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PERSISTENCE IN CRYPTOCURRENCY RETURNS: A COMPARATIVE ANALYSIS OF PRE- AND POST-COVID PERIODS

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ABSTRACT

This article examines the persistence and market behavior of five major cryptocurrencies, Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Tether (USTD), and Binance Coin (BNB), during the Pre-COVID and Post-COVID periods. The selected five cryptocurrencies are compared to check which currency shows more persistence before and after the COVID-19 pandemic. Using the R/S analysis methodology, the values of the Hurst exponent show the varying persistence levels across cryptocurrencies, with BTC exhibiting a slight persistence reduction (from 0.625 to 0.577) post-COVID. In contrast, ETH and BNB show increased persistence. Conversely, USTD demonstrates consistent mean-reverting behavior. Statistically significant results confirm the existence of long-term memory in cryptocurrency returns, rejecting the random walk hypothesis. The results indicate the impact of external shocks, such as the COVID-19 pandemic, on trading behavior and market efficiency, providing valuable insights for investors and portfolio managers.

Keywords: Cryptocurrency, Hurst exponent, COVID-19 pandemic, market efficiency, Persistence

Introduction

The COVID-19 pandemic caused unprecedented disruptions in global financial markets, affecting various asset classes, including equities, commodities, crude oil, and cryptocurrencies. Cryptocurrencies, in particular, are known for their volatility and unpredictability, and they were significantly impacted by the economic shockwaves resulting from the pandemic. Numerous studies have investigated the broader implications of COVID-19 on different markets, including equities (Adekoya & Oliyide, 2022; Aslam et al., 2020), commodities (Arouri et al., 2012), crude oil (Narayan, 2020; Ortiz-Cruz et al., 2011), and foreign exchange (Barunik & Kristoufek, 2010; Stosic et al., 2016). However, a significant gap remains in understanding the cryptocurrency markets' long-term persistence and efficiency dynamics during such crises. Studies show that Cryptocurrencies have exhibited multifractality and irregularities during turbulent periods (Lahmiri & Bekiros, 2020). There was increased volatility and structural inefficiencies in the Bitcoin market during the pandemic (Sarkodie et al., 2022). Moreover, Elgin et al. (2021) found sustained volatility among financial markets due to the pandemic. Despite these findings, few studies have specifically compared the persistence of top cryptocurrencies pre- and post-COVID, which is critical for understanding their long-term behavior and potential as resilient assets during crises. Although during the financial crisis, gold has been considered traditionally a dominant safe haven (Esparcia et al., 2022; Jalan et al., 2021), major cryptocurrencies like Bitcoin play a similar role and remain a topic of debate in recent times. Previous studies found mixed findings related to the safe haven characteristics of Bitcoin and other cryptocurrencies (Smales, 2019). Additionaly, a pandemic like COVID-19 provided a unique opportunity to assess the evolution of cryptocurrency markets, particularly the persistence and efficiency of top cryptocurrencies. This study also aims to check the persistent behavior of the top five cryptocurrencies, Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Tether (USTD), and Binance Coin (BNB) to make addition to the literature of understanding the behavior of digital currencies during the turbulent time-period. It can analyze how these currencies behave during pre and post behavior.

This study addresses the gap by employing R/S analysis to measure and compare the persistence of the top five cryptocurrencies by market capitalization across the pre- and post-COVID periods. Unlike prior studies, this work focuses on persistence to explore the implications for market efficiency and resilience. We aim to uncover the patterns of long range dependence in the analysis of the digital markets by taking top five cryptocurrencies based on the market cap and to analyze whether these patterns align with traditional financial assets or shows some unique characteristics in the pandemic induced market turmoil such as COCID-19. This investigation contributes to the literature by providing fresh insights into cryptocurrency behavior during economic shocks and advancing our understanding of their role in financial markets.

