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LONG-RANGE CORRELATIONS AND CRYPTOCURRENCY MARKET EFFICIENCY

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Abstract. *This paper examines the market efficiency of the most significant cryptocurrencies, Bitcoin and Ethereum. In the paper, we use several different tests to check the normality of return distribution, long-run correlation and heteroscedasticity of return volatility. We compare the characteristics of cryptocurrency returns with the returns on stocks of the most important companies producing hardware components for cryptocurrency mining. The correlation of returns, trading volume and volatility between cryptocurrencies and selected stocks is tested using a Granger causality test. The research results reject the efficient market hypothesis and show that the cryptocurrency market is a completely new speculative market that is weakly correlated with the stock market.*

Key words: *efficient market hypothesis, cryptocurrency markets, random walk hypothesis, the long-run correlations.*

JEL Classification: G14, G15

INTRODUCTION

Cryptocurrencies are not issued by monetary authorities, but are privately issued money based on cryptographic algorithms; they are not legal tender, they have not reached the status of a generally accepted means of payment, and they may face a limited supply due to the limitation of the total available amount or the annual amount which can be "mined". The creation and transfer of cryptocurrencies is based on the blockchain technology where each block contains transactions, a time stamp, a digital signature to identify the account and a unique

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identification link (Van der Auwera et al., 2020). Investors treat cryptocurrencies as an asset and see them as an investment alternative for investing savings, as a way to diversify a portfolio or as an asset for speculation (Elliott & de Lima 2018).

After the success of Bitcoin, other cryptocurrencies appeared, but Bitcoin maintained its dominant position on this market. Bitcoin and Ethereum have the largest share of the total market capitalization on the cryptocurrency markets. In early 2017, the share of Bitcoin in total market capitalization was about 85%, and in late 2021, the share of Bitcoin was 40.21%, and Ethereum's 20.03% (Coinmarketcap, 2022). The cryptocurrency market is continuously developing and the popularity of cryptocurrencies is growing, which increases the volume of trading, and with it, interest in its effectiveness.

The aim of this paper is to check the market efficiency of the most important cryptocurrencies, Bitcoin and Ethereum. We compare the characteristics of cryptocurrency returns with the stock returns of the most important companies producing hardware components for cryptocurrency mining, Intel, AMD, Nvidia and TSMC. Also, the SP500 index is used as a proxy for global market trends.

The paper is organized as follows: the theoretical framework is presented in the first part of the paper. The second part of the paper presents an overview of literature. Research methodology and results are presented in the third part of the paper. Finally, the conclusion of the research is given in the fourth part of the paper.

1. Theoretical Framework

1.1. Efficient Market Hypothesis

Examining the efficiency of the cryptocurrency market is based on the Efficient Market Hypothesis (EMH). Fama (1970) uses the term "efficient" to describe a market where "prices always fully reflect available information" but ignores the costs of obtaining and processing information. In his later paper, Fama (1991) modifies the EMH to make the simplest but economically reasonable statement that the prices of securities at any point in time fully reflect all available information to the extent that the profit based on that information does not exceed the cost of obtaining the information and transaction costs. When stock prices satisfy this claim, market participants cannot make above-average profits based on available information.

Within EMH, three sub-hypotheses of information efficiency can be distinguished, namely weak, semi-strong and strong form of EMH (Fama, 1970). The mentioned EMH forms differ in the information set and the perception of the information flow speed, that is, the speed and ability of the investor to adequately interpret the information.

The weak form of EMH assumes that current stock prices reflect all the information that has already been generated on the market at a given moment (historical prices, returns, volatility, etc.). Investors cannot make above-average profits based on historical market information, but they can create "above-average" returns by looking for private information that is not yet available to the market and trading in it at times when its appearance disrupts the market.

The semi-strong form of EMH assumes that the price of stocks quickly adjusts to all public information, which, in addition to market information, includes non-market information such as announcements of dividends, various coefficients (P/E, D/P, P/BV, etc.), companies' financial statements, competition, macroeconomic factors (inflation, unemployment), etc.

The strong form of EMH assumes that stock prices at any point in time fully reflect all available information (from public and private sources). No investor has monopolistic access to "sensitive" information, that is, there is no "superior" investor.

1.2. Random walk theory

The efficient market hypothesis evolved from the random walk theory. When the term random walk is applied to stock markets, it means that short-term changes in stock prices cannot be predicted. The random walk model and the submartingale represent two basic cases of the fair game model that describes expected sequences of price changes. The correlation of stock returns r_t at time t and r_{t+k} at time $t+k$ is expressed by their covariance. On an efficient market, with an appropriate choice of $f(\cdot)$ and $g(\cdot)$,

$$Cov\left[f(r_t), g(r_{t+k})\right] = 0 \tag{1}$$

for each t and $k \neq 0$, where $f(\cdot)$ and $g(\cdot)$ are arbitrarily chosen functions. Equation (1.5) includes all versions of the random walk and martingale models. Campbell et al. (1997) consider three random walk models: *RW1*, *RW2* i *RW3*.

RW1 model ("independently and identically distributed returns") implies that the increase in prices is independently and identically distributed (IID), and in that case the process P_t is

$$P_t = \mu + P_{t-1} + e_t, \quad e_t \sim IID\,(0,\sigma^2) \tag{2}$$

where μ is the expected price change or *drift*. The price increase (innovation) e_t is independently and identically distributed with mean zero and variance σ^2, denoted $IID(0, \sigma^2)$.

RW2 ("independent returns") further relaxes the assumption of identical distribution and allows heteroscedasticity to appear in the innovation e_t, i.e. it allows time variability of the variance in the time series of stock returns.

