TEME, Vol. XLVIII, Nº 1, January – March 2024, pp. 93–112

Original research paper
Received: December 28, 2022
Revised: December 28, 2022
Accepted: May 22, 2023

https://doi.org/10.22190/TEME221228014R
UDC 004.9:[616.98:578.834

THE EFFECTS OF COVID-19 ON MULTIFRACTALITY AND LONG-MEMORY IN ETHEREUM'S RETURNS

Jelena Radojičić*, Ognjen Radović

University of Niš, Faculty of Economics, Niš, Serbia

ORCID iDs: Jelena Radojičić https://orcid.org/0000-0003-3444-0138
Ognjen Radović https://orcid.org/0000-0001-7428-565X

Abstract

The global COVID-19 pandemic has shaken the global economy, not sparing the cryptocurrency market. In this paper, we investigate the impact of the COVID-19 pandemic on the dynamics of log returns of the Ethereum. The observed period is divided into three parts: the pre-pandemic period, the pandemic-induced shock, and the period after the pandemic-induced shock on the cryptocurrency market. The research focuses on the impact of the pandemic on the degree of non-linearity and multifractality of log returns. To assess the degree of non-linearity, we used the BDS test and the value of the largest Lyapunov exponent. For multifractality, long-range correlations and information efficiency, we used MF-DFA (Multifractal Detrended Fluctuation Analysis). The research results show that all observed periods have a pronounced non-linearity, but that there is no evidence of the existence of low-dimension chaos. Also, based on the results of the MF-DFA analysis, we conclude that the COVID-19 pandemic has significantly affected the long memory of the log returns of the Ethereum; however, their dynamics and characteristics are returning to the trends present before the pandemic.

Key words: COVID-19, cryptocurrency market, multifractality, chaos, market efficiency.

ЕФЕКТИ КОВИД-19 ПАНДЕМИЈЕ НА МУЛТИФРАКТАЛНОСТ И ДУГОРОЧНУ МЕМОРИЈУ ПРИНОСА *ETHEREUM*-а

Апстракт

Глобална пандемија КОВИД-19 узбуркала је глобалну економију, па и тржиште крипотовалута није било поштеђено. У овом раду истражујемо утицај КОВИД-19 пандемије на динамику логаритамског приноса Ethereum-a. Посматрани период подељен је на три дела: период пре пандемије, период шока који је изазан пандемијом и период након шока изазваног пандемијом на тржишту

* Corresponding author: Jelena Radojičić, University of Niš, Faculty of Economics, Trg kralja Aleksandra 11, 18000 Niš, Serbia, jelena.radojicic@eknfak.ni.ac.rs

криптовалута. Акценат истраживања је на утицају пандемије на степен нелинеарности и мултифракталности приноса. За процену степена нелинеарности користили смо BDS тест и вредност највећег Лапуновљевог експонента. За мултифракталност, дугорочне корелације и информациону ефикасност користили смо MF-DFA (Multifractal Detrended Fluctuation Analysis). Резултати истраживања показују да сви посматрани периоди имају изразиту нелинеарност, али да нема доказа о постојању нискодимензионалног хаоса. Такође, на основу резултата MF-DFA анализе закључујемо да је пандемија КОВИД-19 значајно утицала на дугорочну меморију логаритамских приноса *Ethereum*-а. Међутим, њихова динамика и особине враћају се трендовима присутним пре пандемије.

Кључне речи: COVID-19, тржиште криптовалута, мултифракталност, хаос, тржишна ефикасност.

INTRODUCTION

Cryptocurrencies are privately-issued digital money based on a decentralised network relying on blockchain technology. It is a system that is independent of monetary authorities, where the security of cryptocurrencies is based on the security of the algorithm that monitors all transactions. Since the appearance of Bitcoin, as the first successful implementation of the concept of a decentralised money transfer system (Nakamoto, 2009), the cryptocurrency market has been continuously developing. The cryptocurrency market is significantly different from traditional markets because it can be transacted 24 hours a day, there is no limit to the fluctuation range, and the barrier to entry is low (Cheng, Liu, & Zhu, 2019). Cryptocurrency users increasingly treat their investments as a speculative financial asset rather than a means of payment (Glaser, Zimmermann, Haferkorn, Weber, & Siering, 2014; Elliott & de Lima, 2018). Low barriers to market entry allow the presence of a large number of inexperienced investors (outsiders), whose behaviour can be irrational (susceptible to rumours, emotions, etc.), which, along with market immaturity, can lead to its inefficiency. Cryptocurrency markets are subject to oscillations, with episodes of extreme volatility. Financial markets can react to natural disasters, crises, terrorist attacks and epidemics. One such event is the COVID-19 pandemic (Goodell, 2020). Due to the rapid spread of the coronavirus around the world, the World Health Organization officially declared the beginning of the pandemic on 11 March 2020. Concerns about the transmission of the coronavirus, and uncertainty about the duration and the economic consequences of the pandemic have affected people's economic behaviours. In conditions of uncertainty, people generally react more to public information and follow the behaviour of the majority, which can also reflect on market trends in the form of herd behaviour. Repeated patterns of behaviour among investors on the market can lead to a rise in volatility, speculative bubbles and crashes.

The smallest cryptocurrencies follow the largest, which indicates that investors base their decisions on the performance of the leading cryptocurrencies (Vidal-Tomás, Ibáñez, & Farinós, 2019). Bitcoin is still the dominant cryptocurrency that, along with Ethereum, accounts for the largest share of the total market capitalisation on cryptocurrency markets. Launched in 2015, Ethereum is a special Blockchain, with a special token called Ether (ETH symbol in exchanges). While Bitcoin is only a payment network, Ethereum is programmable technology for building apps and organisations, holding assets, transacting and communicating without being controlled by a central authority (www.ethereum.org). In late 2022, the share of Bitcoin in total market capitalisation was around 39%, and Ethereum’s was around 19%. (Coinmarketcap, 2022). The duration of the Covid-19 pandemic brought about the need to assess how it affected cryptocurrency market dynamics. Research by Naeem, Bouri, Peng, Shahzad & Vo (2021) shows that the COVID-19 pandemic has had negative effects on the efficiency of leading cryptocurrencies. Danylchuk et al. (2020) applied fractal and entropy analysis to simulate the cryptocurrency market, and concluded that the cryptocurrency market has indeed reacted to the COVID-19 crisis, but that pre-pandemic trends are returning. Lahmiri & Bekiros (2021) found that the level of stability in cryptocurrency markets significantly dropped during the pandemic, and that they showed greater instability and more irregularities during the COVID-19 pandemic compared to international stock markets. Using asymmetric multifractal detrended analysis, Kakinaka & Umeno (2021) investigated the market efficiency of major cryptocurrencies during the COVID-19 pandemic, and found that they showed stronger multifractality in the short term, but weaker multifractality in the long term. A study on the level of efficiency of the cryptocurrency market before and after the COVID-19 pandemic based on multifractal analysis showed a positive impact of COVID-19 (Mnif, Jarboui & Mouakhar, 2020). Diaconaşu, Mehdian & Stoica (2022) used abnormal returns and abnormal trading volumes methodologies to find that the efficiency of Bitcoin increased during the pandemic, thus turning this stressful period into an advantage for this cryptocurrency. Wu, Wu, & Chen (2022) showed that the Bitcoin market kept efficient during the pandemic, had a similar efficiency to spot gold, and was more efficient than Ethereum, Binance Coin, and the S&P 500 were during the pandemic. Mnif, Salhi, Trabelsi, & Jarboui (2022) applied multifractal analysis to quantify the impact of the spread of COVID-19 on gold-backed cryptocurrencies, and found the presence of herd behaviour, but at a lower level than in the case of the Bitcoin market. Assaf, Bhandari, Charif, & Demir, E. (2022) investigated long-memory behaviour in cryptocurrency returns and their fractal characteristics. The authors found a change in long-range correlation for most cryptocurrencies, with a noticeable downward trend in persistence after the 2017 bubble, and then a dramatic drop after the outbreak of COVID-19.

