“Persistence in the cryptocurrency market: does size matter?”

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PERSISTENCE IN THE CRYPTOCURRENCY MARKET: DOES SIZE MATTER?

Abstract

This paper investigates the persistence in the cryptocurrency market, focusing on five distinct groups categorized by their market capitalization during the sample period from 2020 to 2023. The study aims to test two hypotheses: (H1) The degree of persistence in the cryptocurrency market is contingent on market capitalization, and (H2) The efficiency of the cryptocurrency market has increased in recent years. The methodology employed for this examination is R/S analysis. The results indicate that the cryptocurrency market maintains its inefficiency, and no significant variations in persistence are discerned among different cryptocurrency groups, leading to the rejection of H1. Outcomes related to H2 present a nuanced scenario. Specifically, Litecoin and Ripple exhibit supportive evidence for the Adaptive Market Hypothesis, suggesting an improvement in the efficiency of the cryptocurrency market in recent years. A noteworthy revelation pertains to the anomaly observed in Bitcoin. Despite being the most capitalized and liquid cryptocurrency, it demonstrates inefficiency akin to levels observed five years ago. The implications of this study contribute to the comprehension of cryptocurrency market efficiency. The findings challenge the assumptions of the Efficient Market Hypothesis, favoring instead the Adaptive Market Hypothesis. For practitioners, the results hold significance, providing evidence of price predictability, particularly in the case of Bitcoin. This suggests that trend trading strategies remain viable for generating abnormal profits in the cryptocurrency market.

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INTRODUCTION

Despite the youthfulness of the cryptocurrency market, with active trading in the oldest cryptocurrency Bitcoin commencing only in 2013, there has been notable interest among academics regarding the market's efficiency (Urquhart, 2016; Bariviera et al., 2017; Caporale et al., 2018; Wei, 2018; Zargar & Kumar, 2019; López-Martín et al., 2021; Keshari et al., 2022; Sahoo & Sethi, 2023, among others) and other issues such as cryptocurrencies and financial stability (Panigrahi, 2023), cryptocurrencies and energy consumption (Bublyk et al., 2023), cryptocurrency market during COVID-19 (Waspada et al., 2023), etc. This academic curiosity is justified by the potential for profits resulting from inefficiencies in the cryptocurrency market, which, in many instances, contradicts the Efficient Market Hypothesis (Fama, 1970). One of the most widely used methods for investigating market efficiency is the analysis of its persistence – the presence of correlations between past and future prices (Greene & Fielitz, 1977; Lo, 1991; Caporale et al., 2019).

Caporale et al. (2018) found evidence of persistence in the cryptocurrency market, with the degree of persistence evolving over time. Among the cryptocurrencies analyzed (Bitcoin, Litecoin, Ripple, Dash), Bitcoin emerged as the most efficient, likely due to its superior liquidity. This explanation is supported by Wei (2018), who investigated the liquidity of 456 cryptocurrencies and established a strong correlation between the Hurst exponent and liquidity on a cross-sectional basis. Wei (2018) concluded that return predictability diminishes in cryptocurrencies with high market liquidity.

An additional crucial aspect in persistence analysis is its dynamic nature. As per the Adaptive Market Hypothesis (Lo, 1991), financial markets undergo evolution, leading to instability in data parameters like persistence (Aslam et al., 2023). The general consensus suggests that the cryptocurrency market progresses from lower efficiency to higher efficiency, indicating a shift from higher persistence to lower persistence (Bariviera, 2017). Results obtained by Karasiński (2023) substantiate the Adaptive Market Hypothesis. The cryptocurrency market is dynamically evolving, making results obtained 2-3 years ago potentially outdated, compounded by the significant turbulence caused by the pandemic in financial markets overall and the cryptocurrency market in particular (Łęt, et al., 2022). Consequently, further research on persistence in the cryptocurrency market is urgently needed.

1. LITERATURE REVIEW

The issue of cryptocurrency market efficiency has been a subject of academic interest since 2015–2016, and existing evidence presents a mixed picture. Some authors view cryptocurrencies as standard economic goods priced through the interaction of supply and demand in the market. According to Bartos (2015), the price of the most well-known cryptocurrency, Bitcoin, adheres to the Efficient Market Hypothesis. Hu et al. (2019) expanded this analysis to include the top 31 market-cap cryptocurrencies and provided further evidence in favor of cryptocurrency market efficiency.