2. Research Methodology

2.1. Long Memory Tests for Fractal Time Series

Fractal characteristics are often characteristic of the financial markets, due to non-linear clustering behavior of the time series data. This means that prices in financial markets have strong tendency to revert to the mean. This characteristic is particularly analyzed by the Hurst exponent (H). Which is a measure of long memory alternatively known as persistence in time series data (Barunik & Kristoufek, 2010). Rescaled range analysis (R/S) and H are mostly used in the assessment of the memory process of time series (Narayan, 2020; Ortiz-Cruz et al., 2011). The hurst exponent values is used as statistical measure of the fractal geometry and helps to determine long range relationship and whether series are interdependent or not in time series even when separated by intervals. In this study we also used the R/S analysis to calculate the Hurst values to examine the persistence behavior of top five cryptocurrencies pre and post COVID era. The steps of H calculation through R/S analysis are given below:

Step 1: Calculate the mean of subsample using following is computed as:

m = $1/n\sum_{t=1}^{n} Xt$

Step 2: The demeaned return (deviate) mean adjusted series (Y_t) is computed as follows:

$Y_t = X_t - m$, t = 1, 2, · · · · · ·

Step 3: The cumulative deviate series (D_t) representing the cumulative sum of diminished returns can be computed as:

$D_t = \sum_{i=1}^{t} Y_i$, t = 1, 2, · · · · · · , n

By rearranging the above equation it can alternatively be written as $D_t = \sum_{i=1}^{t} X_i - tm$.

Step 4: The subsample range is computed as the max minus min of the cumulative deviate, based on the following equation:

$R_t = \max(D1, D2, \cdots, Dt) - \min(D1, D2, \cdots, Dt)$, t = 1, 2, · · · · · · , n.

Step 5: Compute the standard deviation of the S series as follows:

$S_t = \sqrt{\frac{\sum_{i=1}^{t}(X_i - m)^2}{t}}$, t = 1, 2, …., n.

Step 6: Calculating the rescaled range (R/S) series, it is easy to infer the following definition:

$(R/S)_t = Rt/St$ t = 1, 2, · · · , n.

The value of H indicates the behavior of the time series:

i. H=0.5: The series follows a random walk, with no correlation between past and future values (Brownian motion).
ii. 0 < H < 0.5: The series is anti-persistent, displaying mean-reverting properties.
iii. 0.5 < H < 1.0: The series exhibits persistence, with trends likely to continue in the same direction (trend-reinforcing behavior).

Importantly, R/S analysis does not require the data to follow a normal distribution, making it robust for analyzing cryptocurrency returns. This study leverages the Hurst exponent to compare the persistence of top cryptocurrencies before and after the COVID-19 pandemic, providing insights into their long-range dependencies and market behavior during crisis periods.

3. Research Data

For this study, the daily closing prices of the top five cryptocurrencies, BTC, ETH, USTD, XRP, and BNB, are extracted from Coinmarketcap from 1 August 2017 to 30 June 2024. We divided the sample into two sub-periods: The pre-COVID period ranges from 1 August 2017 to 30 November 2019. The second sub-sample is the post-COVID period, which ranges from 1 July 2021 to 30 August 2024. We calculated returns from the closing prices of each cryptocurrency for further analysis.

4. Empirical Result and Discussion

Tables I and II show the descriptive statistics of five sample cryptocurrency returns pre and post-COVID-19 pandemic. The statistics highlight significant variations in their statistical properties. In the post-COVID period, the mean returns decreased for most cryptocurrencies, including BTC, ETH, and BNB, and represented lower average performance than the pre-COVID period. Markedly, USTD experienced a shift from a small positive mean return to near zero, suggesting reduced stability. Standard deviation, the measure of volatility, increased for most cryptocurrencies, specifically XRP, which demonstrated a significant rise in variability, pointing to heightened post-pandemic market fluctuations. The values of kurtosis and skewness also reflect a shift in return distributions, with XRP showing a more substantial positive skew and much higher kurtosis, indicating more frequent extreme positive returns. Moreover, the Jarque-Bera tests confirm significant non-normality in both periods, with considerable deviations for USTD, XRP, and BNB. These findings highlight a fundamental change in cryptocurrencies' behavior and risk dynamics in the aftermath of COVID-19, characterized by increased volatility and more pronounced outliers.