The largest number of studies deals with the study of Bitcoin dynamics, and a small number with other cryptocurrencies (Corbet, Lucey, Urquhart, & Yarovaya, 2019). In this research, we choose to study the returns of Ethereum as the second cryptocurrency by market capitalisation. Accordingly, the aim of the paper is to test the multifractality and long-term memory of Ethereum returns, proceeding from the assumption that the COVID-19 pandemic had an impact on the dynamics of the time series of cryptocurrency returns. The paper is organised as follows. After the introduction, the second part of the paper gives a theoretical overview of the used methodology. The third part of the paper presents the research results, and the final part summarises our conclusions.

METHODOLOGY

The research focuses on the impact of the pandemic on the degree of non-linearity and multifractality of the log return. Tsallis entropy (TsEn) is one of the indicators of critical phenomena in complex systems, and represents a measure of orderliness, uncertainty and randomness of time series. We used the value of the TsEn indicator to separate the observed period into three segments: the period before the pandemic, the period of the pandemic-induced shock, and the period after the pandemic-induced shock on the cryptocurrency market. To assess the degree of non-linearity, we used the BDS test, Hurst exponent, and the value of the largest Lyapunov exponent. For multifractality, long-range correlations and information efficiency, we used MF-DFA (Multifractal Detrended Fluctuation Analysis).

BDS Test

The BDS test (Brock, Dechert, Lebaron, & Scheinkman, 1996) is applied to identify non-linear serial dependence in time series. Due to the apparently random numbers, the series can give the impression of white noise. In that case, the non-linear pattern can remain hidden. In order to gain insight into the behaviour of such time series, it is important to detect non-linear hidden patterns. The BDS test is essentially a statistic based on the correlation integral, which measures how many times a pattern repeats itself in the data. Before testing for non-linearity, a simple linear dependence, or certain daily seasonality in the data is filtered out. For X_t, where t=1,2,...,T-m data m-histories are defined as $X_t^m = (x_t, x_{t+1,}, \dots, x_{t-m+1})$. The correlation integral at embedding dimension m is computed as (Gunay & Kaşkaloğlu, 2019):

$$C_m(\varepsilon) = \frac{1}{(T - m + 1(T - m))} \sum_{\forall t,s} I_\varepsilon (x_t^m, x_s^m) \quad (1)$$

,

where $I_{\varepsilon}(x_t^m, x_s^m)$ is an indicator function that equals one if $\|x_t^m - x_s^m\| \leq \varepsilon$, and zero otherwise. According to Brock, Dechert, Lebaron, & Scheinkman (1996) the BDS test statistic follows as:

$$W_{m,T}(\varepsilon) = \sqrt{T}\,\frac{(Cm,_T(\varepsilon) - C_1, T(\varepsilon)^m)}{\sigma_{m,\tau}}, \tag{2}$$

where σ is the standard deviation of the sample data.

Tsallis Entropy

Entropy represents a measure of orderliness, uncertainty and randomness of time series. Financial time series can rarely be described as a stochastic process with a Gaussian probability density function. Distributions are often elongated with the so-called heavy tail due to the existence of extreme values. Tsallis entropy, which is often called non-extensive or non-additive entropy, simply describes a system with a long memory and is effective in detecting tails in the obtained data entropy distributions. The entropy presented by Tsallis (1988) is based on a generalisation of the Shannon entropy and is defined as follows:

$$S_q = \frac{k}{q-1}\left(1 - \sum_{i=1}^{n} p_i^q\right), \tag{3}$$

where k is a positive constant, n is the number of microstates in the system, p_i probabilities that correspond to microstates and meet the condition $\sum_{i=1}^{n} p_i$=1. The number $q \in R$ represents an entropic index that describes a system with non-extensive properties and is used to characterise the degree of non-extensivity of the system. For continuous probability distributions, the entropy is computed as:

$$S_q = \frac{1}{q-1}\left(1 - \int f(x)^q dx\right), \tag{4}$$

where $f(x)$ is the probability density function. When $q < 1$, it indicates rare occurrences; when $q > 1$, it indicates recurring occurrences, and $q \to 1$ reduces Tsallis entropy to Shannon entropy. High entropic index values can be considered a long memory parameter because they occur when there is a long-term relationship between states in the system (Danylchuk et. al., 2020).

Lyapunov Exponents

The assessment of the properties of non-linear dynamic systems and the presence of low-dimensional chaos in the data can be performed using Lyapunov Exponents. These exponents represent a quantitative measure of the system's chaotic behaviour, that is, they measure its sensitivity to initial conditions. Chaos produces a certain loss of information in the initial phase, which can explain the complex behaviour of real systems. Calculating the largest Lyapunov exponent makes it possible to distinguish deterministic chaos from 'noise' caused by random external influences. In a chaotic system, the distance between two initially close points increases exponentially. The change in distance over time $d(t)$ is shown by the following formula:

$$d(t) = Ce^{\lambda t}\,, \tag{5}$$

where C is a constant that normalises the initial separation, and λ is the Lyapunov exponent. For an n-dimensional system, there are n different values of the Lyapunov exponent. If $x_{t+1} = f(x_t)$, $t \in T$, $x \in R^n$, Lyapunov exponents can be defined as (Wolf, Swift, Swinney, & Vastano, 1985):

$$\lambda = \lim_{T\to\infty} \frac{1}{T} \log_e \| J_{t-1.}\, J_{t-2\ldots}\; J_0 \|, \tag{6}$$

where J is a Jacobian matrix of partial derivatives for the map f.

