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Chaos and Predictability in Cryptocurrencies

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Highlights

What are the main findings?

- Chaos is present in prices, returns, and trading volume changes in cryptocurrencies.
- Prices, returns, and trading volume changes are nonlinear and deterministic.
- Prices, returns, and trading volume changes are predictable on daily basis.

What are the implications of the main findings?

- Prior information on nonlinear dynamics and chaos in cryptocurrency data can be considered to implement intelligent forecasting systems.
- Profits can be generated as cryptocurrency markets are not efficient.

Abstract

Background: Lyapunov exponent has been used in many science and engineering problems to quantify chaos in systems and understand their nonlinear dynamics. In financial engineering and forecasting, evaluation of chaos in financial data helps determine whether the data are predictable and if profits can be generated. The purpose of this study is to examine presence of chaos in cryptocurrency markets. Methods: To examine chaos, Lyapunov exponent is computed from a set of 50 cryptocurrencies and statistical one-sided and two-sided Student-*t* tests are performed to check if on average the computed Lyapunov exponents are equal, less, or larger than zero. Results: The statistical results reveal strong evidence that prices, returns, and trading volume changes are all chaotic; hence, they show nonlinear and deterministic characteristics. Conclusions: Prices, returns, and trading volume changes in cryptocurrencies could be predicted in the short run; for instance, on a daily basis. In this regard, active traders and investors may implement predictive systems to generate daily profits.

Keywords: efficient market hypothesis; predictability; cryptocurrency markets; chaos; Lyapunov exponent

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1. Introduction

Chaos theory [1,2] is used to study the patterns of dynamic and chaotic systems. For instance, it involves the study of unstable and aperiodic performance exhibited by nonlinear dynamical systems. In recent years, there has been large scholarly attention on discovering chaotic motion and oscillations in nonlinear dynamical systems spanning across various problems, including image encryption [3,4], market of raw material shipping [5], information processing in the brain [6–8], strawberry production [9], authorship

attribution [10], analysis of analog circuits and lumped electronic networks [11], assessment of the impact of media coverage on disease outbreak models [12], structural-acoustic systems evaluation [13], secure communications [14], susceptible-infected-recovered epidemic modeling with vaccination [15], image segmentation [16], high dimensionality of transferred data over the Social Internet of Things (SIoT) system [17], and design of data security systems [18].

In addition, chaos theory is receiving growing attention in the evaluation of predictability of financial markets. For instance, in an early study, Serletis and Shintani [19] tested for the presence of random walk and chaos in the US stock market. The empirical findings suggest absence of random walk and chaotic behavior. Tsionas and Michaelides [20] found the presence of noisy chaos both before and after the 2008 worldwide financial crisis in stock return in the USA, UK, Switzerland, Netherlands, Germany, and France. Kumar and Gupta [21] found solid evidence in favor of chaos in daily and monthly returns in capital markets including Canada, France, Germany, Italy, Japan, the UK, and the USA. The study conducted by Lahmiri [22] examined chaos in returns and volatility in family business stock and in aggregate stock market in Morocco. The empirical results indicated that business family stock returns are not chaotic whereas the aggregate market returns display sign of chaotic behavior. Further, it was found that volatility in family business stock returns is not chaotic, whereas chaos is present in volatility of the aggregate market. Vogl et al. [23] studied presence of chaos in green and conventional bond indices namely the S&P Green Bond Index and the S&P500 Bond Index. They found evidence that both market indices display a mixture of quasi-periodic cycles and deterministic/chaotic behavior. Lahmiri et al. [24] examined chaos in prices of family business, green, Islamic, and common stock indices in Europe. The empirical mode decomposition algorithm was used to extract short and long fluctuations in each market. The empirical results showed that short fluctuations are chaotic, whereas long fluctuations are not. The presence of chaos in crude oil markets (Brent and WTI) before and after 2008 international financial crisis was scrutinized by Lahmiri [25]. The observed findings indicated strong evidence that chaos is absent in prices and returns in both crude oil markets before and after international crisis. Nevertheless, volatility in Brent and WTI was found to be chaotic after 2008 international financial crisis. Chaos was examined in different Moroccan exchange rate markets in short and long movements obtained by stationary wavelet transform by Lahmiri [26]. It was found that chaos is present in both long and short movements in prices of Moroccan exchange rates. However, chaos is absent in their short and long returns. In addition, it was concluded that some exchange rate markets displayed different chaotic forms in short and long movements.

