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Examining Cryptocurrency Market Efficiency in Light of the COVID-19 Pandemic: A Comparative Analysis

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Abstract

This article delves into the intricacies of financial market efficiency, with a particular emphasis on the impact of long memory on market inefficiency. Contrary to the efficient market hypothesis, the presence of long memory suggests a departure from efficiency, influencing investment decisions and the adaptability of investors. The study transitions its focus to the realm of cryptocurrencies, underscoring their susceptibility to behavioral biases and offering a comparative analysis between Islamic and conventional models. The empirical investigation is anchored in the context of the COVID-19 pandemic, employing the Multifractal Detrended Fluctuation Analysis (MFDFA) methodology to evaluate market efficiency, fractality, and herding behavior within cryptocurrency markets. The findings not only highlight the distinctive characteristics of these markets but also underscore their practical implications for policymakers and financial managers, particularly in light of the pandemic's unprecedented challenges.

Keywords: *Cryptocurrencies, Efficiency, COVID-19, Herding Behavior, stablecoins.*

Introduction

As stated by Fama (1970), markets that are informationally efficient do not retain memory, which means investors cannot gain excess returns in relation to the risk they take. If a series exhibits long memory, it contradicts the Efficient Market Hypothesis (EMH) and suggests market inefficiency. In an inefficient market characterized by long memory, prices depend on past values, enabling the prediction of returns and the realization of excess profits. The weak form of market efficiency, focusing on the past values of prices and trading volumes (Nan & Kaizoji, 2019), influences investors' allocation decisions, impacting their investment horizon (Rejichi & Aloui, 2012).

The study of the weak form of market efficiency includes analyses of linear autocorrelation, unit root, as well as tests of variance ratio in returns. Contemporary and causal studies also examine the price-volume relationship. Mandelbrot & Mandelbrot (1997) argue that asset returns exhibit a multi-fractal nature. Market inefficiency is often studied using this multi-fractal characteristic of assets.

In markets characterized by inefficiency, investment choices are influenced by investor behavior and constrained by their rational comprehension of market dynamics over time. Consequently, investors adjust their investment strategies in response to evolving business conditions, thereby contributing to the adaptability of the market. Studies by Cajueiro & Tabak (2009) have observed that numerous underdeveloped markets demonstrate long memory characteristics.

The existence of long memory in financial markets holds significance for policymakers, urging them to devise strategies aimed at mitigating investment disparities. Therefore, before policy implementation, it is crucial to confirm the presence of long memory in a

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series. Since 2009, Bitcoin has garnered the interest of both investors and researchers, sparking a growing fascination with cryptocurrencies and blockchain technology in recent times.

From a behavioral perspective, cryptocurrencies produce extensive data that delineates investor preferences (Böhme et al., 2015). Without inherent fundamental value, cryptocurrencies are susceptible to sentiment-related challenges and behavioral biases (Kaiser & Stöckl, 2019). Incidents such as disasters or pandemics, such as COVID-19, can trigger particular behavioral biases, especially among Muslim investors endeavoring to align their investments with religious principles.

From an Islamic viewpoint, the majority of cryptocurrencies lack backing from tangible assets, thereby conflicting with Sharia principles (Siswantoro et al., 2020). However, innovative solutions have emerged, utilizing blockchain technology to anchor cryptocurrencies to assets like gold, as seen in projects such as X8X and HelloGold, to comply with religious guidelines. In contrast to conventional cryptocurrencies, Sharia-compliant ones are backed by quantitative financial components to guarantee stability in pricing. Gold-backed cryptocurrencies derive their value from physical gold, offering enhanced stability as a result. This study proposes a comparison of inefficiency level and herding bias across conventional, Islamic, and stablecoin cryptocurrency markets.

The empirical part aims to explore herding behavior biases and estimate the level of efficiency and fractality during the COVID-19 pandemic, using a trendless multi-fractal detrended fluctuation analysis (MFDFA). The first section presents prior work on inefficiency and fractality, as well as the presence of herding behavior. The second section outlines the methodology employed and provides an overview of the data utilized. The third section delves into the outcomes and their interpretations, while the conclusion examines practical and managerial implications.

Literature Review

Financial stability and market efficiency have been central to previous research. In accordance with Fama's Efficient Market Hypothesis (1970), the valuation of assets incorporates all accessible information and is promptly mirrored in investor actions. Hence, it's crucial to emphasize that a decrease in market inefficiency indicates reduced predictability in pricing.

Several academic inquiries have delved into assessing the efficacy of cryptocurrency markets, with studies conducted by Bariviera (2017), Nan and Kaizoji (2019), Meng and Khan (2023). These investigations have collectively challenged the notion of market efficiency, as their findings consistently refute the hypothesis. Additionally, another strand of research, as explored by Bariviera (2017), has analyzed the progression of market inefficiencies in cryptocurrency markets through the application of technical and fundamental methodologies. Multi-fractal models have emerged as more resilient alternatives to previous Gaussian distribution-based theories for discerning financial market stability (Fry & Cheah, 2016). Mandelbrot (1975) introduced fractal theory, characterizing fractals as intricate geometric entities with scaling properties. This theoretical framework has been utilized in the analysis of Sharia-compliant markets by Selmi et al., (2018), utilizing MFDFA to assess Islamic market efficiencies. Consequently, this study embraces fractal theory to assess the efficiency of cryptocurrency markets across various scales and formulate an inefficiency index for comparative analysis of their distinct behaviors.