If the largest Lyapunov exponent has a value greater than zero, it indicates a deterministic chaotic behaviour of the system. A positive Lyapunov shows the average rate at which the distance between two close points grows exponentially. A negative value indicates a stochastic system.

Fractal Analysis and Hurst Exponent

The presence of long memory and the existence of long-range correlations in the observed data is verified by appropriate non-parametric tests. Hurst (1956) developed rescaled range analysis (R/S), a non-parametric methodology that measures the intensity of long-range correlations in time series, and enables the distinction between random and non-random series. The Hurst exponent is one of the methods for time series analysis with fractal characteristics. To measure the degree of complexity, we look for a relationship between how quickly the size changes as the scale decreases. The self-similarity of a fractal time series can be described by the value of the fractal dimension. The law that establishes the relationship between the magnitude of the change and the scale is the power law, which is shown by the following relation:

$$y \sim x^D\,, \tag{7}$$

where D represents the fractal dimension.

The multiscale method is based on the correlation of multifractal analysis and the Hurst exponent. The multifractal spectrum identifies deviations of the fractal structure in time periods with large and small fluctuations. Kantelhardt et al. (2002) developed a method for multifractal characterisation of non-stationary time series, which is based on a generalisation of detrended fluctuation analysis (DFA). Multifractal detrended fluctuation analysis (MF-DFA) estimates the multifractal spectrum of time series by estimating the multifractal spectrum of power law exponents. According to Kantelhardt et al. (2002) the generalised multifractal DFA (MF-DFA) procedure involves the following five steps.

In the first step, the 'profile' or cumulative sum $Y(i)$ is identified as follows:

$$Y_i \equiv \sum_{k=1}^{i} [x_k - \langle x \rangle], \qquad i = 1, \dots, N \tag{8}$$

where x_k is the time series of length N, and $\langle x \rangle$ is the mean value of the entire series.

The second step involves dividing the profile Y_i into non-overlapping segments of equal length s. In order not to ignore the parts of the series that remain due to the divisibility of N with time scale s, the same procedure is repeated from the other end. Thus, $2N_S$ is obtained.

The next step estimates the local trend of the segments using the least-square fitting polynomial $y_v(i)$ for each segment of length v:

$$F^2(s,v) \equiv \frac{1}{s}\sum_{i=1}^{s} \{Y[(v-1)s+i] - y_v(i)\}^2, \text{for } v = 1, \dots, N \tag{9}$$

and

$$F^2(s,v) \equiv \frac{1}{s}\sum_{i=1}^{s} \{Y[N-(v-N_s)s+i] - y_v(i)\}^2, \text{for } v = N_{s+1}, \dots, 2N_{s.} \tag{10}$$

Local trends are removed in all segments, and the trend removal process is repeated for different values of s.

In the fourth step, the average for all segments is calculated to obtain the fluctuation function of the q-th order ($q \neq 0$):

$$F_q(s) \equiv \left\{\frac{1}{2N_s}\sum_{v=1}^{2N_s} [F^2(s,v)]^{q/2}\right\}^{1/q} \tag{11}$$

$F_q(s)$ depends on DFA of order m, and is defined only for $s \geq m + 2$. To see how the generalised q-dependent fluctuation functions $F_q(s)$ depend on the time scale s for different values of q, steps 2 to 4 are repeated for several time scales s.

Finally, the scaling behaviour of the fluctuation functions is determined by analysing the log-log plots $F_q(s)$ versus s for each value of q. $F_q(s)$ grows as a power-law:

$$F_q(s) \sim s^{h(q)}. \tag{12}$$

For stationary time series, $h(2)$ is identical to the Hurst exponent H, so the function h(q) represents the generalised Hurst exponent (Kantelhardt et al., 2002). The DFA method shows long-term correlations of non-stationary time series, and ignores obvious random correlations that are a consequence of non-stationarity (Danylchuk et al. 2020). It is significant for the investigation of multifractality in financial time series. With-in MF-DFA, the power-law relation between the q-order RMS (root-mean-square) is equal to the Hurts exponent of the q-th order (Ihlen, 2012).

If the value of the Hurst exponent is H= 0.5, the observed series is stochastic, that is, it follows a random walk. If H is in the range $0 < H < 0.5$ the observed series shows the existence of antipersistence, generating reversals much more often than a random walk. Processes are short-range dependent. When H is in the range $0.5 < H < 1$, the observed series is the trend-resistant time series, and shows a long memory. As multifractality is associated with the presence of long-memory in cryptocurrency returns data, it opposes the efficient market hypothesis (EMH) in finance theory.

Based on the Hurst exponent, the inefficiency index can be defined as follows (Gu, Shaob & Wang, 2013):

$$InffIdx = |H(2) - 0.5|, \tag{13}$$

where $H(2)$ is the Hurst exponent calculated by the MF-DFA method when q = 2. If $H(2) > 0,55$ or $H(2) < 0,45$ then we assume that the market is inefficient.

RESULTS AND DISCUSSION

Data and Descriptive Statistics

In this paper, we use the hourly closing prices of the Ethereum cryptocurrency in the interval between 6 January 2019 and 17 January 2022 (data source: Coinbase). The interval is divided into three parts: Ethereum price trend before Covid-19 (symbol ETH-Pre-Covid19, from 06/01/2019 to 16/3/2020, 10461 observations), Ethereum price trend during Covid-19- induced shock (symbol ETH-Covid19, from 16/3/2020 to 24/5/2021, 10440 observations), and Ethereum price trend after Covid-19-induced shock (symbol ETH-Post-Covid19, from 24/5/2021 to 17/1/2022, 5713 observations). We use logarithmic returns on prices in our analyses. For the sake of comparison, some tests show the results for the white noise series – WNOISE. A graphic representation of the observed series is shown in Figure 1. A graphical representation of the log return of each series is given in Figure 2.

Figure 1. Graphic presentation of Ethereum price and return trends
Source: Authors' calculations

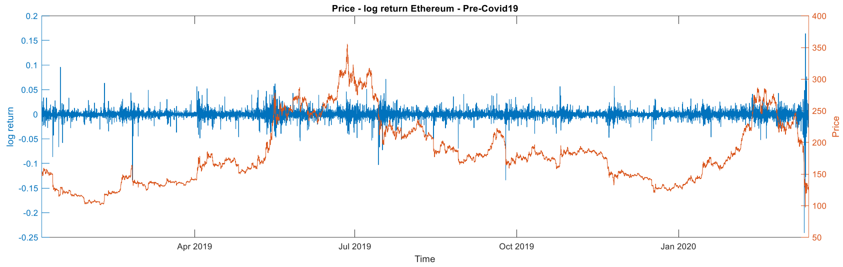
Summary statistics are given in Table 1. The results of the Jarque-Bera test statistic reject the null hypothesis of normality of the distribution of log returns for all observed series. Also, all unit root and stationarity tests show that log returns are stationary for all series. All observed series have a significantly negative coefficient of skewness, but for ETH-Post-Covid19 it is not significantly large. The kurtosis value is significantly higher than 3 for all observed series, but the value for the period before Covid-19 (ETH-Pre-Covid19) is extremely high. Based on the presented tests, we can conclude that none of the observed series have a normal distribution of log returns.