Recently, Albulescu et al. [27] studied chaos in Central and Eastern European stock markets and found evidence of chaotic patterns in their returns. Also, evidence of the presence of chaos was found in the Baltic dry index, investor sentiment index, and the global stock market indicator [28]. Escot et al. [29] studied the impact of the COVID-19 pandemic on structural change in stock returns across international markets including the United States (S&P, Dow Jones, NASDAQ, NYSE), United Kingdom, Europe 50, Europe 100, Germany, France, Belgium, Spain, Italy, Switzerland, Norway, Russia, Japan, China, South Korea, Brazil, and Mexico. The empirical results indicated evidence that the COVID-19 pandemic was followed by at least two structural changes in international financial markets. Alves [30] studied chaos patterns in international stock market indices including S&P 500, NASDAQ, IBEX 35, EURONEXT 100, Nikkei 225, and SSE Composite before and during the pandemic. They found that the North American stock markets (S&P 500 and NASDAQ) exhibited a growing level of chaos during the pandemic. Also, no significant change in chaos was observed after the first week of January 2020 in the European index IBEX and the Asian index N225. Furthermore, as the level of chaos in S&P 500, NASDAQ

Composite, and EURONEXT 100 increased due to the pandemic, these markets were the riskiest investment. Inversely, the level of chaos decreased in the SSE Composite Index; the latter was the safest investment. Finally, the dynamics in the IBEX 35 and Nikkei 225 stock markets remained basically the same before and during the crisis. Sandubete et al. [31] examined chaos in main currency markets in the United States, Europe, and the United Kingdom. They concluded the presence of a random irregular evolution; however, there is possibly a generating system which could be deterministically (and nonlinear) used to allow for predicting opportunities.

Previous research has shown evidence of presence of chaos in the US stock market [19], Western stock markets [20,21], family business companies listed on the Moroccan stock market [22], green and conventional bond markets [23,24], Islamic financial markets [24], major Western crude oil markets (Brent and WTI) [25], Central and Eastern European stock markets [27], and exchange markets [26,31]. However, little is known about chaos in cryptocurrencies. For instance, Gunay et al. [32] found evidence of the presence of chaos in returns of Bitcoin, Litecoin, Ethereum, and Ripple. Omane-Adjepong and Alagidede [33] found evidence of high-level chaos in weekly scale in returns of eight cryptocurrency markets. Also, Partida et al. found evidence of chaos in Bitcoin and Ethereum price series [34]. Finally, it was concluded that the COVID-19 pandemic has not affected the mean of estimated chaos in prices of cryptocurrencies, but it increased its variability [35]. Also, the pandemic has not affected chaos estimated from the level of trading volume.

Most of the works in the literature focused on conventional equity markets and showed evidence of chaos in return series. In addition, limited studies were devoted to cryptocurrencies and demonstrated the presence of chaos in returns [32,33] or in prices [34,35]. In addition, previous studies used a limited number of cryptocurrencies to study chaos; except for the study in [35] where 41 were considered. As a result, it is hard to draw general conclusions about chaos from a limited number of cryptocurrencies studied. Furthermore, no study has examined chaos on major cryptocurrency data including price, return, volatility, and trading volume. Therefore, knowledge of chaos characteristics across data records is missing.

The main purpose of this paper is to examine chaos in cryptocurrencies. To this end, we consider computing Lyapunov exponent [36–39] in a large set and evaluate its positivity, for instance, the presence of chaos in the underlying population of cryptocurrencies under study. Indeed, the presence of chaos in the underlying time series implies that the data process could be predicted in short periods of time [40]. Thus, if cryptocurrency time series are random process, then they are not predictable. In contrast, if cryptocurrency time series are chaotic, then its process could be predicted in the short run. In this regard, examining chaos (short run predictability) in cryptocurrencies allows testing the efficient market hypothesis [41] in these markets. Indeed, the efficient market hypothesis (EMH) [41] states that asset prices reflect all available information; hence, they are not predictable.