Table I: Descriptive Statistics Pre period

	BTC	ETH	USTD	XRP	BNB
Mean	0.001638	0.000541	0.000146	0.002733	0.005589
Median	0.001790	0.000201	-5.07E-05	-0.001220	-0.000472
Maximum	0.285206	0.255581	0.138558	0.823972	0.612181
Minimum	-0.187252	-0.227187	-0.247493	-0.336021	-0.333945
Std. Dev.	0.043668	0.051756	0.016095	0.072121	0.075124
Skewness	0.356188	-0.014592	-2.144322	3.837970	1.528576
Kurtosis	7.417688	5.730483	95.06389	38.19514	14.58400
Jarque-Bera	695.8149	259.1094	295171.8	45092.23	4987.853
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	1.366377	0.451382	0.121929	2.279711	4.661586
Sum Sq. Dev.	1.588475	2.231343	0.215783	4.332798	4.701111
Observations	834	834	834	834	834

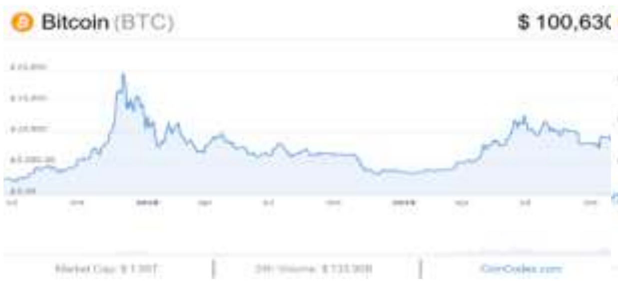
Table II: Descriptive Statistics Post period

	BTC	ETH	USTD	XRP	BNB
Mean	0.001013	0.001042	-3.37E-06	0.000566	0.001194
Median	0.000232	0.000301	0.000000	-0.000417	0.000956
Maximum	0.144949	0.187776	0.008790	0.722084	0.168591
Minimum	-0.157112	-0.178124	-0.008843	-0.196972	-0.186030
Std. Dev.	0.029697	0.036782	0.001384	0.044902	0.033139
Skewness	-0.043369	0.041193	-0.324926	4.108073	-0.149845
Kurtosis	6.436974	6.666392	15.19010	66.51013	7.089000
Jarque-Bera	539.3019	613.6207	6799.077	187110.1	766.9440
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	1.109174	1.141180	-0.003692	0.619555	1.307484
Sum Sq. Dev.	0.964842	1.480126	0.002096	2.205722	1.201412
Observations	1095	1095	1095	1095	1095

Graphical Representation

The graphical representations of the pre, post, and full period are displayed in **Figures 1, 2 & 3.** Before COVID struck, the market in the cryptocurrency space was somewhat more stagnant, with Bitcoin and Ethereum as the leading digital currencies and other coins, such as Ripple (XRP), Tether (USTD), Binance Coin (BNB), enjoying a slow but consistent rise in popularity. It can also be expected that since Bitcoin is the market leader, it has shown steady growth because of its narrative of being digital gold. Ethereum, in contrast, appeared more appealing, thanks to its smart contract prospects for future development. As expected, the XRP, emphasizing financial institution relationships, still proved less volatile, providing evidence of the potential for cross-border payments. Similar to Bitcoin with some differences, Tether suggested the same trajectory but at a different range as it was known as an altcoin. However, Binance Coin maintained a relatively gradual and unimpressive altcoin performance, which is logical because of its function in lowering exchange fees on Binance. In this period, the fundamentals of the newer generation of cryptocurrencies were created, led by Bitcoin and Ethereum in terms of market impact, and the others started to develop their positions.