RW3 ("uncorrelated returns") relaxes the assumption of independence of returns by introducing the possibility of dependence but not correlation of price innovations e_t. This is the weakest form of the random walk hypothesis and contains RW1 and RW2 as special cases.

1.3. Long-range correlations

In the case of a weak form of efficiency, investors cannot profit above average based on historical market information. However, if the presence of long-term memory in returns on financial assets allows investors to make above-average profits, then the hypothesis of a weak form of market efficiency is not supported. If we proceed from the assumption that cryptocurrency returns may not be independent and identically distributed, checking the existence of long-range correlations in the observed data must be done with some of the non-parametric tests. Hurst (1951) developed a robust R/S (rescaled range) non-parametric methodology for distinguishing between random and non-random series. R/S statistic is the range of partial sums of deviations of a time series from its mean, rescaled by its standard deviation (Peters, 1994):

$$(R/S)_n = \frac{1}{S_n}\left[\max_{1\le k\le n}\sum_{t=1}^{k}(r_t - \bar{r}_n) - \min_{1\le k\le n}\sum_{t=1}^{k}(r_t - \bar{r}_n)\right] = Cn^H \tag{3}$$

where r_t is calculated as $r_t = \left((x_1 - \bar{x}) + (x_t - \bar{x}) \right)$ and $\bar{x}$ denotes the mean of a time series of length N. The H exponent in the relation (3) is the Hurst exponent, R_n is the adjusted range S_n is its standard deviation and C is a constant.

If H=0.5, the observed series follows a random walk. If 0.5<H<1, observed series shows persistence and long memory. In the case that 0<H<0.5, the observed series shows the existence of anti-persistence, generating reversals much more often than a random walk**.**

Using the results of multifractality research in financial time series, the Inefficiency Index can be defined as follows (Gu et al., 2013):

$$InffIdx = |H(2) - 0.5| \quad (4)$$

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

2. Review of Literature

The first research on the efficiency of the Bitcoin market shows its inefficiency, but also that this inefficiency decreases over time (Urquhart, 2016). The results of a portion of subsequent studies also do not support the EMH for the cryptocurrency market (Cheah et al., 2018; Al-Yahyaee et al., 2018; Vidal-Tomás et al., 2019) suggesting that cryptocurrency returns are not independent but predictable. Some authors, however, find evidence of cryptocurrency market efficiency (for example, Bariviera et al., 2017; Tiwari et al., 2018; Dimitrova et al., 2019, Mnif et. al, 2020). Tiwari et al. (2018) apply the market efficiency index based on the time-varying Hurst exponent and conclude that the Bitcoin market is efficient. Bariviera et al. (2017) apply Detrended Fluctuation Analysis (DFA) over a sliding window to calculate the Hurst exponent and find that the Hurst exponent significantly changes during the first years of Bitcoin's existence, with a tendency to stabilize since the beginning of 2014 around a value of 0.5 ± 0.05 which indicates a more informationally efficient market.

Assuming that the efficiency of the cryptocurrency market changes over time, some authors base their research on the adaptive market hypothesis (AMH), and their results support AMH on these markets (Chu et al., 2019; Khuntia & Pattanayak; 2018, Noda; 2021).

The majority of studies focus on the Bitcoin market, while some examine market efficiency and multiple cryptocurrencies. Noda (2021) focuses his research on the Bitcoin and Ethereum markets and finds that the degree of their efficiency changes over time and that the level of efficiency on the Bitcoin market is higher than on the Ethereum market. Caporale et al. (2018) investigate long-memory behavior in the returns of several cryptocurrencies (Bitcoin, Litecoin, Ripple and Dash) and find evidence of market inefficiency. Vidal-Thomas et al. (2019) find market inefficiency by applying a portfolio approach to investigate the market efficiency of 118 cryptocurrencies. Mnif et al. (2022) conclude that the Bitcoin market is the most efficient on the short trade horizon.

3. Methodology and Research Results

3.1. Data and descriptive statistics

In this paper, we analyze the logarithmic returns of the two most important cryptocurrencies: Bitcoin (BTC) and Ethereum (ETH). A comparison with the properties of the financial series of stock price trends is made regarding the AMD (AMD), Intel (INTC), Nvidia (NVDA) and TSMC (TSMC) stocks. In addition, the stock market index S&P500 (SP500) is used as an indicator of market trends. Daily prices of cryptocurrencies (Bitcoin and Ethereum) expressed in US dollars are taken from the Coinbase website. The daily prices of the observed stocks are taken from the Yahoo!Finance website. Data on all series are in the interval from 04/01/2017 - 31/12/2021 (1258 observations).