The ongoing COVID-19 pandemic has resulted in significant disruptions to financial stability and the global economy. Numerous studies have investigated the impact of COVID-19 on stock market efficiency, as evidenced by research conducted by Meng and Khan (2023) and Raza et al., (2024), which highlighted the negative reactions of capital markets to the rise in confirmed cases and fatalities. Similarly, within the same context, various works have investigated financial market stability (Abida and Mnif ,2023; Baek et al.,2020), confirming the adverse effects of the pandemic on capital market stability. Additionally, Ha et al. (2022) explored the efficiency of the gold market during the pandemic and its role as a safe haven, with a particular focus on gold markets. Henceforth, numerous studies have validated the pandemic's role in amplifying the inefficiency of the cryptocurrency market, as exemplified by Lahmiri & Bekiros (2020), who juxtaposed efficiency and informational stability. Concerning gold-backed cryptocurrencies, Yousaf and Yarovaya (2022) scrutinized the performance of these assets amidst the pandemic. However, the exploration of inefficiency levels in gold-backed cryptocurrencies during the pandemic remains relatively limited. Thus, we propose to bridge this gap by investigating the following hypothesis:

H1: The cryptocurrency market is predictable.

Furthermore, it has been widely observed in numerous studies that both the COVID-19 pandemic and the 2008 crisis have led to an increase in herding behavior among investors (Abida and Mnif, 2023; Ferreruela et al., 2021). Espinosa-Méndez and Arias (2020) conducted a study investigating the presence of herding behavior in European stock markets during pandemics. Their research revealed a notable surge in herding bias amidst the crisis. Additionally, they scrutinized the prevalence of herding behavior in oil and energy stock markets during both the COVID-19 pandemic and the global financial crisis. Their findings indicated an uptick in herding behavior during both crisis periods in these markets, particularly during extreme losses in the cryptocurrency market.

The association between multifractality and herding behavior has been investigated in other empirical studies, such as those conducted by Meng and Khan (2023) and Cajueiro and Tabak (2009). These studies have emphasized a correlation between market persistence and the prevalence of herding behavior. Mnif et al. (2020) explored this connection to assess efficiency and the presence of bias in the cryptocurrency market. They demonstrated that herding behavior leads investors to act synchronously, causing persistence in price dynamics ($H>0.5$) and creating long-term memory in price behavior. Expanding on this research, our study aims to detect herding behavior using the inefficiency index (IEI).

Despite the considerable body of literature discussing the effects of the pandemic on financial markets and investor behavior, there remains a gap in understanding its impact on gold-backed cryptocurrencies and stable cryptocurrencies during this period. Thus, this research aims to address this gap by examining the following hypothesis:

H2: The market for Islamic cryptocurrencies is more efficient than conventional and stable ones.

Data

The study used financial data from three types of cryptocurrencies (Bitcoin, Ethereum, Ripple), Islamic currency (X8X), and stable cryptocurrencies (USD Tether) retrieved daily until October 8, 2022. The data came from www.coinmarketcap.com and were divided into two periods: before and after December 31, 2019, when the COVID-19 pandemic began (Table 1).

TABLE 1: DATA DESCRIPTION

Cryptocurrencies	Start Date	Number of Observations
Bitcoin	28/04/2013	2439
Ethereum	07/08/2015	1608

Ripple	04/08/2013	2341
X8X	06/08/2018	512
USDT	25/02/2015	1766

The calculation of cryptocurrency returns is performed as follows:

$$r_t = \text{Log}\left(\frac{p_t}{p_{t-1}}\right) \quad \text{Eq (1)}$$

"r_t and P_t respectively the returns and prices of cryptocurrencies at date t".

Table 2 present the asymmetric characteristics of the distribution of cryptocurrency prices, reflecting the level of inefficiency in these markets. The outcomes of skewness and kurtosis tests indicate that none of the series distributions conform to a Gaussian distribution.