The post-COVID period witnessed a significant shift in the cryptocurrency market owing to institutional and retail investors' fear of inflation. Bitcoin's graph will most probably show steep incline movements; its price will skyrocket as large organizations such as Tesla incorporate the cryptocurrency. Ethereum resulted from DeFi growth and NFT increased significantly more as the demand for its smart contracts emerged. Some tokens performed better than others during this period, primarily because Binance Coin benefited from the growth of its ecosystem, namely the Binance Smart Chain, which is cheaper than Ethereum for developing DeFi projects. Ripple (XRP), on the other hand, showed modest growth because of the SEC lawsuit that continuously creates investors' doubts, although the currency has been utilized actively in the payments industry. Bitcoin and Tether both trended into the next year, though with less volatility, showing that Tether remained an appropriate alternative investment asset. This period highlighted the dollar store fulfilling Bitcoin's purpose as a store of value, Ethereum dominating in technology delivery, and the emergence of Binance as a player not to be underestimated.



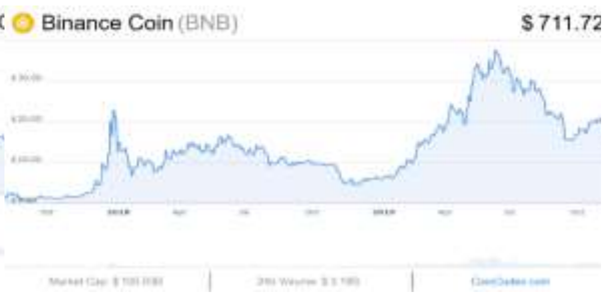


Fig 1: Pre-COVID Graphical Representation (adapted from CoinCodex.Com)

Fig 2: Post-COVID Graphical Representation (adapted from CoinCodex.Com)

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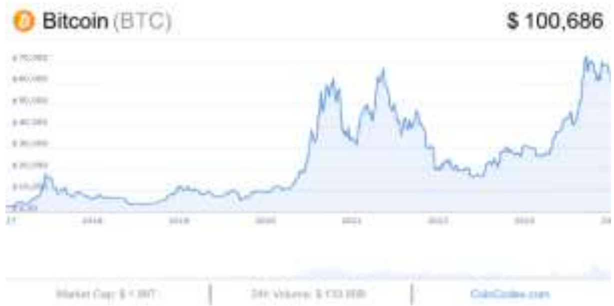