Table 1 Descriptive statistics of logarithmic returns

	AMD	*BTC*	*ETH*	*INTC*	*NVDA*	*TSMC*	*SP500*
			Descriptive statistics				
Mean	0.002	0.003	0.005	0.000	0.002	0.001	0.001
Median	0.001	0.003	0.003	0.001	0.003	0.001	0.001
Maximum	0.182	0.258	0.410	0.178	0.164	0.119	0.090
Minimum	-0.277	-0.368	-0.323	-0.199	-0.208	-0.151	-0.128
Std. Dev.	0.035	0.050	0.068	0.022	0.030	0.020	0.012
Skewness	-0.243	-0.500	0.193	-0.872	-0.595	-0.182	-1.145
Kurtosis	8.919	8.239	7.303	18.935	9.248	8.508	24.923
			Nonnormality test				
Jarque-Bera (CV=5.9433)	1849.056	1491.363	978.527	13468.910	2120.322	1597.366	25466.460
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Kolmogorov-Smirnov (5%) (CV=0.0381)	0.454	0.439	0.421	0.466	0.463	0.472	0.479
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000
			Unit Root tests				
Augmented Dickey-Fuller test statistic	-37.756	-36.025	-35.154	-19.108	-39.789	-42.271	-10.606
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Phillips-Perron test statistic	-37.874	-36.152	-35.352	-43.550	-39.658	-42.065	-44.314
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000
KPSS-Kwiatkowski-Phillips-Schmidt-Shin test statistic	0.071	0.110	0.282	0.181	0.181	0.117	0.079
Unit Root with Break Test	-38.548	-36.981	-36.001	-44.802	-40.509	-43.655	-45.249
Break Date:	5/2/2017	3/12/2020	6/12/2017	3/12/2020	11/19/2018	7/27/2020	1/25/2017
			Random Walk hypothesis/Variance/Heteroskedasticity test				
Variance Ratio Test	2.032	0.893	0.854	2.579	1.584	3.085	2.409
p-val	**0.158**	**0.844**	**0.864**	0.039	**0.382**	0.008	0.063
Rank Score Variance Ratio Test	2.791	1.701	1.584	4.277	2.717	4.709	3.594
p-val	0.012	**0.206**	**0.243**	0.000	0.018	0.000	0.001
Sign Variance Ratio Test	2.621	3.907	1.748	1.012	3.214	1.353	1.410
p-val	0.031	0.001	**0.185**	**0.596**	0.011	**0.374**	**0.727**
ARCH test (a=0.01, Lag=10, CV=23.209)	27.567	17.990	76.636	283.897	283.897	299.319	543.390
p-val	0.002	**0.055**	0.000	0.000	0.000	0.000	0.000
			Nonlinearity test				
BDS (Dim=6, S=1.0)	0.020	0.024	0.026	0.062	0.033	0.033	0.143
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Source: Authors' calculations

Table 1 shows the descriptive statistics of the logarithmic returns of the cryptocurrencies Bitcoin (BTC) and Ethereum (ETH), as well as the returns of selected financial series. The table clearly shows, based on the values of the maximum and minimum values, as well as on the basis of the standard deviation, that the returns on cryptocurrencies are significantly higher compared to the selected stocks and significantly higher than the returns on the SP500 market index. The median for cryptocurrencies is lower than the mean, which indicates the presence of positive deviations. On the other hand, for the selected returns (except for AMD), the median is higher than the mean, which shows that in the observed period, the stocks of the selected companies and the SP500 index have more negative deviations. Taking into account the difference of the highest and lowest values, as well as the value of the standard deviation, the cryptocurrency Ethereum (ETH) has the most volatile behavior.

The returns of all series show a significantly higher value of the coefficient of kurtosis than expected for a normal distribution of returns, indicating that the distributions of returns are likely to have fat tails. The kurtosis of cryptocurrencies is slightly lower than that in selected stocks, and significantly lower than Intel (INTC) and SP500. The coefficient of skewness of daily returns is positive for all series except for Ethereum (ETH). This positive skewness is generally not present in stock markets.

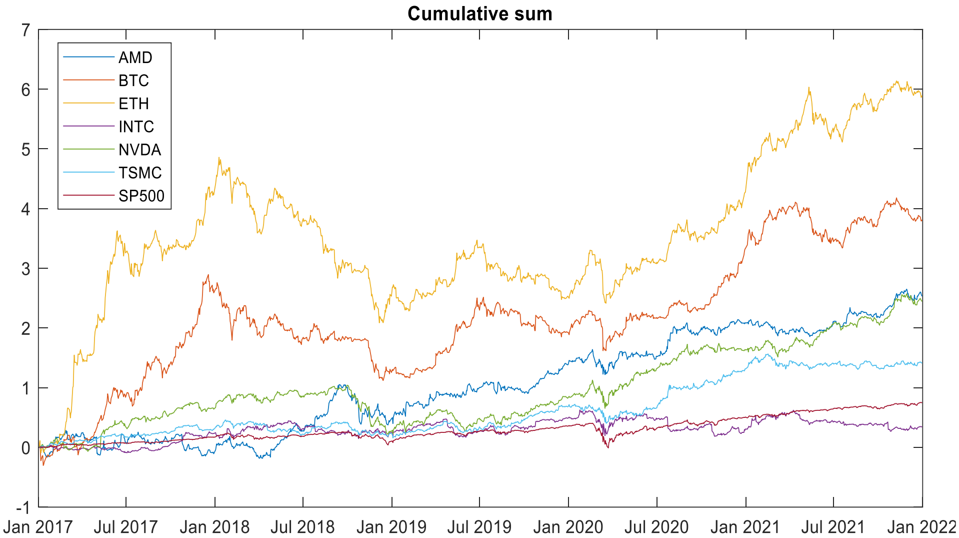
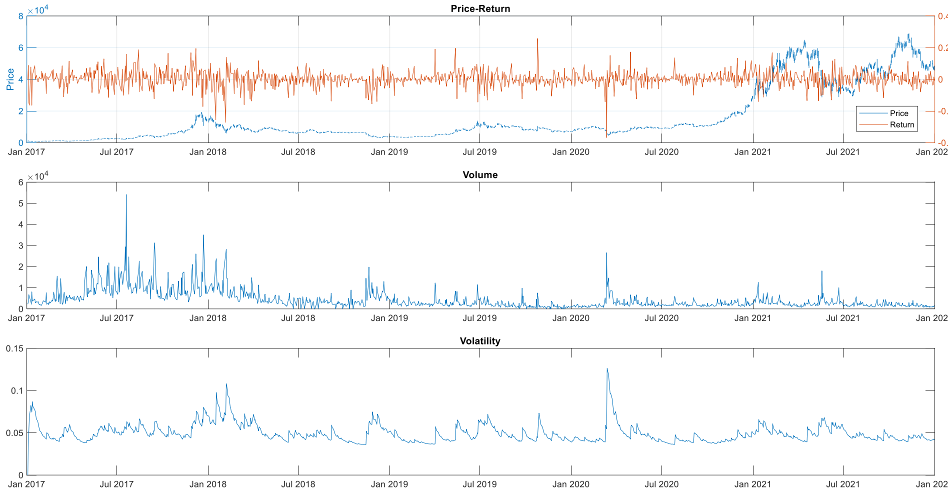
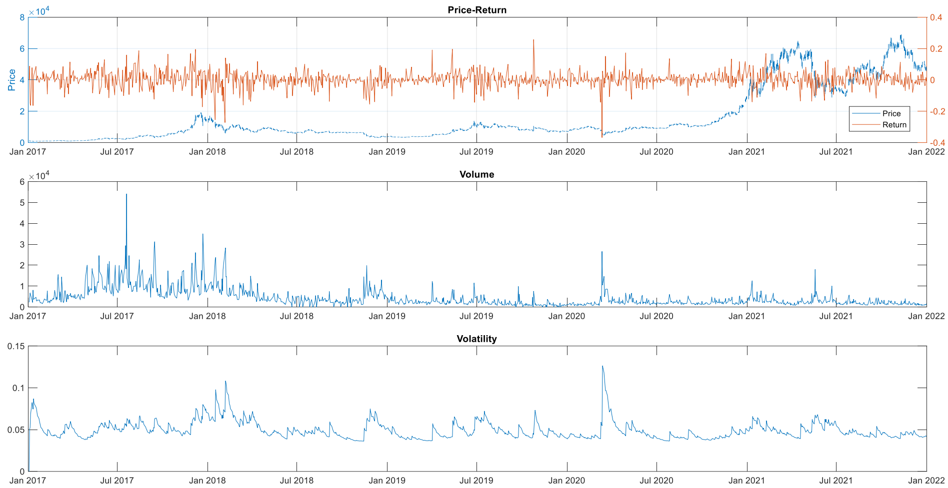