Table 1. Summary statistics of the hourly log returns of ETH-Pre-Covid19, ETH-Covid19 and ETH-Post-Covid19.

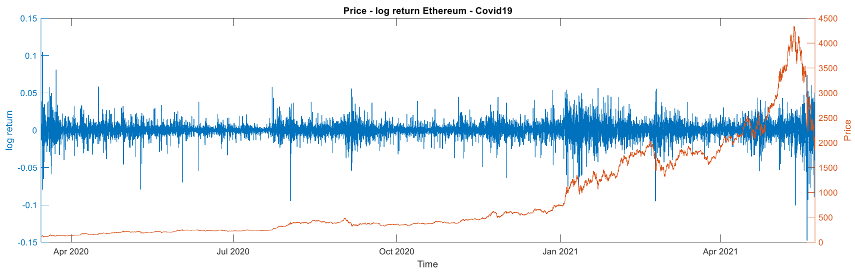
	Pre-Covid-19	***COVID-19***	***Post-COVID-19***
Observation	10461	10440	5713
	Descriptive statistics		
Mean	0.000	0.000	0.000
Median	0.000	0.000	0.000
Maximum	0.164	0.081	0.070
Minimum	-0.241	-0.148	-0.087
Std. Dev.	0.010	0.011	0.010
Skewness	-1.672	-0.765	-0.152
Kurtosis	74.721	14.787	8.588
	Nonnormality test		
Jarque-Bera (CV=5.9433)	2246959.000	61450.100	7455.438
p-val	0.000	0.000	0.000
	Unit Root tests		
Augmented Dickey-Fuller test statistic	-105.854	-75.382	-74.560
p-val	0.000	0.000	0.000
Phillips-Perron test statistic	-106.017	-103.119	-74.560
p-val	0.000	0.000	0.000
KPSS-Kwiatkowski-Phillips-Schmidt-Shin	0.204	0.047	0.120
	Random Walk hypothesis		
Variance Ratio Test	2.000	1.667	0.686
p-val	0.170	0.331	0.934
Rank Score Variance Ratio Test	8.728	5.876	1.969
p-val	0.000	0.000	0.135
Sign Variance Ratio Test	9.360	8.365	3.946
p-val	0.000	0.000	0.001

Source: Authors' calculations

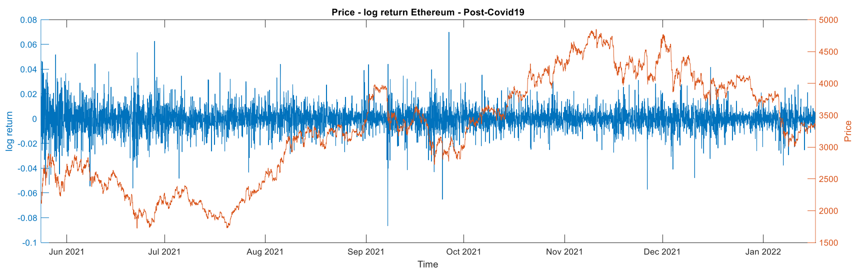
Table 2 shows the results of the ARCH test. The ARCH test examines the existence of volatility clustering (heteroscedasticity) in time series. The results of the test strongly reject the null hypothesis of no volatility correlation in all observed periods. The clustered volatility (clustered) and persistence are much more pronounced during the pandemic.



a)



b)



c)

Figure 2. Graphic presentation of price and return trends:
a) Pre-Covid19 b) Covid_19 and c) Post-Covid19.
Source: Authors' calculations

Table 2. Results of the ARCH test on data heteroskedasticity.

	ARCH (CV=18.3070)	
	Stat	p-val
Pre-Covid-19	858.806	0.000
Covid-19	1091.271	0.000
Post-Covid-19	219.073	0.000

Source: Authors' calculations

Figure 3 shows the CDF (Cumulative distribution function) of absolute normalised log returns. Power-law distribution of tails is clearly observed for all observed periods. The widest range of scaling was in the period before the COVID-19 pandemic, and the narrowest in the period after the pandemic shock.

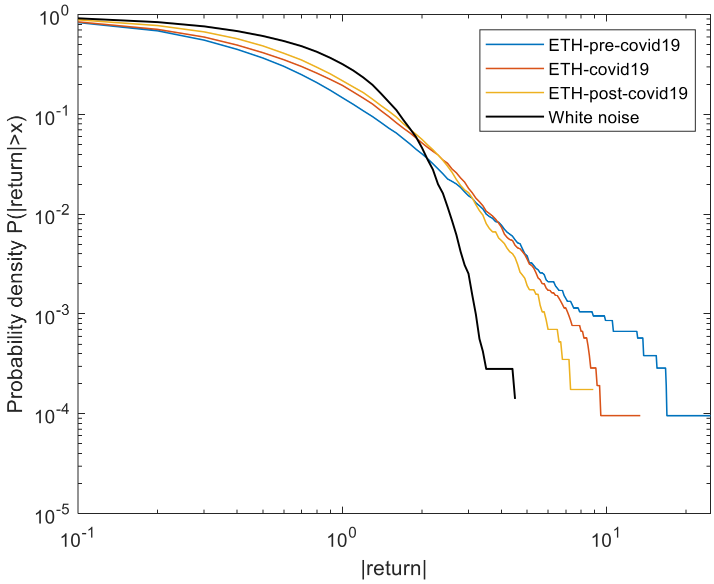


Figure 3. Cumulative distribution of normalised absolute log-returns for Ethereum

Source: Authors' calculations

Table 3 shows the values of parameters α and x_{min}, calculated according to the procedure described by Clauset, Shalizi and Newman (2007). The table shows the results for the distribution of positive returns α (+), negative returns α (-), and the range between the slopes of positive and negative returns (Range=|α (+)-α (-)|). The difference between the negative and positive tails of the distribution during the pandemic is very small, indicating a relative uniformity of positive and negative events. The difference between the negative and positive tail after the pandemic-induced shock is significantly higher than the difference in the pre-pandemic period. During the observed period after the pandemic, negative events are dominant, in contrast with the period before the pandemic.