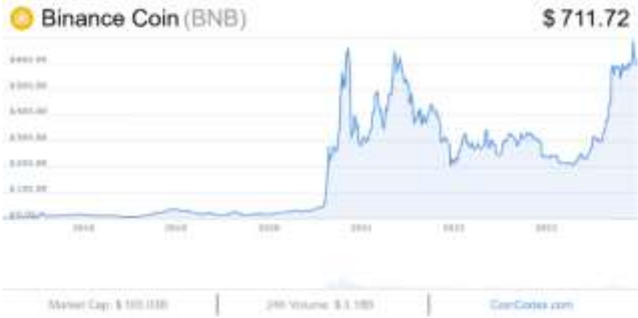

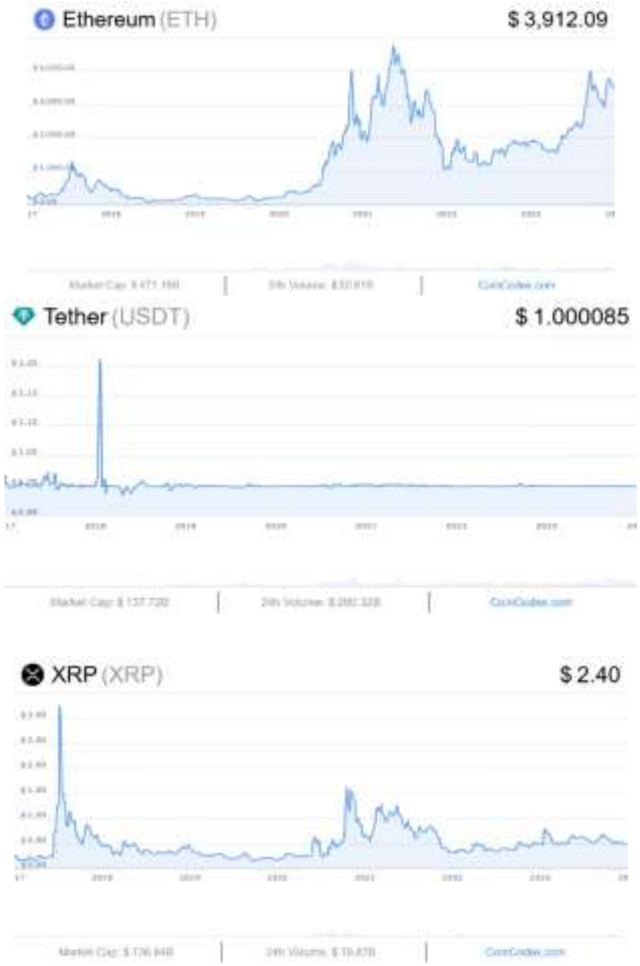

Fig 3: Full Sample Period Graphical Representation (adapted from CoinCodex.Com)

The graphs in question demonstrate an average increasing tendency of all five cryptocurrencies for the entire period, along with the cycles of fluctuation. Bitcoin dominated the market again as it remains the most stable cryptocurrency during market growth and decline periods. This trend probably reflects Ethereum's transformation from a promising platform to a core building block of blockchain technology and its stable monthly growth due to its domination in the DeFi and NFT markets. The graph of Binance Coin, when observed in the full period, may show the gradient, which will be the steepest, indicating the shift of the token from a mere utility token to a vital cog in the cryptocurrency wheel. Ripple, limited by the legal issues that were arising globally, recorded modest but not very impressive growth as compared to others but remained in the fray of cross-border payment solutions. The expanded movements in Tether presumably reflect its performance over the whole period as a more stable but not quite as striking representation of Bitcoin's movements. Altogether, these digital assets depict more than one horse in the market dominated by Bitcoin and Ethereum, with BNB, a rising star, and Ripple and Tether having unique positions.

R/S Analysis

The Hurst exponent with the R/S analysis is employed to look at long-term memory in overall returns for Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Tether (USTD), and Binance Coin (BNB), with the results summarized in **Table III**. As shown in the analysis, the Hurst exponent values during the Pre-COVID and Post-COVID periods for BTC are 0.625 and 0.577, respectively, while for ETH, XRP, USTD, and BNB, the values range from 0.418958 to 0.597126. These findings are indicative of differing levels of market behavior among the cryptocurrencies. Using log returns as a standard proxy for daily information arrival, the R/S methodology reveals statistically significant results across all analyzed cryptocurrencies. Statistically significant results confirm the existence of long-term memory in the return series for each cryptocurrency. For instance, Bitcoin, with a pre-COVID Hurst exponent of 0.625 and a post-COVID value of 0.577, reflects a persistent property before and after the pandemic. However, the persistence diminishes slightly in the post-COVID period.

The stability index, depicted by Hurst exponent, rises in the post-COVID period for Ethereum and Binance Coin, rising from 0.552371 to 0.597126 and 0.537709 to 0.567498, respectively. This implies that externalities, including the pandemic, may have affected trading behavior and market efficiency. On the other hand, Tether (USTD) has the properties of mean reversion both before and after COVID-19 with a Hurst exponent of 0.418958 in the Pre-crisis phase and 0.390731 in the post-crisis phase. This characteristic suggests that movements in the Tether prices cannot be correlated with trends in other cryptocurrencies. The calculated t-statistic values of all cryptocurrencies indicated the non-random walk hypothesis with the computed t-values majoring critical thresholds. For instance, the t-statistic for Bitcoin is 6.25 Pre-COVID and 3.85 Post-COVID based on p-values of 0.0003 and 0.025, respectively, reinforcing the persistence property. Likewise, the results obtained for Ethereum and Ripple present high long-term memory processes, as the committed p-values are below 0.05 in both analyzed periods.