Fig. 1 Cumulative sum of logarithmic returns
Source: Authors' calculations

Figure 1 shows the cumulative returns of the selected time series in the observed period. During the entire observed period, the returns on cryptocurrencies are significantly higher than the returns on selected stocks and the SP500 index. In addition, cryptocurrencies have an upward trend from the beginning of 2017 to the end of 2017, and from May 2020 to the end of 2021. From 2018 to May 2020, returns are mostly negative. There is similar behavior on the stock market since May 2020.



a) Bitcoin – Price-Return, Volume, Volatility



b) Ethereum – Price-Return, Volume, Volatility

Fig. 2 Graphical presentation of price and returns, trading volume and volatility for cryptocurrencies: a) Bitcoin (BTC) and b) Ethereum (ETH)
Source: Authors' calculations

3.2. Test of normality of distribution of returns

Checking the normality of return distribution can be done using various statistical tests. One of the most famous is the Jarque-Bera test (Jarque and Bera, 1987), which is based on coefficients of skewness and kurtosis. The Kolmogorov-Smirnov test is based on the analysis of the deviation of the empirical cumulative distribution of the sample from the normal distribution. Both tests clearly reject the null hypothesis of normality of the daily return distribution of the selected financial time series (Table 1). Figure 3 shows the histograms of Bitcoin and Ethereum cryptocurrencies, which clearly graphically show the deviation of the distribution of log returns from the expected normal distribution. Both tests clearly reject the null hypothesis of normality of the daily return distribution of the selected financial time series (Table 1)

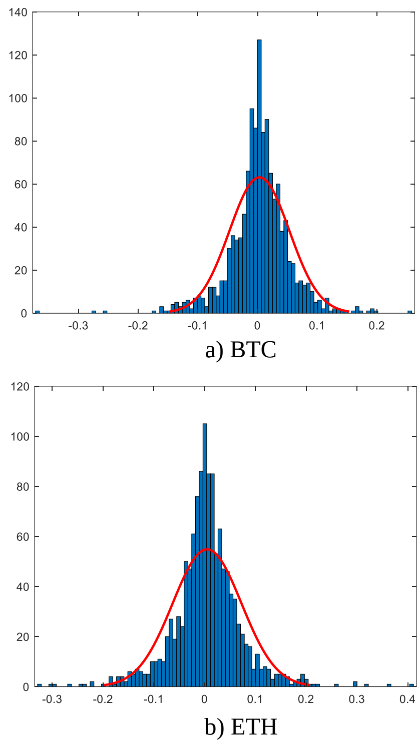


Fig. 3 Histograms of cryptocurrencies compared to normal distribution

3.3. Tests of stationarity of returns

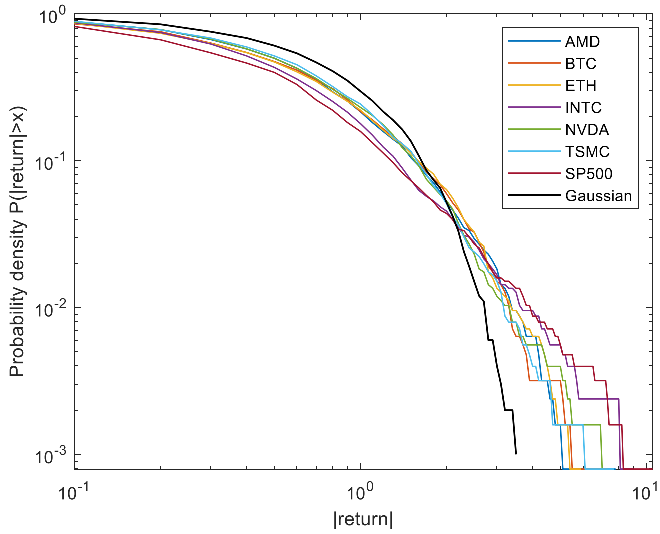
Testing the stationarity of the returns of the selected series is done using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. The null hypothesis of these tests is that the time series is non-stationary. Table 1 shows that the null hypothesis is rejected at the 1% significance level because the p-value for the ADF and PP test is less than 0.01, indicating that the process is stationary. The null hypothesis for the PP test is that the observed series has a unit root. For the KPSS test, the null hypothesis is that the observed series is stationary. The tests (Table 1) clearly show (with 5% statistical significance) that all observed series do not have unit roots and are stationary. For all series (except Ethereum) weak stationarity cannot be rejected.