Table 3. Power law parameters. (+) and (-) indicate coefficients for positive log returns and negative log returns, respectively.

	Power Law distribution ($p(x) \sim x^{-\alpha}$ for $x >= x_{min}$)						
	α	X_{min}	α (+)	X_{min}(+)	α (-)	X_{min}(-)	Range
Pre-Covid-19	3.41651	1.65648	3.58361	1.65648	3.30347	1.86590	0.28014
Covid-19	3.21486	1.21891	3.23549	1.16953	3.20581	1.27852	0.02968
Post-Covid-19	3.53977	1.38137	3.13618	1.04362	3.56085	1.34977	0.42467
WNOISE	5.12818	1.47546	4.60354	1.30508	4.50117	1.27456	0.10237

Source: Authors' calculations

Tests for Non-linearity and Chaos

The results of the non-linearity check on the Ethereum market in all observed periods were obtained using the BDS test. The results are shown in Tables 4, 5 and 6. In all combinations of embedding dimension (*m*=2...6) and epsilon (*s*=0.5, 1.0, 1.5, 2.0), the null hypothesis of linear dependence of log returns is rejected (*p-val*=0.000) for all observed periods. The BDS test clearly suggests that the Ethereum market is characterised by a non-linear dependence structure. These results provide strong evidence against the IID assumption of returns on efficient markets.

Table 4. BDS results for ETH-Pre-Covid19

ETH-Pre-Covid19	BDS-Non-linearity test			
m	*s*=0.5	*s*=1.0	*s*=1.5	*s*=2.0
2	0.020	0.026	0.018	0.010
3	0.026	0.049	0.039	0.024
4	0.022	0.065	0.058	0.039
5	0.016	0.073	0.076	0.055
6	0.012	0.075	0.090	0.068

Source: Authors' calculations

Table 5. BDS results for ETH-Covid19

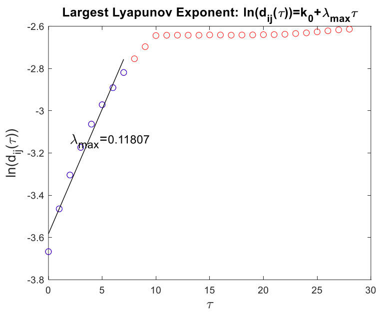
ETH-Covid19	BDS-Non-linearity test			
m	*s*=0.5	*s*=1.0	*s*=1.5	*s*=2.0
2	0.020	0.029	0.023	0.014
3	0.024	0.055	0.051	0.035
4	0.020	0.071	0.077	0.058
5	0.015	0.076	0.097	0.080
6	0.010	0.075	0.112	0.099

Source: Authors' calculations

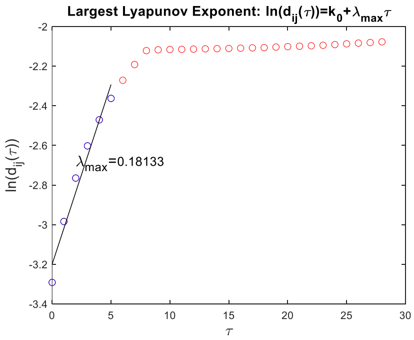
Table 6. BDS results for ETH-Post-Covid19

Post-Covid-19	BDS-Non-linearity test			
m	*s*=0.5	*s*=1.0	*s*=1.5	*s*=2.0
2	0.015	0.017	0.014	0.009
3	0.021	0.029	0.030	0.021
4	0.020	0.032	0.041	0.032
5	0.017	0.031	0.050	0.044
6	0.013	0.028	0.055	0.055

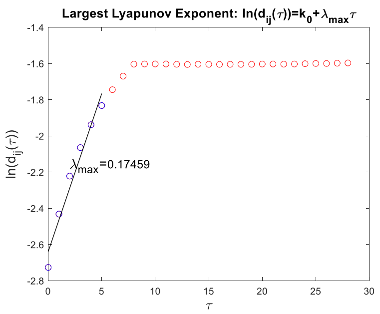
Source: Authors' calculations



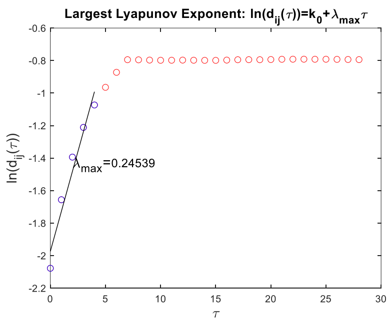
a) ETH-Pre-Covid19



b) ETH-Covid19



c) ETH-Post-Covid19



d) WNOISE

Figure 4. Largest Lyapunov exponent (λ)
Source: Authors' calculations

Table 6. Largest Lyapunov exponent (λ)

Largest Lyapunov exponent	λ_{max}
Pre-Covid-19	0.11807
Covid-19	0.18133
Post-Covid-19	0.17459
WNOISE	0.24539

Source: Authors' calculations

As we mentioned earlier, the largest Lyapunov exponent (LLE) is used to estimate the chaos in the observed time series. The results of the LLE calculation, based on the procedure (Mohammadi, 2020a), are shown graphically (Figure 4) and in Table 6. The calculations show the existence of a positive Lyapunov exponent in all observed periods. A smaller value of λ in the pre-pandemic period indicates a potentially greater predictability of returns based on past information. However, the calculation of the largest Lyapunov exponent for high-frequency financial time series tends to be larger than the true exponent due to noise. To overcome this problem, Gencay and Dechert (1992) proposed an algorithm for LLE estimation based on the use of feedforward neural networks. The calculation of LLE by this algorithm according to the procedure (Mohammadi, 2020b) is given in Table 7 for overlapping dimensions m from 2 to 6. For all observed series, *λ* is negative, so we can reject the null hypothesis of a positive largest Lyapunov exponent, i.e. we can reject the hypothesis of the existence of low-dimensional chaos.