Specifically, following the EMH, asset price efficiency is represented by the adjustment of the market to all accessible information for accurate price evaluation. Based on the random walk model, the EMH assumes independent random movements used to follow a Gaussian distribution. Therefore, the more efficient the market is, the more random the price variations are. However, in real-world equity markets, the informational weaknesses may lead to a delay in price adjustment with respect to new information. In this regard, Lo [42] introduced the adaptive markets hypothesis (AMH) used to assume that market efficiency evolves due to the dynamics of market participants, the readiness of profit opportunities, and the ability of investors to learn and adapt. In this framework, AMH predicts that if market efficiency is not permanent, then it varies with the market environment over time.

In addition, the fractal market hypothesis (FMH) [43] adopts a non-Gaussian perspective and allows dependence and serial correlations within the underlying time series. In other words, in FMH framework, across all time intervals, market prices exhibit self-similar and fractal patterns. Hence, trends in non-stationary data can be analyzed and profits can be generated. In chaos theory [43,44], an apparently complex, random or unpredictable system can be governed by deterministic laws. In this framework, if the underlying series is globally chaotic, then it is predictable in the short term. Therefore, we seek to measure and test chaos in cryptocurrencies to check if they are chaotic; hence, they are predictable in the short time which violates the EMH.

The contributions of the current study are as follows. First, we test predictability (efficiency) in cryptocurrencies by means of chaos theory based on the estimation of Lyapunov exponent (characteristic) on a large data set of 50 cryptocurrencies to cover the most traded digital assets in the market to generalize the statistical results. In this regard, we enrich the literature on chaos in cryptocurrency markets as limited studies were conducted on this topic. Second, for each individual cryptocurrency, the chaos exponent is estimated from the price, return, volatility, and trading volume data. Indeed, such global investigation of chaos across different types of records related to cryptocurrencies would increase our understanding of predictability in cryptocurrency markets and of the sources of predictability. Third, statistical tests (one-sided and two-sided Student-*t* tests) are applied to scrutinize the value, sign, and statistical significance of the population of computed Lyapunov exponents from each type of data record. In this regard, robust and general conclusions can be drawn.

The remainder of the paper is organized as follows. Section 2 presents the method used to compute Lyapunov exponent. Section 3 describes data and provides statistical results. Finally, discussion and conclusion are in Section 4.

2. Methods

To compute the Lyapunov exponent (denoted λ) for each individual cryptocurrency, we adopt the method in [45–47]. Then, we perform the following Student-*t* tests to check the following null hypotheses: (1) H_0: λ = 0, (2) H_0: λ > 0, and (3) H_0: λ < 0. A positive Lyapunov exponent λ indicates that the original time series is chaotic; hence, it could be predictable in the short run; for instance, on a daily basis.

The noisy chaotic system of signal $\{x_t\}_{t=1}^{T}$ can be represented by:

$$x_t = f(x_{t-L}, x_{t-2L}, \ldots, x_{t-mL}) + \varepsilon_t \quad (1)$$

where L is the time delay, m is the embedding dimension, ε noise term, f is an unknown function used to approximate a chaotic map, and t is time script. A noise-free system has zero variance: $Var(\varepsilon_t) = 0$. The Lyapunov exponent λ of noisy chaotic system is computed as [38,39]:

$$\lambda = \lim_{M\to\infty} \frac{1}{2M} \log(v_1) \quad (2)$$

where v_1 is the largest eigenvalue of the matrix ${T'}_M T_M$ and T_M is expressed as [45,46]:

$$T_M = \prod_{t=1}^{M-1} J_{M-1} \quad (3)$$

where $M \leq T$ is the block-length of equally spaced evaluation points, and J is the Jacobian matrix of the chaotic map f. The Jacobian matrix J at a starting point x_0 is expressed as follows:

$$J^t(x_0) = \left.\frac{df^t(x)}{dx}\right|_{x_0} \tag{4}$$

The unknown chaotic map f can be estimated by using a multilayer feed-forward neural network trained with gradient descent algorithm [45–47] and given by:

$$x_t \approx \alpha_0 + \sum_{j=1}^{q} \alpha_j A\left(\beta_{0,j} + \sum_{i=1}^{m} \beta_{i,j} x_{t-iL}\right) + \varepsilon_t \tag{5}$$