3.4. Power law of distribution of returns

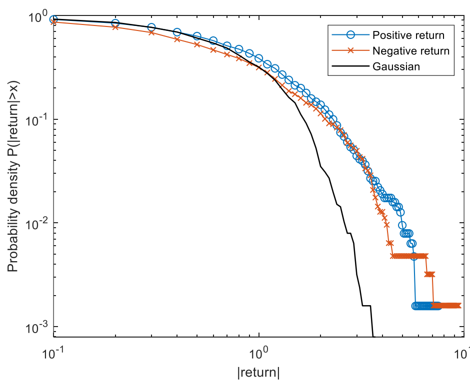
The random variable X shows the properties of the power law of the tail distribution if there are constants A and λ so

$$P(X > x) \sim x^{-\alpha}, x \geq x_{min} \tag{5}$$

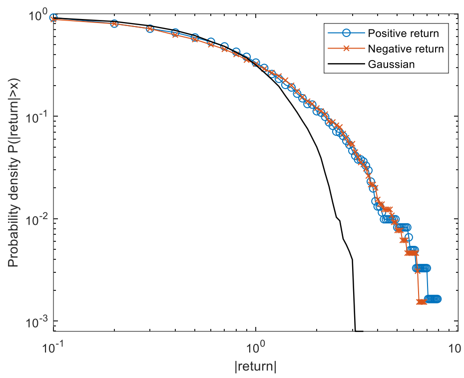
where α is the power coefficient. The correlation is tested using a log-log plot of the tail of the distribution (X>x). Linear regression log(P(X>x)) against log(x) gives coefficient α. As the law is directed towards the tail of the distribution, the regression is calculated only for values of x that exceed some given threshold (x_{min}). The presence of a power law distribution of returns has been observed in the stock market (Gabaix et al., 2003). Figure 4(a) shows the power law for the selected set of stocks. Also, Figure 4 (b,c) shows the power law for positive and negative log returns of Bitcoin and Ethereum cryptocurrencies.



a) Power law distribution of selected time series



a) BTC



b) ETH

Fig. 4 Power law distribution of cryptocurrencies. a) distribution of returns of selected time series; b) Distribution of positive and negative log returns of Bitcoin (BTC); c) Distribution of positive and negative log returns of Ethereum (ETH)

Source: Authors' calculations

$$P(X > x) \sim x^{-\alpha}, x \geq x_{min}$$

The estimation of parameters α and x_{min} is based on the procedure described by Clauset, Shalizi, Newman (2007). The results are shown in Table 2 for all log returns of the selected series. In addition, the results for the distribution of positive returns and negative returns are shown separately. Finally, the range between the slopes of positive and negative returns is given (Range=|α (+)-α (-)|). Research results show that cryptocurrencies have similar dynamics to the stock market (parameter α is close to 3). The difference between the negative and positive tails of the distribution is significant, but similar to stock market behavior. However, significantly lower than the global market represented by the SP500 index.

Table 2 Power law parameters for selected data series. (+) 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*
AMD	2.80475	0.72892	2.45786	0.50282	2.90595	0.72892	0.44808
BTC	2.85607	0.78591	3.07467	0.84342	2.74668	0.78593	0.32799
ETH	2.94765	0.91062	2.69633	0.68397	2.99773	0.92091	0.30140
INTC	3.09913	0.91523	3.13352	0.84037	3.13837	0.96179	0.00485
NVDA	3.53004	1.15357	2.95134	0.75291	3.14708	1.03856	0.19574
TSMC	3.20485	0.95544	3.12442	0.93705	3.26226	0.95544	0.13784
SP500	2.96575	0.98602	3.22375	0.78258	2.31110	0.48015	0.91265

Source: Authors' calculations

3.5. Serial correlation of returns

The efficient market hypothesis assumes that there is no significant serial autocorrelation of returns. The autocorrelation function of returns drops to zero very quickly and is one of the first documented stylized facts that gives indirect support to the EMH. To check serial correlation, we use the Ljung-Box Q-test, which tests the null hypothesis that all autocorrelation coefficients are equal to zero. The test is also used to check for randomness in time series. The test results are shown in Table 3. The table shows that despite the high statistical value, the null hypothesis can be accepted.

3.6. Serial correlation of volatility

Figure 1 clearly shows that the returns of both cryptocurrencies show periods where high and low returns are clustered together indicating volatility clustering.

The previously mentioned Ljung-Box Q-test and Engle's ARCH test are used to test the null hypothesis of the absence of significant serial autocorrelation of volatility. In contrast to returns, the Ljung-Box Q-test of the absolute value of returns and squared returns of the selected financial series strongly rejects the null hypothesis and indicates a significant temporal correlation of volatility (Table 3). The ARCH test examines the existence of clustering of volatility (heteroscedasticity) in time series. Like the previous test, the ARCH test strongly rejects the null hypothesis of no volatility correlation (Table 3). It is a general observation that the volatility of financial series is clustered and persistent. Also, there is an asymmetry in volatility, with some stocks volatility more sensitive to negative returns (Takaishi, 2018).

Table 3 Results of Ljung-Box Q-test of serial correlation of returns (r), absolute value of returns ($|r|$) and square of returns r^2, and ARCH of existence of heteroscedasticity in the data.