Table 7. Largest Lyapunov exponent (λ) with feedforward neural networks

Largest Lyapunov exponent (λ)	*m*=1	*m*=2	*m*=3	*m*=4	*m*=5	m=6
Pre-Covid-19	-0.43754	-0.50558	-0.54127	-0.58009	-0.63549	-0.74441
Covid-19	-0.57014	-0.59477	-0.62820	-0.67290	-0.74558	-0.94951
Post-Covid-19	-0.51328	-0.54867	-0.58901	-0.64918	-0.77071	-

Source: Authors' calculations

Tsallis Entropy

Tsallis entropy (TsEn) is one of the indicators of critical phenomena in complex systems. Figure 5 shows the movement of Tsallis entropy during the entire observed period. The TsEn indicator shows a rapid decline at the beginning of the pandemic (16/3/2020), and rapid growth on 24 May 2021. Therefore, the value of the TsEn indicator clearly separates three periods: the period before the pandemic (ETH-Pre-Covid19, from

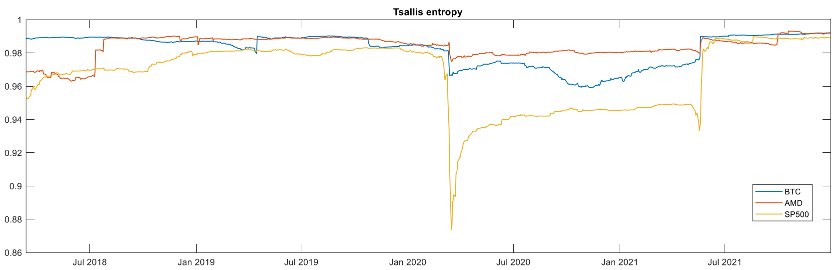
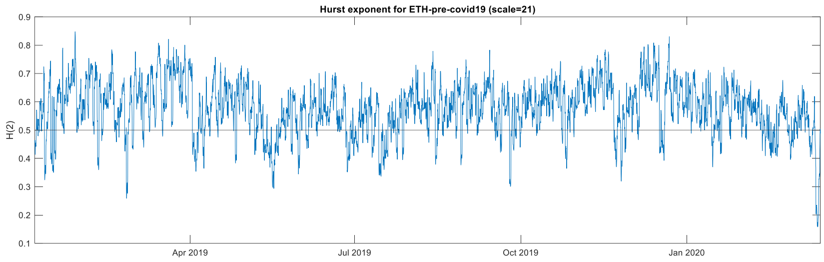


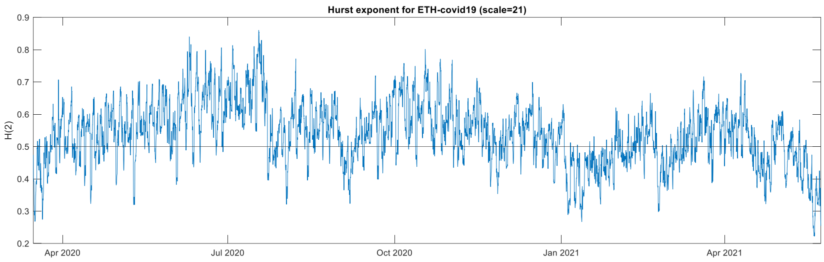
Figure 5. Dynamics of Tsallis entropy from 6/1/2019 to 17/1/2022.
Source: Authors' calculations

6/1/2019 to 16/3/2020), the period of the pandemic-induced shock (ETH-Covid19, from 16/3/2020 to 24/5/2021), and the period after the pandemic-induced shock (ETH-Post-Covid19, from 24/5/2021 to 17/1/2022).

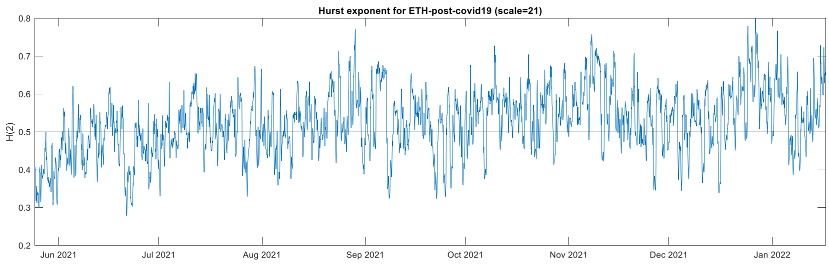
Multifractality



a) ETH-Pre-Covid19



b) ETH-Covid19



c) ETH-Post-Covid19

Figure 6. Hurst exponent (scale=21):
a) ETH-Pre-Covid19; b) ETH-Covid-19; c) ETH-Post-Covid19
Source: Authors' calculations

In Figure 6(a), we see that the Hurst exponent during the entire period before the pandemic shows the existence of long-memory ($H(2)>0.5$). The beginning and end of the pandemic period is marked by anti-persistence ($H(2)<0.5$) (Figure 6(b)). The first half of the observed after pandemic shock period remains anti-persistent. However, in the second half of the observed period, the Hurst exponent indicates long-memory and a return to the dominant behaviour of the period before the pandemic (Figure 6(c)).

Table 8. Results of testing the long-memory.

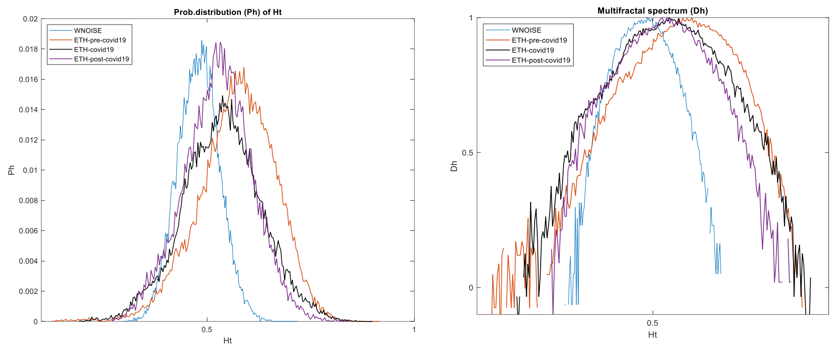
Hurst exponent (scale=21)	*H*(2)	InffIdx	Min Hurst	Max Hurst	Range
Pre-Covid-19	0.58899	0.08899	0.15792	0.84756	0.68964
Covid-19	0.53732	0.03732	0.22210	0.85997	0.63787
Post-Covid-19	0.53740	0.03740	0.27886	0.79903	0.52017
WNOISE	0.48712	0.01288	0.29810	0.63735	0.33925

Source: Authors' calculations

The verification of the existence of long-term correlation of returns, and the existence of long-memory for the observed periods is shown in Table 8. The verification of the existence of long-memory is based on the estimation of the Hurst exponent using the MF-DFA (Multifractal detrended fluctuation analysis) method for different scales of the observed time series ($scale_{min}$ = 11, $scale_{max}$=1024), taking into account different degrees (q) of the partition function. The table shows the results for q=2, used to estimate the index of market inefficiency (InffIdx). Hurst's *H*(2) exponent is significantly higher than 0.55, that is, InffIdx is significantly higher than zero for the period before the pandemic. These results show that the Ethereum market was inefficient before the pandemic. However, during and after the pandemic, the Hurst exponent does not show that the Ethereum market behaves inefficiently ($H(2)<0.55$). Taking into account the results on the graphic (Figure 3(c)), we can conclude from the second half of the observed period after the pandemic shock that the market is returning to the behaviour before the pandemic, i.e.. the Ethereum market is inefficient.

