to be influenced by recent events or random factors during periods of uncertainty in the global economy. These implications are significant for investment
strategies, as they highlight the importance of cautious portfolio allocation and the search for assets that offer stability in periods of uncertainty.

ACKNOWLEDGEMENT

Rui Dias is pleased to acknowledge the financial support from Instituto Superior de Gestão (ISG) [ISG - Business & Economics School], CIGEST.

REFERENCES