	Ljung-Box Q-test (CV=18.3070)						ARCH (CV=18.3070)	
	r		$\|r\|$		r^2			
	Q-test	p-val	Q-test	p-val	Q-test	p-val	Stat	p-val
AMD	30.131	0.000	95.870	0.000	36.886	0.000	27.566	0.000
BTC	13.118	0.217	133.206	0.000	25.144	0.005	17.990	0.005
ETH	19.203	0.038	154.245	0.000	102.722	0.000	76.6360	0.000
INTC	138.601	0.000	682.162	0.000	472.631	0.000	283.897	0.000
NVDA	54.662	0.000	397.421	0.000	235.553	0.000	129.562	0.000
TSMC	95.219	0.000	488.278	0.000	520.639	0.000	299.319	0.000
SP500	363.258	0.000	2491.000	0.000	1756.100	0.000	543.389	0.000

Source: Authors' calculations

Based on the ARCH test, we conclude that returns are variable and choose the GJR-GARCH (Glosten-Jagannathan-Runkle GARCH) model for volatility modeling. The econometric literature is rich in various models from the ARCH/GARCH family (Bollerslev, 1992). In this paper, we use GJR-GARCH(1,1) to estimate the conditional mean and variance of returns on selected time series assuming a t distribution of returns. The assumed GJR-GARCH (1,1) process can be expressed as follows:

$$r_t = \mu + \varepsilon_t, \varepsilon_t = \sigma_t z_t \tag{6}$$

$$\sigma_t^2 = \omega + (\alpha + \gamma I_{t-1})\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{7}$$

$$I_{t-1} := \begin{cases} 0 \text{ if } r_{t-1} \geq \mu \\ 1 \text{ if } r_{t-1} < \mu \end{cases} \tag{8}$$

Table 4 gives the specifications of the GJR-GARCH(1,1) model for the selected time series. All estimated GJR-GARCH coefficients are statistically significant.

Table 4 Parameters of GJR-GARCH(1,1) model for selected time series

GJR-GARCH(1,1)-t	ω	β	α	γ
AMD	0.00007	0.88166	0.05415	0.04188
BTC	0.00003	0.92046	0.09529	-0.03152
ETH	0.00032	0.82304	0.17377	-0.04015
INTC	0.00001	0.91383	0.12578	-0.07923
NVDA	0.00009	0.73457	0.07570	0.21101
TSMC	0.00001	0.88769	0.07964	0.03606
SP500	0.00000	0.77255	0.04105	0.37279

Source: Authors' calculations

Since the value of the GARCH coefficient (β) is greater than the value of the ARCH coefficient (α), we can conclude that volatility is very persistent and clustered. A high value of the GARCH coefficient (β) implies persistent volatility clustering. The existence of Leverage effect (γ), indicates that negative news has a greater impact (γ >0) in AMD, NVDA, TSMC, SP500, while positive news has a greater impact (γ <0) in BTC, ETH, INTC. That is, cryptocurrency volatility is more sensitive to positive news.

3.7. Non-linearity test

The presence of non-linearity in the data can be checked using various tests; however, most empirical research on financial time series uses the Brock-Dechert-Scheinkman test (BDS test) (Brock et al., 1996). This test is based on the serial independence check of the correlation integral and serves as an indirect proof of the existence of nonlinearity in the sample of the unknown distribution of the time series. That is, it serves to distinguish random time series from non-linear stochastic processes. The null hypothesis about the IID process is rejected when the value of the BDS statistic is greater than the given critical value for the given confidence interval (1.645 (90% CI), 1.960 (95% CI), 2.326 (2% CI) and 2.576 (99% CI)). BDS test statistics show significantly higher values than the critical value (CV=1.960) of the selected time series so that the null hypothesis about the IID process can be rejected. Table 1 shows only the results for the embedding dimension DIM=6 and S=1.0. These results strongly suggest the potential existence of non-linear dependence in the selected time series.

3.8. Long-run correlation test

Checking the existence of long-term correlation of cryptocurrency returns and selected stock returns is based on the Hurst exponent and is shown in Table 5. To estimate the Hurst exponent, the MFDFA (Multifractal detrended fluctuation analysis) method is used for different scales of the observed time series (scale = [16, 32, 64, 128, 256, 512]), 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 both cryptocurrencies, which indicates that the cryptocurrency market is inefficient. However, individual stocks (AMD) and the market index SP500 also show inefficiency. The range between the highest and lowest values for the Hurst exponent (Range) shows that during the observed interval all time series had variable exponent values and had periods of high market efficiency. For the sake of comparison, Table 5 also shows the standard estimate for the Hurst exponent using the R/S analysis method. And its values for cryptocurrencies are significantly higher than the 0.5 expected for normally distributed data and an efficient market.

Table 5 Results of testing the long-term correlation in the data and the index of inefficiency

	H(2)	*InffIdx*	*Min Hurst*	*Max Hurst*	*Range*	*R/S Hurst*
AMD	0.58917	**0.08917**	0.21618	0.81897	0.60279	0.46130
BTC	0.59947	**0.09947**	0.31394	1.02880	0.71486	0.61250
ETH	0.62955	**0.12955**	0.28887	0.95359	0.66472	0.66690
INTC	0.52057	0.02057	0.19280	0.87512	0.68232	0.46640
NVDA	0.50463	0.00463	0.19871	0.77676	0.57805	0.53150
TSMC	0.49650	0.00350	0.17906	0.79443	0.61537	0.50700
SP500	0.57306	**0.07306**	0.05215	0.88239	0.83024	0.45320

Source: Authors' calculations

3.9. Correlation between series

Table 6 shows the return correlation coefficients between cryptocurrencies and selected stocks. All correlations have a statistical significance of 1% (p-value less than 0.001) and all are positive. Bitcoin (BTC) and Ethereum (ETH) show a high positive correlation during the observed period (r=0.665) which indicates that cryptocurrency returns have similar behavior and that the cryptocurrency market as a whole is moving in the same direction. Note that a large number of other cryptocurrencies are purchased using Bitcoin or Ethereum.