The Hurst exponent (*H*(2)) is not sufficient for a multiscale analysis of the complexity of time series. For this purpose, the generalised Hurst exponent $h(q)$ is used, with degree q belonging to some predefined range according to the properties of return tails. It can be calculated with the help of MF-DFA. A measure of time series complexity and multifractality properties can be found in the Hurst exponent distribution and the multifractality spectrum (Figure 7).

The width of the multifractal spectrum – Range (Table 8) shows that the Ethereum market of the period before the pandemic and during the pandemic shock was significantly less efficient than the market of the period after the pandemic shock. Also, the spectrum width shows that the pre-pandemic Ethereum market was less multifractal than was the case during and after the pandemic shock.



a) *b)*

Figure 7. *The probability distribution (a) and multifractal spectrum (b).*
Source: Authors' calculations

CONCLUSION

In this paper, we studied the properties of long-term correlation, multifractality, and chaotic hourly logarithmic returns of the Ethereum cryptocurrency. The time period of the analysis is the interval between 6 January 2019 and 17 January 2022, and this interval is divided into three parts: the period before the COVID-19 pandemic (from 6/1/2019 to 16/3/2020), the period of the COVID-19 pandemic-induced shock (from 16/3/2020 to 24/5/2021) and the period after pandemic-induced shock (from 24/5/2021 to 17/1/2022). The limits of the interval are determined by the Tsallis entropy indicator, which has sharp peaks on 16/3/2020 and 24/5/2021.

Based on the results of the ARCH and BDS tests, we can conclude that Ethereum returns in all observed periods have pronounced heteroscedasticity and non-linearity. The research results show that return distribution corresponds to a power law in all observed periods. The difference between the negative and positive tails of the distribution of returns during the pandemic shock is very small, indicating a relative uniformity of positive and negative events. In contrast, the difference between the negative and positive tails is pronounced in the pre- pandemic period and the period after pandemic shock.

The study of the multifractal and chaotic characteristics of Ethereum return volatility is based on the use of MF-DFA (Multifractal Detrended Fluctuation Analysis) and LLE (Largest Lyapunov Exponent) methods. From the perspective of non-linearity and chaos, returns in the pre-pandemic period had slightly higher predictability than in the periods during and after the pandemic shock. The value of the Hurst exponent $H(2) > 0.5$, in all observed periods, shows that the Ethereum volatility market has a long memory in all periods, which also indicates that the market of Ethereum can be predictable based on past data. The dynamics of the Hurst exponent during the entire period before the pandemic show the existence of long-memory. The beginning and end of the pandemic-induced shock period was marked by anti-persistence (*H*(2)<0.5). The first half of the period after pandemic shock remained anti-persistent. However, in the second half of the observed period, the Hurst exponent indicates long-memory and a return to the dominant behaviour of the period before the pandemic. Anti-persistence is present in the second half of the pandemic shock period and in the first half of the period after the pandemic-induced shock. However, the long-memory effect is re-established in the second half of the observed period after the pandemic-induced shock, indicating that Ethereum's return behaviour is returning to pre-pandemic characteristics.

The results of the efficient market hypothesis (EMH) tests are in line with the results Cheng, Liu & Zhu (2019), Corbet, Lucey, Urquhart and Yarovaya (2019), Kakinaka and Umeno (2022), and Mnif, Salhi, Trabelsi and Jarboui (2022) reached in their studies. More specifically, the non-linearity, non-normality of the return distribution and potential predictability in all observed periods provide strong evidence against the efficient market hypothesis.

REFERENCES

Assaf, A., Bhandari, A., Charif, H., & Demir, E. (2022) Multivariate long memory structure in the cryptocurrency market: The impact of COVID-19. *International Review of Financial Analysis*, 82, 102132. doi: 10.1016/j.irfa.2022.102132.

Brock, WA., Dechert, D., Lebaron, B., & Scheinkman, J. (1996). A test for independence based on a correlation dimension, *Econometric Review*, 15, 197-235.

Cheng, Q., Liu, X., & Zhu, X. (2019). Cryptocurrency momentum effect: DFA and MF-DFA analysis. *Physica A: Statistical Mechanics and its Applications,* 526, 120847. doi:10.1016/j.physa.2019.04.083

Coinmarketcap (2022). Global Cryptocurrency Charts, Total Cryptocurrency MarketCap. Retrieved from https://coinmarketcap.com/charts/.

Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2019) Cryptocurrencies as a financial asset: a systematic analysis. *International Review of Financial Analysis*, 62, 182-199. doi:10.1016/ j.irfa.2018.09.003.

Danylchuk, H., Kibalnyk, L., Kovtun, O., Kiv, A., Pursky, O., & Berezhna, G. (2020). Modelling of cryptocurrency market using fractal and entropy analysis in COVID-19, CEUR Workshop Proceedings 2713 (2020) 352–371. https://doi.org/10.31812/123456789/4477.

Diaconașu D-E, Mehdian S, & Stoica O. (2022) An analysis of investors' behavior in Bitcoin market. *PLoS ONE*, 17(3): e0264522. doi: 10.1371/journal.pone.0264522.

Elliott D. J., & de Lima, L. (2018). Crypto-assets: their future and regulation. Oliver Wyman, October. Retrieved from https://www.atlantafed.org/-/media/documents/news/conferences/2018/1018-financial-stability-implications-of-new-technology/papers/elliott_crypto-assets.pdf.

Gencay, R., and Dechert, WD., 1992. An algorithm for the n Lyapunov exponents of an n-dimentional unknown dynamical system, Phisica D, 59,142-157.

Glaser, F., Zimmermann, K., Haferkorn, M., Weber, M. C. and Siering, M. (2014), Bitcoinasset or currency? Revealing users' hidden intentions, in: Avital, M., Leimeister, M. and Schultze, U. (eds), *Proceedings of the European conference on information systems*, Israel: Tel Aviv, pp. 1-14.

Goodell, J.W. (2020). COVID-19 and finance: agendas for future research. *Finance Research Letters*, 35, 101512. doi:10.1016/j.frl.2020.101512.

CryptoDataDownload (2022) Coinbase. https://www.cryptodatadownload.com/data/coinbase/.

Gu, R., Shaob, Y., & Wang, Q. (2013) *Physica A* 392, 361–370.

Gunay, S., & Kaşkaloğlu, K. (2019) Seeking a Chaotic Order in the Cryptocurrency Market. Mathematical and Computational Applications, 24(2), 36. doi: 10.3390/mca24020036.

Hurst, H. E. (1965). *Long-term storage: An experimental study*. London: Constable.