TABLE 2: DESCRIPTIVE STATISTICS OF THE STUDIED CRYPTOCURRENCIES

Cryptocurrency Retunrs	Period	Mean	Std. Dev.	Skewness	Kurtosis	ADF
BTC	Before	0.00066	0.01850	-0.160	7.5847	-49.3***
	After	0.00037	0.01716	-1.635	20.270	-34.0***
ETH	Before	0.00092	0.03095	-3.545	73.526	-38.0***
	After	0.00093	0.02272	-1.369	14.453	-34.3***
XRP	Before	0.00060	0.03138	2.101	29.933	-46.0***
	After	0.00040	0.02761	-0.158	14.380	-33.0***
X8X	Before	-0.00032	0.06372	-2.323	53.119	-30.8***
	After	-0.00044	0.05745	-0.417	23.119	-41.2***
USDT	Before	4.686e-05	0.00264	0.8956	19.738	-51.6***
	After	3.006e-06	0.00146	1.889	77.188	-49.3 ***
USDcoin USDC	Before	-3.229e-05	0.00253	-0.168	2.164	-31.10***
	After	1.532e-05	0.00150	2.295	46.945	-46.5***
Binance USD BUSD	Before	8.473e-05	0.00271	-0.013	-0.0137	-15.24***
	After	-7.883e-06	0.00156	-0.4449	104.706	-51.9***

Methodology

The Our proposed methodology involves two main components:

Initially, we analyze cryptocurrency movements to identify trading opportunities over both short and long periods. Then, we assess the impact of the COVID-19 pandemic on cryptocurrency performance, evaluating efficiency and detecting herding behaviors before and after the pandemic outbreak.

In the first phase, we focus on studying the dynamics of both gold-backed and traditional cryptocurrencies, using fractal theory to identify trading prospects and market inefficiencies. We utilize the MFDFA method, where a series is classified as monofractal if its H(q) remains constant across all values of q. We estimate the multifractal spectrum using different values of m and focus on m = 1 to avoid potential overfitting issues. To measure the roughness of financial markets, we estimate the Holder exponent and define the fractal dimension (d) according to Mandelbrot (1963).

$d = 2 - H$ and $0 < H < 1$ Eq (2)

$d = 1.5 - \alpha$ with $-0.5 < \alpha < 0.5$ Eq (3)

The scale function of the multifractal process τ(q) exhibits concavity, whereas for the monofractal process, it is linear. The formulation of τ(q) can be based on the generalized Hurst exponent as follows:

$$H(q) = \frac{1+\tau(q)}{q}$$ Eq (4)

We set the scaling parameters for the MFDFA method with smin at 10 and smax at (T/4), where T represents the length of the cryptocurrency time series (Ameer et al., 2023). Additionally, τmin was fixed at 1, while τmax was varied from 5 to 20, following the recommendation of Kukacka and Kristoufek (2020). This section also introduced a metric for inefficiency using the generalized Hurst exponent. An IEI value of 0 signifies complete market efficiency, indicating no herding behavior or persistence. The inefficiency index (IEI), as utilized by Mnif et al. (2020), quantitatively evaluates market inefficiency by considering factors such as price fluctuations, trading volumes, and volatility.:

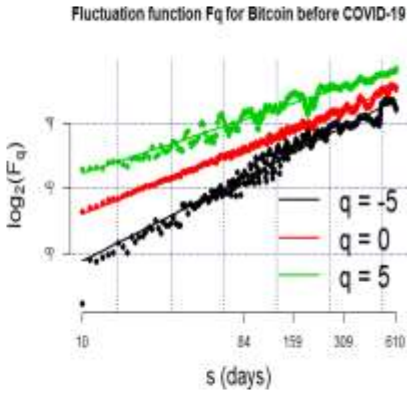
$$IEI = \frac{1}{2}(|h(-5)-0.5| + |h(5)-0.5|)$$ Eq (5)

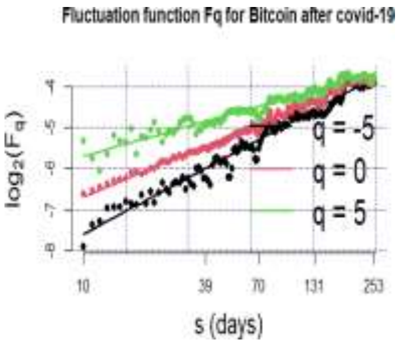
Empirical Findings and Discussion

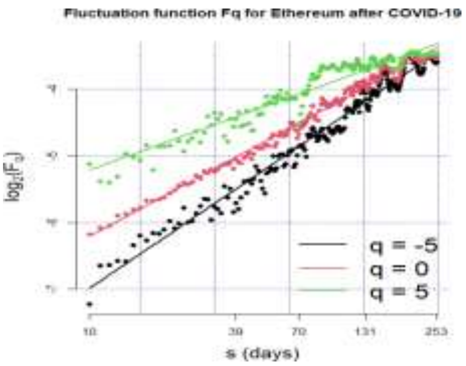
After generating price and return graphs for cryptocurrencies (Figure 1), this study proceeded to analyze their multifractal properties and efficiency dynamics. Figure 1 depicts the relationship between the fluctuation order Fq(s) and length scale (s) in a log- log plot for various cryptocurrency markets including Bitcoin, Ethereum, Ripple, X8X, and USDT, with q ranging from -5 to 5. The q-order RMS offers valuable insights into the magnitude and microstructure of the time series, as discussed by Ghosh and Kozarevic (2019).