Contrastingly, Kristoufek (2018) finds strong evidence of Bitcoin markets mostly remaining inefficient between 2010 and 2017. Similar conclusions were later reached by Zhang et al. (2018). Urquhart (2016) reveals that Bitcoin returns are significantly inefficient over the full sample of data. However, when the sample is split into two subsample periods, some tests indicate that Bitcoin is efficient.

As a result, assumptions of cryptocurrency market efficiency were challenged, but no final conclusions could be drawn. Khuntia and Pattanayak (2018) and Khursheed et al. (2020) explained these results with evidence that market efficiency evolves with time. These conclusions open a door to a new dimension of research: the variability of market efficiency caused by the evolutionary processes in the cryptocurrency market.

For example, Bariviera (2017) finds that Bitcoin daily returns exhibit persistent behavior during 2011–2014, whereas its behavior is more informationally efficient since 2014. Khursheed et al. (2020) showed that price movements with linear and nonlinear dependences vary over time, suggesting the implementation of the adaptive market hypothesis for the case of the cryptocurrency market: predicting changes in cryptocurrency prices over time must consider the time-varying market conditions for efficient forecasting. López-Martín et al. (2021) observe that overall, the degree of efficiency tends to increase with time. The most recent evidence provided by Yi et al. (2023) implies that as Bitcoin evolves into an efficient market, speculators might encounter difficulty in exploiting profitable trading strategies.

The evolutionary nature of the cryptocurrency market is not the only explanation for differences in market efficiency and persistence. Variations in data frequency can also contribute to disparities in conclusions related to data persistence and market efficiency. Apopo and Phiri (2021) explored efficiency for five of the most dominant cryptocurrencies (Bitcoin, Ethereum, Litecoin, Bitcoin Cash, and Ripple) and showed that, with the exception of Litecoin, daily series are generally market-efficient, while all weekly returns are informationally inefficient. Zargar and Kumar (2019) investigated different data frequencies (15, 30, 60, and 120 min and daily data) and provided evidence of the presence of informational inefficiency in the Bitcoin market at higher frequency levels.

Another explanation for differences in results is provided by Aslam et al. (2023), who argue that the level of efficiency depends on the cryptocurrency: Bitcoin and Litecoin are the two most inefficient cryptocurrencies, whereas Cardano and Binance Coin exhibit the least inefficiency. Ripple and Ethereum remain in the middle. They concluded that cryptocurrencies exhibit persistent behavior. An explanation for these results was proposed by Wei (2018), who showed that the level of persistence is correlated with the liquidity of cryptocurrency: the higher the liquidity, the less persistent the data are.

One of the reasons for differences in the most recent results, according to Mgadmi et al. (2023), can be the pandemic and the shocks it has caused in the financial markets. This reason can be generalized as follows: potential differences in the level of persistence can be caused using different data periods. Karasiński (2023) revealed that the returns of the majority of the examined cryptocurrencies were unpredictable most of the time, but a significant portion of them also experienced some short periods of weak-form inefficiency.

Data sources can also influence the results. Souza and Carvalho (2023) suggested that discrepancies in the levels of efficiency may be related to the use of different exchanges.

As can be seen, the data regarding the efficiency of the cryptocurrency market, as well as its persistence, were and still are mixed. Differences in results can be explained by the use of different objects of analysis (different sets of cryptocurrencies), different data frequencies (daily, weekly, etc.), applied methodologies and data periods, as well as evolutionary processes in the cryptocurrency market. That is why further investigation is needed to expand existing results. This paper aims to expand the result of Caporale et al. (2018) by applying the same methodology (R/S analysis) to avoid differences in results caused by the use of different methodologies.

2. DATA AND METHODOLOGY

This study focuses on five groups of cryptocurrencies divided by market capitalizations with the longest span of data (see Table 1) with 4 cryptocurrencies in each group: overall 20 assets. The frequency is daily, and the data source is Binance (https://www.cryptodatadownload.com/data/binance/).

Table 1. Groups and cryptocurrencies (October 18, 2023)

Source: https://coinmarketcap.com/coins/.