Table 6 Correlation results of cryptocurrencies, selected stocks and SP500 index. Correlations greater than 0.5 are marked in red

Correlation	*AMD*	*BTC*	*ETH*	*INTC*	*NVDA*	*TSMC*	*SP500*
AMD	1						
BTC	0.10460	1					
ETH	0.09263	**0.66518**	1				
INTC	0.35295	0.14118	0.11647	1			
NVDA	**0.64016**	0.15930	0.15554	**0.53257**	1		
TSMC	**0.47279**	0.09446	0.11301	**0.51571**	**0.59454**	1	
SP500	**0.50012**	0.18567	0.18850	**0.67673**	**0.65033**	**0.62876**	1

Source: Authors' calculations

Correlations of cryptocurrencies and selected stocks and the SP500 index show a positive but small correlation. However, a high positive correlation exists among the selected stocks, especially with the market trend as a whole represented by the SP500 index. All stocks are highly positively correlated with each other as well as with the SP500 index. The correlation between Intel (INTC) and AMD is positive but not that high. The results indicate that the behavior of cryptocurrencies differs from the behavior of the stock market.

3.10. Granger correlations

One way of testing statistical causality between stationary time series is the Granger causality test (Granger, 1969). Causality refers to the time sequence between observed series. According to the test, if the past values of the potentially causal variable (data series) better predict the current (lagged) value of the dependent variable (time series) than the past values of the dependent variable itself, we say that the hypothesized explanatory variable Granger-causes the hypothesized dependent variable. Granger causality is based on the generally accepted observation that a cause occurs before its effect. Granger tests the null hypothesis that there is no evidence of a causal relationship. If the null hypothesis is rejected with statistical significance, we conclude that there is causality in the tested direction. Then the test is repeated in the opposite order, to see if there is causality between the two variables in the opposite direction. The F-statistic shown is the Wald statistic for the null hypothesis.

Table 7 shows the results of Granger causality testing between volatility (VTY) and trading volume (VOL) of all observed time series. At the 5% significance level, the null hypothesis of mutual Granger causality cannot be rejected for all observed time series. The results show that cryptocurrencies do not show differences in volatility behavior and trading volume compared to the stock market. The results are in agreement with earlier research.

Table 7 Granger causality test between volatility and trading volume

Pairwise Granger Causality Tests
Sample: 1/04/2017 12/31/2021

Null Hypothesis:	*F-Statistic*	*Prob.*
AMDVTY does not Granger Cause AMDVOL	6.69286	0.0013
AMDVOL does not Granger Cause AMDVTY	190.257	0.0000
BTCVTY does not Granger Cause BTCVOL	14.8545	0.0000
BTCVOL does not Granger Cause BTCVTY	211.535	0.0000
ETHVTY does not Granger Cause ETHVOL	20.763	0.0000
ETHVOL does not Granger Cause ETHVTY	33.7269	0.0000
INTCVTY does not Granger Cause INTCVOL	3.50474	0.0303
INTCVOL does not Granger Cause INTCVTY	155.351	0.0000
NVDAVTY does not Granger Cause NVDAVOL	2.8523	0.0581
NVDAVOL does not Granger Cause NVDAVTY	209.425	0.0000
TSMCVTY does not Granger Cause TSMCVOL	5.77802	0.0032
TSMCVOL does not Granger Cause TSMCVTY	313.154	0.0000

Source: Authors' calculations

Table 8 shows the results of Granger causality testing between returns of all observed time series. The results show that cryptocurrencies do not show a significant correlation with the returns of the listed stocks. However, the results show that there is a Granger causality between the movement of stock returns of Intel (INTC) with all selected stocks and the market movement (SP500). Also, market movements (SP500) Granger-cause movements in the stock market

Table 8 Granger causality test between cryptocurrency returns and market movements

Pairwise Granger Causality Tests
Sample: 1/04/2017 12/31/2021

Null Hypothesis:	*F-Statistic*	*Prob.*
BTC does not Granger Cause AMD	2.78484	0.0621
INTC does not Granger Cause AMD	6.51704	0.0015
AMD does not Granger Cause INTC	9.58769	0.0000
AMD does not Granger Cause NVDA	2.6172	0.0734
SP500 does not Granger Cause AMD	3.86631	0.0212
BTC does not Granger Cause NVDA	2.32612	0.0981
BTC does not Granger Cause TSMC	2.74578	0.0646
ETH does not Granger Cause SP500	2.46053	0.0858
INTC does not Granger Cause NVDA	12.6769	0.0000
SP500 does not Granger Cause INTC	11.9537	0.0000
INTC does not Granger Cause TSMC	19.4915	0.0000
SP500 does not Granger Cause NVDA	24.2994	0.0000
NVDA does not Granger Cause SP500	3.10401	0.0452
TSMC does not Granger Cause NVDA	3.27035	0.0383
SP500 does not Granger Cause TSMC	22.5196	0.0000

The table only shows causes that cannot be rejected with a 5% confidence interval
(The null hypothesis is not rejected at 5% significant level).
Source: Authors' calculations

The results of testing the Granger causality between the trading volume of all observed time series are shown in Table 9. The results show that cryptocurrencies show a certain Granger causality with the trading volume of the selected stocks. The correlation between the trading volume of Bitcoin (BTC_VOL) and the trading volume of Nvidia (NVDA_VOL) and TSMC (TSMC_VOL) cannot be dismissed. Also, the correlation of Ethereum (ETH_VOL) trading volume with Nvidia (NVDA_VOL) trading volume cannot be dismissed. Finally, the trading volumes of Bitcoin (BTC_VOL) and Ethereum (ETH_VOL) are mutually Granger related.