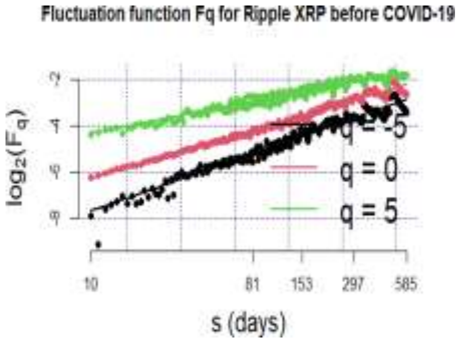
In multifractal analysis, the mass exponent (τ(q)) is a function that describes how the measure (or "mass") of a set scales with the size of the set. It is used to characterize the multifractality of a time series or signal. The mass exponent is related to the qth-order moments of the measure distribution, where q is a real number that can take positive or negative values.

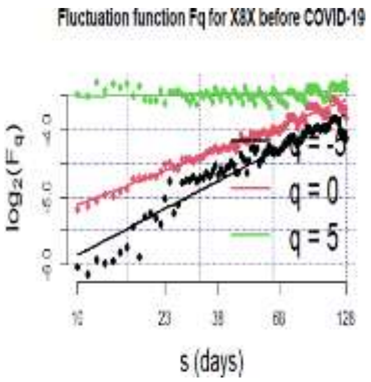
In the context of your study, which investigates cryptocurrency market efficiency before and after COVID-19, the mass exponent graph could be utilized to compare the multifractal properties of the market in these two periods. A change in the shape or position of the τ(q) curve could indicate a shift in the market's multifractal nature, potentially linked to alterations in market efficiency or investor behavior due to the pandemic.

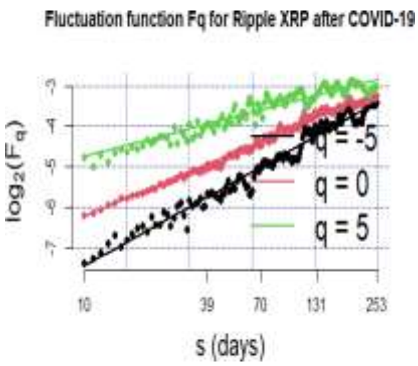

Fluctuation function Fq for Bitcoin before COVID-19
log2(Fq)
q = -5
q = 0
q = 5
10
84
159
309
610
s (days)

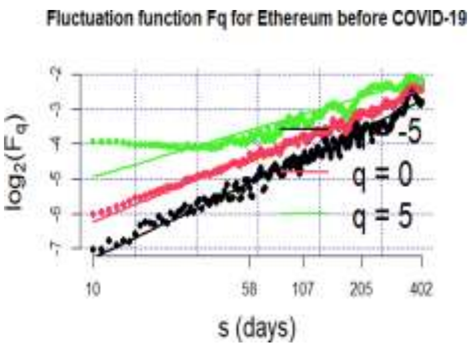

Fluctuation function Fq for Bitcoin after covid-19
log2(Fq)
q = -5
q = 0
q = 5
10
39
70
131
253
s (days)

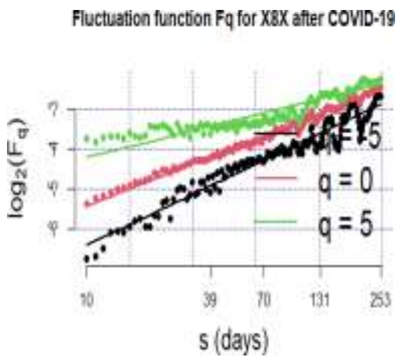

Fluctuation function Fq for Ethereum after COVID-19
q = -5
q = 0
q = 5
s (days)

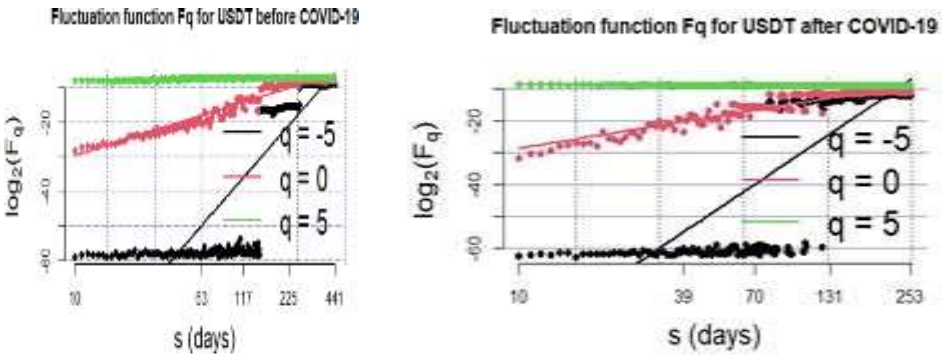

Fluctuation function Fq for Ripple XRP before COVID-19
log2(Fq)
q = 0
q = 5
10
81
153
297
585
s (days)


Fluctuation function Fq for X8X before COVID-19
log2(Fq)
q = 0
q = 5
23
38
128
s (days)


Fluctuation function Fq for Ripple XRP after COVID-19
log2(Fq)
q = 0
q = 5
10
39
70
131
253
s (days)