Group	Name	Ticket	Market Cap*	Volume (24h)	Data starts from
$25B+	Bitcoin	BTC	$554 B	$10 825 M	2017-08-17
	Ethereum	ETH	$190 B	$4 328 M	2017-08-17
	BNB	BNB	$32 B	$268 M	2017-11-06
	Ripple	XRP	$26 B	$803 M	2018-05-04
+/– $5 B	Litecoin	LTC	$4.6 B	$191 M	2017-12-13
	Bitcoin Cash	BCH	$4.5 B	$145 M	2019-11-28
	Polygon	MATIC	$4.8 B	$175 M	2019-04-26
	Polkadot	DOT	$4.6 B	$69 M	2020-08-18
+/– $1 B	Maker	MKR	$1.3 B	$41 M	2020-07-23
	NEAR Protocol	NEAR	$1.0 B	$32 M	2020-10-14
	Filecoin	FIL	$1.5 B	$56 M	2020-10-15
	Hedera	HBAR	$1.6 B	$43 M	2019-09-29
+/– $0.5 B	Decentraland	MANA	$ 0.5 B	$17 M	2020-08-06
	Theta Network	THETA	$ 0.6 B	$8 M	2019-04-10
	Axie Infinity	AXS	$ 0.6 B	$25 M	2020-11-04
	THORChain	RUNE	$ 0.5 B	$28 M	2020-07-24
+/– $0.1 B	DigiByte	DGB	$ 0.1 B	$2 M	2020-07-20
	Kyber Network Crystal v2	KNC	$ 0.1 B	$41 M	2020-06-12
	UMA	UMA	$ 0.1 B	$20 M	2020-09-09
	Lisk	LSK	$ 0.1 B	$3 M	2020-02-06

Note: Cryptocurrency Market Capitalization.

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As evident from the data, the majority of datasets commence in 2020. To mitigate discrepancies arising from the utilization of diverse analysis periods, this paper employs a consistent timeframe for all data, spanning from October 15, 2020, to October 17, 2023. Another rationale for commencing the analysis from 2020 is to extend the findings of Caporale et al. (2018) and investigate the evolution of persistence in comparison to the period of 2013–2017.

The hypotheses examined in this study are as follows:

H1: *The degree of persistence in the cryptocurrency market varies across distinct groups of cryptocurrencies categorized by their market capitalization.*

H2: *The efficiency of the cryptocurrency market has increased in recent years.*

The R/S analysis is employed to assess data persistence, utilizing the algorithm outlined by Caporale et al. (2018) with the following steps:

1. A time series of length M undergoes transformation into one of length $N = M - 1$ using logarithms and converting prices into returns:

$$N_i = \log\left(\frac{Y_{t+1}}{Y_t}\right), \quad t = 1, 2, 3, \ldots (M-1). \tag{1}$$

2. This period is divided into contiguous A sub-periods with length n, where $A_n = N$. Each sub-period is denoted as I_a, with a = 1, 2, 3, ..., A. Each element I_a is represented with N_k with k = 1, 2, 3, ..., N. For each I_a with length n the average e_a is defined as:

$$e_a = \frac{1}{n}\sum_{k=1}^{n} N_{k,a}, \tag{2}$$

$$k = 1, 2, 3, \ldots N, \quad a = 1, 2, 3 \ldots, A.$$

3. Accumulated deviations $X_{k,a}$ from the average e_a for each sub-period I_a are defined as:

$$X_{k,a} = \sum_{i=1}^{k} (N_{i,a} - e_a). \tag{3}$$

4. The range is calculated as the highest index $X_{k,a}$ minus the lowest $X_{k,a}$, within each sub-period (I_a):

$$R_{Ia} = \max(X_{k,a}) - \min(X_{k,a}), \quad 1 \le k \le n. \tag{4}$$

5. The standard deviation S_{Ia} is calculated for each sub-period I_a:

$$S_{Ia} = \left(\left(\frac{1}{n}\right)\sum_{k=1}^{n} (N_{k,a} - e_a)^2\right)^{0.5}. \tag{5}$$

6. Each range R_{Ia} is normalized by dividing it by the corresponding standard deviation S_{Ia}. Consequently, the re-normalized scale during each sub-period I_a is expressed as R_{Ia}/S_{Ia}. In step 2 above, adjacent sub-periods of length n are acquired. Thus, the average R/S for length n is calculated as:

$$(R/S)_n = \left(\frac{1}{A}\right)\sum_{i=1}^{A}\left(\frac{R_{Ia}}{S_{Ia}}\right). \tag{6}$$

The length n is incremented to the subsequent higher level, $(M - 1)/n$, and it must be an integer number. In this scenario, n-indexes that encompass the commencement and conclusion points of the time series are employed. Steps 1-6 are reiterated until $n = (M - 1)/2$.