Therefore, the research evidence supports that dimensions of long-term memory and the non-random walk correspond to cryptocurrency markets and are crucial factors for investors and portfolio managers. In this context, the attributes characteristic of the continuous data series inferred in the analysis suggest the appropriateness of momentum trading strategies in these markets. Furthermore, as elaborated, a Tether is suitable as a hedging instrument. The observed shifts in market dynamics between the pre-COVID and post-COVID periods underline the need for adaptive risk management strategies in response to external shocks. These insights provide a deeper understanding of market efficiency and the evolving nature of cryptocurrency markets.

Table III: Long memory test for log-return among Cryptocurrencies

Crypto	Statistic	Pre COVID	Post COVID
BTC	"Hurst Exponent"	0.625	0.577
	"Standard Error"	0.1	0.15
	"Expected Hurst"	0.5	0.5
	"t-Stat"	6.25	3.85
	"Degrees of Freedom"	2	4
	"p-Value"	0.0003***	0.025*
ETH	"Hurst Exponent"	0.552371	0.597126
	"Standard Error"	0.1	0.15
	"Expected Hurst"	0.5	0.5
	"t-Stat"	5.52	4.0
	"Degrees of Freedom"	2	4
	"p-Value"	0.001***	0.012*
XRP	"Hurst Exponent"	0.556487	0.55952
	"Standard Error"	0.1	0.15
	"Expected Hurst"	0.5	0.5
	"t-Stat"	5.56	3.73
	"Degrees of Freedom"	2	4
	"p-Value"	0.001***	0.022*
USTD	"Hurst Exponent"	0.418958	0.390731
	"Standard Error"	0.1	0.15
	"Expected Hurst"	0.5	0.5
	"t-Stat"	-5.72	-4.69
	"Degrees of Freedom"	2	4
	"p-Value"	0.004**	0.005**
BNB	"Hurst Exponent"	0.537709	0.567498
	"Standard Error"	0.1	0.15
	"Expected Hurst"	0.5	0.5
	"t-Stat"	5.38	3.79
	"Degrees of Freedom"	2	4
	"p-Value"	0.006**	0.017*

Note: Asterisks indicate the level of statistical significance, where * represents significance at the 5% level,
** represents significance at the 1% level and *** at the 0.1% level.

Conclusion

Cryptocurrency markets are increasingly recognized for their complex and dynamic behavior, driven by long-term memory properties and the interplay of various external shocks. This study provides empirical evidence of long-term memory in cryptocurrency returns, as measured by the Hurst exponent and validated through statistical significance tests. By analyzing five leading cryptocurrencies, including Bitcoin, Ethereum, Ripple, Tether, and Binance Coin, we identify significant variations in persistence levels, particularly in response to the COVID-19 pandemic. It is revealed by the Hurst analysis that there is varying persistence level amomg sample digital currencies. The most popular digital currency Bitcoin's persistency decreased in post COVID era, whereas ETH and BNB showed increased persistent behavior in post COVID period, might be due to their roles in DeFi. A mean-reverting behavior is shown by USTD consistently, which confirms it as a stable hedging tool. These findings shows the significant impact on the digital market dynamics from the external pandemic.

Our findings are consistent with the previous studies that focus on the impact of external shocks on the digital markets (e.g., Bouri et al., 2021; Corbet et al., 2022). The Hurst exponent values of all the sample cryptocurrencies support the rejection of the hypothesis of random walk, underpins that the prices can be predicted by historical data. The descriptive and graphical analysis both collectively give the nuanced understanding of market behavior, highlighting a complex interplay of volatility, persistence and external shocks. These findings are important for policymakers and investors. Understanding the mean reverting behavior and persistence level the investors can make good portfolio strategies and hence can manage the risk properly. Post-COVID market dynamics shows the requirement of the adaptive trading tactics and policymakers need to make strong regulatory frameworks to maintain stability and efficiency. So, it is recommended that initiatives of educating investors should be introduced so that their awareness and understandings of mean reverting behaviors and persistence level can be increased, which ultimately enable them to better aligned investment strategies.

Future Research Directions

In future we will explore the impact of macroeconomic variables on the digital currencies' behavior which will provide the broader and better insights of the market behavior.

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