Fluctuation function Fq for Ethereum before COVID-19
log2(Fq)
q = 0
q = 5
10
58
107
205
402
s (days)


Fluctuation function Fq for X8X after COVID-19
log2(Fq)
q = 0
q = 5
10
39
70
131
253
s (days)

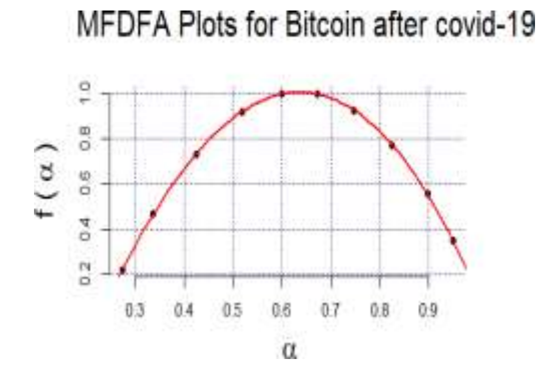


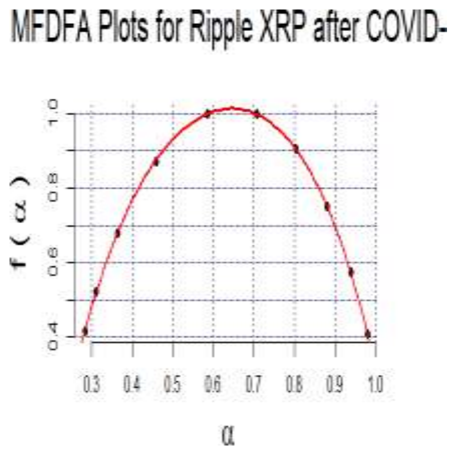
"FIGURE 1: FLUCTUATION FUNCTION BEFORE AND AFTER COVID-19"

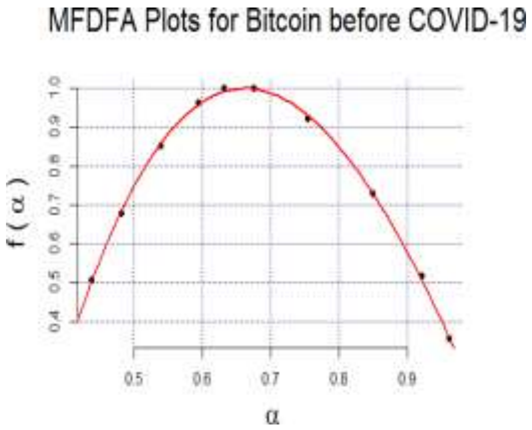
The x-axis represents q, indicating the moment order in multifractal analysis, offering insights into the distribution of returns in financial terms. For instance, q=2 often relates to variance or volatility analysis, while negative q values can signify the analysis of rare events or distribution tails. On the y-axis, τ(q) denotes the mass exponent, characterizing the scaling behavior of probability distribution moments. This analysis, used for datasets with complexity like varying volatility or non-linear correlations over time, provides insights into dataset fluctuations. In financial markets, such analysis aids in understanding the complexity of price changes, such as those of Ripple XRP. The downward trend from q=-4 to q=4 indicates larger fluctuations become less probable compared to smaller ones, a typical multifractal measure characteristic.

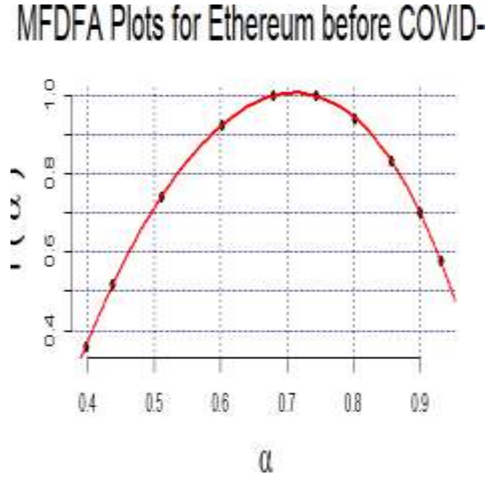
Table 3: "Generalized Hurst Exponent (GHE) Estimation for Cryptocurrencies"