7. Subsequently, the least square method is applied to estimate the equation

$$\log(R/S) = \log(c) + H \cdot \log(n). \tag{7}$$

The slope of the regression line provides an estimation of the Hurst exponent H (Hurst, 1951).

To evaluate the statistical significance of the estimated Hurst exponent coefficients, one can compute p-values and establish 95% confidence intervals using conventional procedures within the framework of regression analysis.

It is crucial to note that the Hurst exponent is constrained within the interval [0, 1]. Based on the values of H, three distinct categories can be discerned:

- The series exhibits anti-persistence, denoting negatively correlated returns ($0 \le H < 0.5$).
- The series is characterized as random, indicating uncorrelated returns and the absence of memory in the series ($H = 0.5$).

- The series demonstrates persistence, signifying highly correlated returns and the presence of memory in price dynamics ($0.5 < H \leq 1$).

In examining market persistence dynamics, this study employs a sliding-window methodology. The procedure involves determining the Hurst exponent's initial value (e.g., on the date 01.04.2020 using data spanning from 01.01.2020 to 31.03.2020). Subsequent values are then computed by advancing the "data window," with the magnitude of the shift contingent on the quantity of observations. It is imperative to secure a sufficient number of estimates to scrutinize the time-varying characteristics of the Hurst exponent. For instance, with a shift of 10, the second value is calculated for 10.04.2020, delineating the market's characteristics from 10.01.2020 to 09.04.2020, and so on.

3. EMPIRICAL RESULTS AND DISCUSSION

The results of the R/S analysis for the return series of the selected cryptocurrencies within groups are presented in Table 2.

As can be seen, group averages exhibit nearly identical values, with no significant differences detected among various groups. The majority of cryptocurrencies, regardless of their capitalization or liquidity, demonstrate long-memory properties in the data. This suggests that the cryptocurrency market is far from being efficient. One of the most noteworthy observations is that Bitcoin, despite being the oldest, most widely used, and highly liquid cryptocurrency globally, accounting for over 50% of the overall cryptocurrency market capitalization, ranks among the most inefficient cryptocurrencies, as indicated by its relatively high Hurst exponent.

A detailed analysis of these findings is presented in Table 3, which includes descriptive statistics and statistical tests for differences between averages.

Based on the data presented in Table 3, it can be inferred that the only group where the average may potentially differ from the overall dataset's average is the group with the least capitalized cryptocurrencies. The results provide evidence of a statistically significant difference in persistence within the 0.1B group compared to the overall dataset. However, in terms of absolute values, this difference appears relatively insignificant: 0.55 compared to 0.56 for the overall dataset. Consequently, it can be concluded that Hypothesis 1 is rejected, indicating that the degree of persistence in the cryptocurrency market does not vary significantly across distinct groups of cryptocurrencies categorized by their market capitalization.

Table 2. Results of the R/S analysis for the selected crypto currencies within groups, 2020–2023

Group	Name	Ticket	Hurst exponent	Confidence interval	Group average
$25B+	Bitcoin	BTC	0.585	0.57-0.60	0.56
	Ethereum	ETH	0.561	0.55-0.57	
	BNB	BNB	0.573	0.56-0.58	
	Ripple	XRP	0.526	0.50-0.55	
+/– $5 B	Litecoin	LTC	0.550	0.54-0.56	0.57
	Bitcoin Cash	BCH	0.555	0.54-0.56	
	Polygon	MATIC	0.617	0.60-0.64	
	Polkadot	DOT	0.555	0.54-0.57	
+/– $1 B	Maker	MKR	0.553	0.52-0.59	0.57
	NEAR Protocol	NEAR	0.565	0.53-0.60	
	Filecoin	FIL	0.587	0.57-0.60	
	Hedera	HBAR	0.594	0.58-0.61	
+/– $0.5 B	Decentraland	MANA	0.544	0.51-0.57	0.56
	Theta Network	THETA	0.565	0.54-0.58	
	Axie Infinity	AXS	0.546	0.53-0.56	
	THORChain	RUNE	0.586	0.57-0.60	
+/– $0.1 B	DigiByte	DGB	0.554	0.54-0.57	0.55
	Kyber Network Crystal v2	KNC	0.556	0.54-0.57	
	UMA	UMA	0.527	0.51-0.54	
	Lisk	LSK	0.549	0.52-0.57	