Table 9 Granger causality test of trading volume between cryptocurrencies and market movements

Pairwise Granger Causality Tests
Sample: 1/04/2017 12/31/2021

Null Hypothesis:	*F-Statistic*	*Prob.*
INTC_VOL does not Granger Cause AMD_VOL	3.07418	0.0466
ETH_VOL does not Granger Cause BTC_VOL	4.92155	0.0074
BTC_VOL does not Granger Cause ETH_VOL	52.7704	0.0000
NVDA_VOL does not Granger Cause BTC_VOL	11.4048	0.0000
BTC_VOL does not Granger Cause NVDA_VOL	14.4122	0.0000
TSMC_VOL does not Granger Cause BTC_VOL	4.57452	0.0105
BTC_VOL does not Granger Cause TSMC_VOL	3.46531	0.0316
NVDA_VOL does not Granger Cause ETH_VOL	15.6268	0.0000
ETH_VOL does not Granger Cause NVDA_VOL	6.37473	0.0018
TSMC_VOL does not Granger Cause ETH_VOL	3.99406	0.0187
TSMC_VOL does not Granger Cause INTC_VOL	2.39853	0.0913
INTC_VOL does not Granger Cause TSMC_VOL	8.66661	0.0002
NVDA_VOL does not Granger Cause TSMC_VOL	3.05422	0.0475

The table only shows causes that cannot be rejected with a 5% confidence interval (The null hypothesis is not rejected at 5% significant level).
Source: Authors' calculations

Table 10 Granger causality test of volatility between cryptocurrencies and market movements

Pairwise Granger Causality Tests
Sample: 1/04/2017 12/31/2021

Null Hypothesis:	*F-Statistic*	*Prob.*
AMD_VTY does not Granger Cause INTC_VTY	16.5478	0.0000
NVDA_VTY does not Granger Cause AMD_VTY	3.03975	0.0482
AMD_VTY does not Granger Cause NVDA_VTY	6.85922	0.0011
BTC_VTY does not Granger Cause INTC_VTY	51.1661	0.0000
BTC_VTY does not Granger Cause TSMC_VTY	2.5083	0.0818
ETH_VTY does not Granger Cause INTC_VTY	6.19997	0.0021
NVDA_VTY does not Granger Cause INTC_VTY	22.0374	0.0000
INTC_VTY does not Granger Cause NVDA_VTY	28.6428	0.0000
TSMC_VTY does not Granger Cause INTC_VTY	9.66306	0.0000
INTC_VTY does not Granger Cause TSMC_VTY	56.8068	0.0000
NVDA_VTY does not Granger Cause TSMC_VTY	4.81175	0.0083

The table only shows causes that cannot be rejected with a 5% confidence interval (The null hypothesis is not rejected at 5% significant level).
Source: Authors' calculations

Table 10 shows the results of Granger causality testing between the volatility of all observed time series. The results show that we cannot reject the causality of Bitcoin return volatility (BTC_VTY) and the volatility of Intel (INTC_VTY) and TSMC (TSMC_VTY). Also, the correlation of the volatility of Ethereum (ETH_VTY) with the volatility of Intel (INTC_VTY) cannot be dismissed. However, the results show that there is no significant volatility correlation between Bitcoin and Ethereum.

CONCLUSION

Our research has shown, using various tests, that the null hypothesis about the normality of the distribution of daily returns of the most important cryptocurrencies, Bitcoin and Ethereum, can be rejected. Research results based on the estimation of the parameter α of the power law show that cryptocurrencies have similar dynamics to the stock market and that the difference between the negative and positive tails of the return distribution is significant. The results of tests of serial autocorrelation of volatility indicate a significant temporal correlation of the volatility of cryptocurrencies. The existence of data non-linearity contradicts the efficient market theory and is strongly confirmed by the BDS test. Additional support for the inefficiency of the cryptocurrency market comes from the Hurst exponent and the Inefficiency Index. The results of testing the correlation and Granger causality of cryptocurrency returns, trading volume and volatility show that the cryptocurrency market is a brand new speculative market that is weakly correlated with the stock market.

Based on all the tests conducted in this research, we can conclude that the cryptocurrency market is inefficient and provides a potential opportunity for investors to predict price trends. In this paper, we did not investigate the strong form of market efficiency and possible profitability of investing in the cryptocurrency market, taking into account the risks and transaction costs.

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DUGOROČNA KORELACIJA I EFIKASNOST TRŽIŠTA KRIPTOVALUTA

Ovaj rad ispituje efikasnost tržišta najznačajnijih kriptovaluta, Bitcoin i Ethereum. U radu koristimo više različitih testova za proveru normalnosti distribucije prinosa, dugoročne zavisnosti i postojanja heteroskedastičnosti volatilnosti prinosa. Osobine prinosa kriptovaluta upoređujemo sa prinosima akcija najznačajnijih kompanija proizvođača hardverskih komponenti za rudarenje (mining) kriptovaluta. Međupovezanost prinosa, obima trgovanja i volatilnosti između kriptovaluta i izabranih akcija izvršena je pomoću Granger testa uzročnosti. Rezultati istraživanja odbaciju hipotezu o efikasnom tržištu i pokazuju da je tržište kriptovaluta potpuno novo spekulativno tržište koje je slabo korelisano sa tržištem akcija.

Ključne reči: *hipoteza efikasnog tržišta, tržište kriptovaluta, hipoteza slučajnog hoda, dugoročna korelacija.*