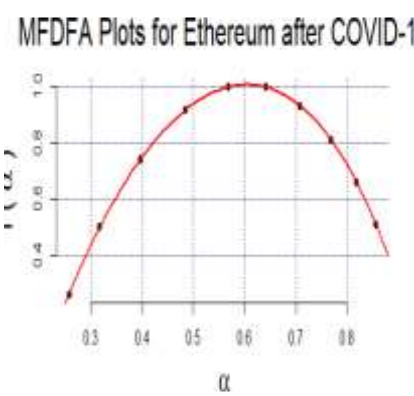
q	Bitcoin		Ethereum		Ripple		X8X		USDT	
	Before	After	Before	After	Before	After	Before	After	Before	After
-5	0,831	0,818	0,847	0,759	0,817	0,861	0,568	0,749	15,899	17,658
-4	0,799	0,786	0,826	0,734	0,796	0,832	0,545	0,731	15,865	17,615
-3	0,759	0,749	0,801	0,706	0,772	0,796	0,518	0,709	15,814	17,517
-2	0,714	0,710	0,773	0,675	0,747	0,755	0,488	0,684	15,722	17,416
-1	0,675	0,673	0,743	0,641	0,723	0,707	0,457	0,656	15,443	17, 033
0	0,649	0,637	0,713	0,606	0,694	0,650	0,421	0,620	4,327	4,213
1	0,631	0,600	0,680	0,568	0,645	0,586	0,369	0,571	0,403	0,251
2	0,613	0,559	0,641	0,526	0,582	0,522	0,284	0,516	0,292	0,087
3	0,588	0,515	0,598	0,483	0,524	0,469	0,178	0,463	0,227	0,013
4	0,561	0,470	0,558	0,442	0,478	0,429	0,086	0,421	0,178	-0,038
5	0,537	0,431	0,526	0,405	0,445	0,400	0,018	0,389	0,141	-0,076

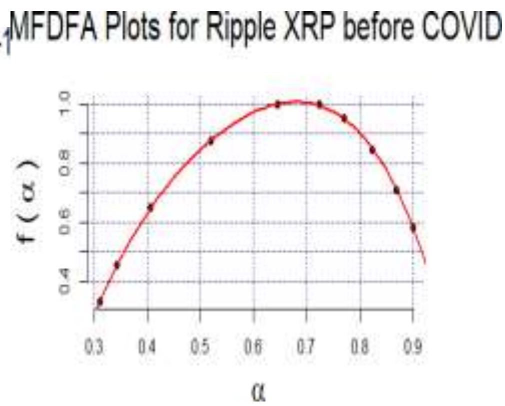

MFDFA Plots for Bitcoin after covid-19
f (α)
α

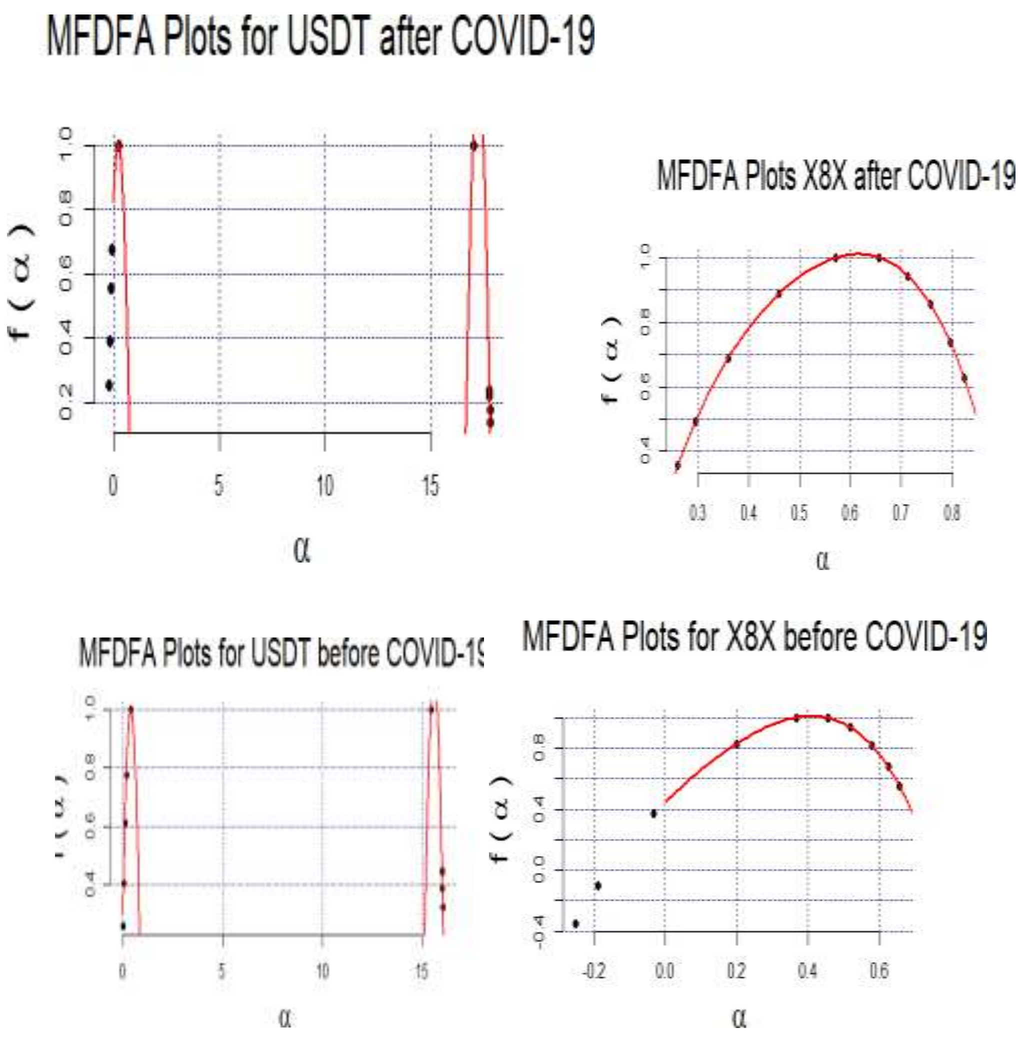

MFDFA Plots for Ripple XRP after COVID-
f (α)
α


MFDFA Plots for Bitcoin before COVID-19
f (α)
α


MFDFA Plots for Ethereum before COVID-
α


MFDFA Plots for Ethereum after COVID-1
α


MFDFA Plots for Ripple XRP before COVID
f (α)
α



"FIGURE 2: MFDFA PLOTS"