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Table 3. Descriptive statistics for the results of the R/S analysis for the selected crypto currencies within groups, 2020–2023

Parameter	25B	5B	1B	0.5B	0.1B	All
Average	0.56	0.57	0.57	0.56	0.55	0.56
Standard error	0.01	0.02	0.01	0.01	0.01	0.01
Median	0.57	0.56	0.58	0.56	0.55	0.56
Standard deviation	0.03	0.03	0.02	0.02	0.01	0.02
Sample variance	0.00	0.00	0.00	0.00	0.00	0.00
Excess	1.48	3.87	–3.55	–0.97	2.90	0.57
Asymmetry	–1.19	1.96	–0.19	0.90	–1.70	0.65
Interval	0.06	0.07	0.04	0.04	0.03	0.09
Minimum	0.53	0.55	0.55	0.54	0.53	0.53
Maximum	0.58	0.62	0.59	0.59	0.56	0.62
Sum	2.25	2.28	2.30	2.24	2.18	11.25
Count	4	4	4	4	4	20
t-test	0.08	0.42	1.14	0.19	1.92	–
Difference is statistically significant	no	no	no	no	yes	–

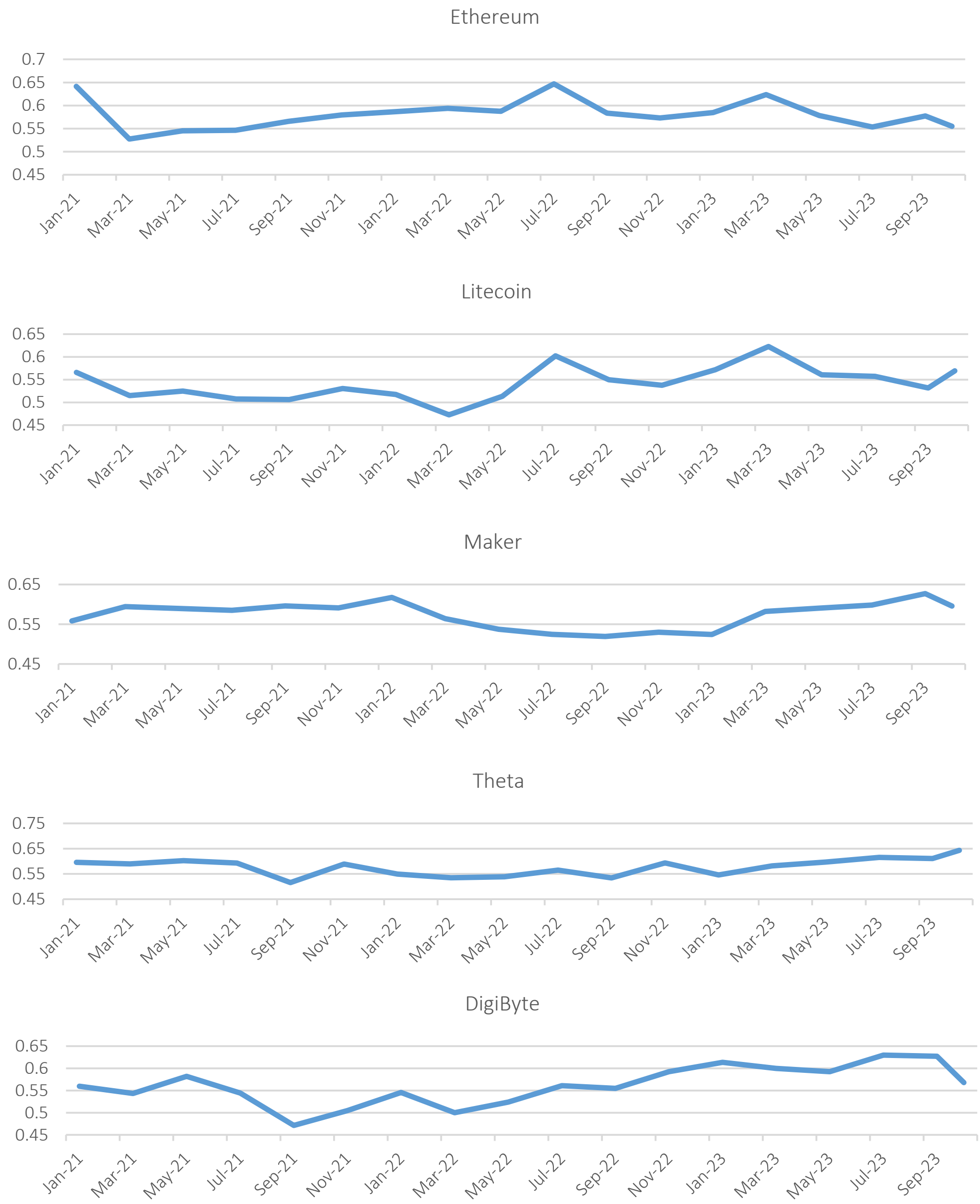

Figure 1. Results of the dynamic R/S analysis (step = 50, data window = 300)

Table 4. Comparative analysis of the current findings with previous research (Caporale et al., 2018)

Period	Current results	Caporale et al (2018)	Difference
Bitcoin	0.59	0.59	0
Litecoin	0.55	0.63	–0.08
Ripple	0.53	0.64	–0.12

For the purpose of dynamic R/S analysis, one of the most representative assets was selected from each group. The results of the dynamic R/S analysis are presented in Figure 1.

As can be seen, the degree of persistence varies over the time, exhibiting fluctuations around its average without discernible stable tendencies. Therefore, no conclusive evidence supporting Hypothesis 2 is discerned.

A comparative analysis of the results is detailed in Table 4, drawing parallels with findings from Caporale et al. (2018).

As evident from the analysis, no discernible differences in persistence are identified for Bitcoin. However, noteworthy changes are observed in the cases of Litecoin and Ripple, both exhibiting a considerable decrease in persistence levels. This suggests a transition from a state of lower efficiency to a more efficient condition. These findings align with the conclusions drawn by Caporale et al. (2018), indicating that Litecoin, initially characterized by inefficiency, evolved into a more liquid market over 2-3 years, marked by increased participant numbers, trade volumes, and overall efficiency. This suggests ongoing and active evolutionary processes in the case of Litecoin, consistent with the tenets of the Adaptive Market Hypothesis (Lo, 1991). Consequently, Hypothesis 2 is confirmed for Litecoin and Ripple, indicating an increase in the efficiency of the cryptocurrency market in recent years.