Ihlen, E. (2012). Introduction to multifractal detrended fluctuation analysis in matlab. *Frontiers in Physiology. Sec. Fractal Physiology*, 3. doi:10.3389/fphys.2012.00141

Kakinaka S., & Umeno K. (2022) Cryptocurrency market efficiency in short- and long-term horizons during COVID-19: An asymmetric multifractal analysis approach. *Finance Research Letters*, 46, 102319. doi: 10.1016/j.frl.2021.102319.

Kantelhardt, J. W., Zschiegner, S. A., Koscielny-Bunde, E., Havlin, S., Bunde, A., & Stanley, H. E. (2002). Multifractal detrended fluctuation analysis of nonstationary time series. *Physica A*, 316, 87–114.

Lahmiri, S., & Bekiros, S. (2021). The effect of COVID-19 on long memory in returns and volatility of cryptocurrency and stock markets. *Chaos, Solitons & Fractals*, 151, 111221. doi: 10.1016/j.chaos.2021.111221.

Mnif, E., Jarboui, A., & Mouakhar K. (2020). How the cryptocurrency market has performed during COVID 19? A multifractal analysis. *Finance Research Letters*, 36, 101647. doi:10.1016/j.frl.2020.101647.

Mnif, E., Salhi, B, Trabelsi, L., & Jarboui, A. (2022) Efficiency and herding analysis in gold-backed cryptocurrencies. *Heliyon*, 8 (12), e11982. doi: 10.1016/j.heliyon.2022.e11982.

Mohammadi, Shapour, (2020a), LYAPROSEN: MATLAB function to calculate Lyapunov exponent; Boston College Department of Economics: Boston, MA, USA.

Mohammadi, Shapour, (2020b), ANNLYAP: MATLAB function to calculate Lyapunov exponents; Boston College Department of Economics: Boston, MA, USA.

Naeem, M. A., Bouri, E., Peng, Z., Shahzad, S. J. H., & Vo, X. V. (2021). Asymmetric efficiency of cryptocurrencies during COVID19. *Physica A: Statistical Mechanics and its Applications*, 565, 125562.

Nakamoto, S. (2009). Bitcoin: A Peer-to-Peer Electronic Cash System. Retrieved from https://Bitcoin.org/en/Bitcoin-paper.

Tsallis, C. (1988). Possible generalization of Boltzmann–Gibbs statistics. *Journal of Statistical Physics*, 52, 1-2, 479–487, 1988.

Vidal-Tomás, D., Ibañez. A.M., & Farinós, J.E. (2019). Herding in the cryptocurrency market: CSSD and CSAD approaches. *Finance research letters*, 30, 181–186.

Wolf, A., Swift, J., Swinney, H., & Vastano, J. (1985). Determining Lyapunov exponents from a time series. *Physica D*, 16, 285-317.

Wu, X., Wu, L., & Chen, S. (2022). Long memory and efficiency of Bitcoin during COVID19. *Applied Economics*, 54(4), 375–389.

ЕФЕКТИ КОВИД-19 ПАНДЕМИЈЕ НА МУЛТИФРАКТАЛНОСТ И ДУГОРОЧНУ МЕМОРИЈУ ПРИНОСА *ETHEREUM*-а

Јелена Радојичић, Огњен Радовић
Универзитет у Нишу, Економски факултет, Ниш, Србија

Резиме

Криптовалуте су приватно-емотовани дигитални новац базиран на децентрализованој мрежи изграђеној на блокчејн технологији. Тржишта криптовалута су подложна осцилацијама, са епизодама екстремне волатилности. Глобална пандемија КОВИД-19 узбуркала је глобалну економију, па и тржиште криптовалута није било поштеђено. Услед тога је настала је потреба да се процени како је пандемија утицала на динамику овог тржишта. Највећи број истраживања бави се проучавањем динамике биткоина, а мали број другим криптовалутама. У овом истраживању определили смо се да истражимо утицај КОВИД-19 пандемије на динамику логаритамског приноса Ethereum–а, као друге криптовалуте по тржишној капитализацији. Анализа је обухватила временски период између 6. јануара 2019. године и 17. јануара 2022. године, и овај интервал је подељен на три дела: период пре КОВИД-19 пандемије (од 06.01.2019. до 16.03.2020.), период шока на тржишту круптовалута изазваног пандемијом КОВИД-19 (од 16.03.2020. до 24.05.2021.) и период после шока изазваног пандемијом (од 24.05.2021. до 17.01.2022). Границе интервала одређене су индикатором Tsallis ентропије која дана 16.03.2020. и 24.05.2021. године достиже највише степене. Акценат истраживања је на утицају пандемије на степен нелинеарности и мултифракталности приноса.

На основу резултата ARCH и BDS тестова можемо да закључимо да приноси *Ethereum*-а у свим посматраним периодима имају изражену хетероскедастичност и нелинеарност. Резултати истраживања показују да у свим посматраним периодима дистрибуција приноса одговара степеном закону (енгл. power law). Разлика између негативног и позитивног репа дистрибуције приноса током шока на тржишту услед пандемије је врло мала, што указује на релативну уједначеност позитивних и негативних догађаја. Насупрот томе, разлика између негативног и позитивног репа изражена је у периодима пре и после пандемијског шока. Проучавање мултифракталне и хаотичне карактеристике променљивости приноса Ethereum засновано је на коришћењу MFDFA (енг. Multifractal Detrended Fluctuation Analysis) и LLE (енг. Largest Lyapunov Exponent) метода. Из перспективе нелинеарности и хаотичности, приноси у периоду пре пандемије су имали нешто вишу предвидљивост него у периодима током и након шока изазваног пандемијом.

Вредност Хурстовог експонента показује да тржиште волатилности *Ethereum*-а има дугорочну меморију у свим периодима, што такође указује да тржиште *Ethereum*-а може да буде предвидљиво на основу података из прошлости. Динамика Хурстовог експонента током целог периода пре пандемије показује постојање дугорочне меморије. Почетак и крај периода шока обележила је област антиперзистенције. Док је прва половина посматраног периода после пандемијског шока задржала антиперзистентност, у другој половини периода Хурстов експонент указује на дугорочну меморију и повратак на доминантно понашање у периоду пре пандемије. Антиперзистентност је присутна у другој половини периода шока и у првој половини посматранаог периода после пандемијског шока. Међутим, ефекат дугорочног памћења се поново успоставља у другој половини посматраног периода после пандемијског шока, што указује на то да се понашање приноса Ethereum-а враћа на особине пре периода пандемије. Нелинеарност, ненормалност дистрибуције приноса и потенцијална предвидљивост у свим посматраним периодима пружају јак доказ против хипотезе ефикасног тржишта (ЕМН).