In contrast to monofractal series, multifractal series exhibit non-normal distributions. By examining the Fq graphs against s (Figure 1), we determined H (q=±5) due to the consistent variation of the slope across the cryptocurrencies analyzed. The negative and positive values of q, obtained from Table 3, were employed to interpret the impacts of small and large variations, respectively.

In the specific case where q=2, the estimation of the Hurst exponent for conventional cryptocurrencies decreased and approached 0.5 after the COVID-19 epidemic. This suggests that this market is becoming nearly efficient. These results, reflecting the change in Hq(), indicate a decrease in the fractal nature of the conventional market. These findings are consistent with the observations made by Mnif et al. (2020), who noted that cryptocurrency markets display diverse regimes with distinct multifractal characteristics before the onset of the COVID-19 epidemic, which tend to become less fractal afterward.

For the Islamic cryptocurrency X8X, in the case where q=2, the estimation of the Hurst exponent increased and approached 0.5 after COVID-19, suggesting that this market also becomes nearly efficient. In contrast, for the stable cryptocurrency USDT, the estimation of the Hurst exponent decreased and approached 0, indicating that this market is not efficient. These results highlight the differentiated impact of COVID-19 on conventional and Islamic cryptocurrency markets, with a positive effect on the former and a negative effect on stable cryptocurrencies.

Figure 2 displays the plots of α against f(α), representing "the multifractal spectrum." The width Δα signifies the disparity between the upper and lower probabilities, as outlined in Table 4. Multifractality amplifies as Δα broadens (Lu, Tian, Zhou, & Li, 2013). Consequently, multifractality escalates for all cryptocurrencies, with the exception of the Islamic cryptocurrency X8X, following the COVID-19 pandemic, as shown in Table 4.

Recent research has associated fractal theory with Hausdorff topology (Hausdorff, 1918) to evaluate the presence of evolutionary levels and other heuristic biases (Ghosh & Kozarevic, 2019). Notably, herding behavior becomes more pronounced as the shape transitions from the Douady rabbit (with a fractal dimension of d = 1.4 and d = 1.38) to a five-circle inversion fractal (d = 1.36), and ultimately to the Julia dendrite (d = 1.18) and the Gosper island contour (d = 1.12). In essence, the manifestation of herding behavior is substantiated when the fractal dimension (d) varies between 1.12 and 1.4.

According to Table 4, the fractal dimension (d) increased after the pandemic for cryptocurrencies Bitcoin, Ethereum, and Ripple, suggesting a decrease in herding behavior after COVID-19. For Bitcoin, the fractal dimension (d) is approximately 1.36, indicating a five-circle inversion fractal during both periods. This suggests a moderate level of herding behavior. These findings are consistent with the research conducted by Ballis and Drakos in 2019. Moreover, there is an increase in the fractal dimension (d) from the first sub-period (pre-outbreak) to the second (post-outbreak), indicating a reduction in herding behavior between these two periods. This trend corresponds with findings from previous studies, including Mnif and Jarboui (2021), which similarly noted a reduction in bubble risk and inefficiency over time.

TABLE 4: "MULTIFRACTALITY RESULTS BEFORE AND AFTER THE COVID-19 PANDEMIC"

		Δα	ΔHq	Hurst Mean	Fractality Dimension (d)	IEI	Ranking
Bitcoin	Before	0.5226	0.295	0.6688	1.3311	0.184	1
	After	0.6745	0.3873	0.6317	1.3682	0.12475	1
Ethereum	Before	0.5346	0.3214	0.7003	1.2996	0.1862	2
	After	0.5991	0.3539	0.5948	1.4052	0.17695	2
Ripple	Before	0.5898	0.3726	0.6566	1.3433	0.1863	3
	After	0.6963	0.4611	0.6369	1.3630	0.23055	4
X8X	Before	0.9092	0.5492	0.3574	1.6425	0.2746	4
	After	0.5633	0.3601	0.5917	1.4082	0.18005	3
USDT	Before	16.0416	15.7584	7.6645	-5.6645	7.8792	5
	After	18.0562	17.7338	8.3380	-6.3380	8.8669	5

In the Ethereum market, the fractal dimension (d) spans from the Douady rabbit form (with a fractal dimension d = 1.4 and d = 1.38) to the Julia dendrite (d = 1.18) in both periods, indicating the highest level of herding behavior. Additionally, there is an increase in the fractal dimension from the first sub-period (pre-outbreak) to the second (post-outbreak), implying a decrease in herding behavior during these intervals. These findings are consistent with previous research conducted by Celeste et al.,(2020), suggesting reduced inefficiency and minimized bubble risks over time.