Conversely, for Bitcoin, Hypothesis 2 is not substantiated. Bitcoin appears to be a notable anomaly, exhibiting immunity to the evolutionary processes observed in the broader cryptocurrency market. Its inefficiency, noted five years ago by Caporale et al. (2018), persists, defying the expectations set by the Adaptive Market Hypothesis (Lo, 1991).

CONCLUSIONS

This study employs R/S analysis to assess the degree of persistence in the cryptocurrency market, with a focus on five distinct groups categorized by their market capitalization. The research aims to test two hypotheses: (*H1*) The degree of persistence in the cryptocurrency market varies across distinct groups of cryptocurrencies categorized by their market capitalization, and (*H2*) The efficiency of the cryptocurrency market has increased in recent years.

The findings suggest that the cryptocurrency market remains inefficient, and no substantial disparities in persistence are observed among various cryptocurrency groups, leading to the rejection of *H1*. Results pertaining to *H2* present a mixed picture. Specifically, Litecoin and Ripple exhibit evidence in support of the Adaptive Market Hypothesis, indicating an enhancement in the efficiency of the cryptocurrency market in recent years. Nevertheless, dynamic R/S analysis reveals no consistent trends in Hurst exponent changes over time, with values exhibiting instability and fluctuating around the mean.

A notable revelation is the anomaly observed in Bitcoin. Despite being the most capitalized and liquid cryptocurrency, it displays inefficiency comparable to levels observed five years ago. This unexpected outcome underscores the complexity of factors influencing Bitcoin's behavior in the market.

The implications of this study contribute to the understanding of cryptocurrency market efficiency. The findings challenge the assumptions of the Efficient Market Hypothesis, favoring instead the

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Adaptive Market Hypothesis. For practitioners, the results are of significance, offering evidence of price predictability, particularly in the case of Bitcoin. This suggests that trend trading strategies retain viability for generating abnormal profits in the cryptocurrency market.

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