In the case of the Islamic cryptocurrency X8X, the fractal dimension exceeds 1.4, suggesting an absence of herding behavior in this market during both sub-periods, both before and after the outbreak. This indicates that investors in the X8X market did not exhibit collective behavior or follow the actions of others during these periods. Moreover, there is evidence to suggest that herding behavior diminished following the pandemic, as reflected by the consistent fractal dimension. These findings underscore a positive impact of COVID-19 on the analyzed cryptocurrencies, potentially indicating greater market stability or investor independence within the X8X market.

To enhance the robustness of our findings, we compute the inefficiency index (IEI) using H(q) as depicted in Table 4. A higher IEI indicates lower market efficiency. The IEI values fall below 0.3 and above 0.18 for all cryptocurrencies except USDT, indicating that these cryptocurrency markets are nearly efficient to differing extents.

It is noted that the IEI decreased after the spread of COVID-19 for the cryptocurrencies Bitcoin and Ethereum, indicating greater efficiency. Conversely, for Ripple, the IEI increased after COVID-19. Thus, it can be concluded that the pandemic has had a positive effect on the conventional cryptocurrency market except for Ripple. The IEI of the cryptocurrency X8X also decreased after the pandemic, making it more efficient, and demonstrating the positive effect of COVID on the Islamic cryptocurrency market. However, the IEI results for USDT were very high before and after the pandemic, showing that this market is not efficient. The values of the IEI closest to zero are attributed to conventional cryptocurrencies, allowing us to conclude that this market is more efficient than the Islamic cryptocurrency market. These results confirm the impact of fractality on herding behavior, as related to Hausdorff topology.

Conclusion

Our study explored blockchain technology, cryptocurrency markets, and concepts like fractality and market efficiency. Fractal theory helped assess herding behavior and quantify market inefficiency across various cryptocurrency categories. We collected data on Bitcoin, Ethereum, Ripple, Islamic cryptocurrency (X8X), and stable cryptocurrency (USDT) until October 8, 2022, then divided the dataset into pre and post-December 31, 2019 periods to analyze the impact of COVID-19 on cryptocurrency efficiencies using the MFDFA method.

The findings indicated that the majority of cryptocurrencies displayed multifractality prior to the COVID-19 pandemic, with a tendency towards reduced multifractality in the aftermath. Changes in the values of H(q) indicated a positive impact of the pandemic on conventional and Islamic markets but a negative impact on stable markets.

The Inefficiency Index (IEI) unveiled that conventional cryptocurrencies (Bitcoin, Ethereum) were the most efficient before and after the pandemic, surpassing the Islamic market (X8X). Fractal dimension (d) exhibited herding behavior in the conventional market, unlike the Islamic market, where investors seemed more rational, and likely influenced by ethical standards.

In conclusion, the analysis suggested that the COVID-19 pandemic exerted a favorable influence on both conventional and Islamic cryptocurrency markets, while the fractal dimension highlighted a decrease in herding behavior post-pandemic. The use of the Fractality and Inefficiency Index (IFI) can be valuable for investors in developing their trading strategies, and future research could extend this analysis to other unexplored cryptocurrencies.

Practical and managerial implications

The study provides valuable insights into cryptocurrency market efficiency during the COVID-19 pandemic, highlighting the impact of long memory on market inefficiency and its implications for investment decisions. It emphasizes the vulnerability of cryptocurrencies to behavioral biases and the importance of policymakers and financial managers understanding market dynamics during crises. The increased inefficiency observed in the gold-backed and stable cryptocurrency markets suggests the need for close attention from speculators and policymakers. The study also indicates a positive influence of the pandemic on the efficiency of conventional cryptocurrencies like Bitcoin and Ethereum, contrasting with negative effects on stable cryptocurrencies. This differentiation in market efficiency between conventional and Islamic cryptocurrency markets has significant implications for investors. The use of fractal theory to assess herding behavior and market inefficiency offers valuable insights for developing trading strategies. Additionally, the study suggests avenues for further research in exploring the efficiency of other cryptocurrencies. Overall, the research's implications are crucial for understanding cryptocurrency market dynamics during global crises, guiding investment and policy-making strategies effectively.

In conclusion, the study underscores practical implications for understanding and navigating cryptocurrency markets during the COVID-19 pandemic. By exploring biases related to herding behavior and evaluating efficiency and fractality levels using MFDFA, the research offers insights for practitioners and managers. For practitioners, understanding these dynamics can inform investment strategies and enhance risk management practices. Managers, particularly in the financial sector, can leverage these insights to develop resilient financial products and services. The findings highlight the importance of considering behavioral biases and market efficiency in decision-making processes, leading to more informed cryptocurrency investments and portfolios management.

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