where q is the number of hidden layers, α_j are the layers connection weights, α_0 is the network bias, and A is a sigmoid function that processes the original signal. In our work, (L, m, q) is determined according to methodology in [46], and the largest Lyapunov exponent variance denoted by $\hat{\Sigma}$ is computed as follows [45]:

$$\hat{\Sigma} = \frac{1}{M}\sum_{j=-M+1}^{M-1}\left[\xi\left(\frac{j}{1.3221 \times M^{1/5}}\right)\sum_{t=|j|+1}^{M}\hat{\eta}_t\hat{\eta}_{t-|j|}\right] \tag{6}$$

The parameter $\hat{\eta}_t$ and the quadratic spectral kernel function $\xi(z)$ are expressed as follows [45]:

$$\hat{\eta}_t = \frac{1}{2}\log\left[\frac{\max\left(eigenvalue\left(T'_t T_t\right)\right)}{\max\left(eigenvalue\left(T'_{t-1} T_{t-1}\right)\right)}\right] - \hat{\lambda} \tag{7}$$

$$\xi(z) = \frac{25}{12\pi^2 z^2}\left(\frac{\sin\left(\frac{6\pi z}{5}\right)}{\left(\frac{6\pi z}{5}\right)} - \cos\left(\frac{6\pi z}{5}\right)\right) \tag{8}$$

Finally, the original signal has chaotic dynamics when $\lambda \geq 0$ (Equation (2)) and its short run oscillations can be predicted.

3. Data and Results

The dataset includes daily observations from 50 cryptocurrencies all collected from the Yahoo Finance website [48] and the sample period ranges from 14 March 2019 to 14 March 2024. This sample period includes major international economic events and the COVID-19 pandemic that have altered the world economy and investments. The major economic events include, for instance, US treasury yield curve inversions, VIX futures in backwardation, duress in the cash markets for US treasuries, the first stock market crash in 33 years (16 March 2020), corporate bond ETF (exchange traded funds) prices below net asset value (17 March 2020), breakdown in the historical gold-silver ratio (18 March 2020), largest historical gold spot-future spreads (24 March 2020), and Bitcoin's historic moonshot (30 November 2020) leading to rise of over 250% that year [49]. The list of their symbols includes AAVE, ADA, ALGO, AR, ATOM, AVAX, AXS, BCH, BNB, BSV, BTC, CHZ, CRO, DAI, DODGE, DOT, EGLD, ETC, ETH, FET, FIL, FLOW, FTM, GRT, HBR, HNT, ICT, LINK, LTC, MANA, MATIC, MKR, QNT, RUNE, SAND, SHIB, SNX, SOL, STX, THETA, TRX, TUSD, UNI, USDC, USDT, VET, XLM, XMR, XRP, and XTZ.

For each cryptocurrency, the Lyapunov exponent λ is computed from the closing price (P(t)), return (R(t)), and trading volume change (VC(t)) time series, where t is time script. Prices and trading volume (V(t)) are expressed in US dollars. Return series are calculated as R(t) = log(P(t)) − log(P(t − 1)) and (VC(t)) as rate of change in trading volume (V(t)). Figure 1a–d display respectively (P(t)), (R(t)), (V(t)), and (VC(t)) of Bitcoin (BTC).

Table 1 provides a summary of descriptive statistics of the price and return of each cryptocurrency. Table 2 provides the computed *p*-values from statistical tests used to check if the price and return of each cryptocurrency are stationary. The list includes standard tests including augmented Dickey–Fuller (ADF) [50] and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) [51]. The ADF test is used to test the null hypothesis of the presence of a unit root, that is the time series is not stationary, whilst KPSS tests the null hypothesis of stationarity (absence of unit root). Both tests are performed at the 5% statistical significance level. Accordingly, in most cases, the ADF test accepts the null hypothesis of non-stationarity in prices. However, for all cryptocurrencies, the ADF test strongly rejects the null hypothesis of no stationarity in returns and trading volume changes. In addition, the KPSS test strongly rejects the null hypothesis of stationarity in prices and accepts the null hypothesis of stationarity in returns and trading volume changes.

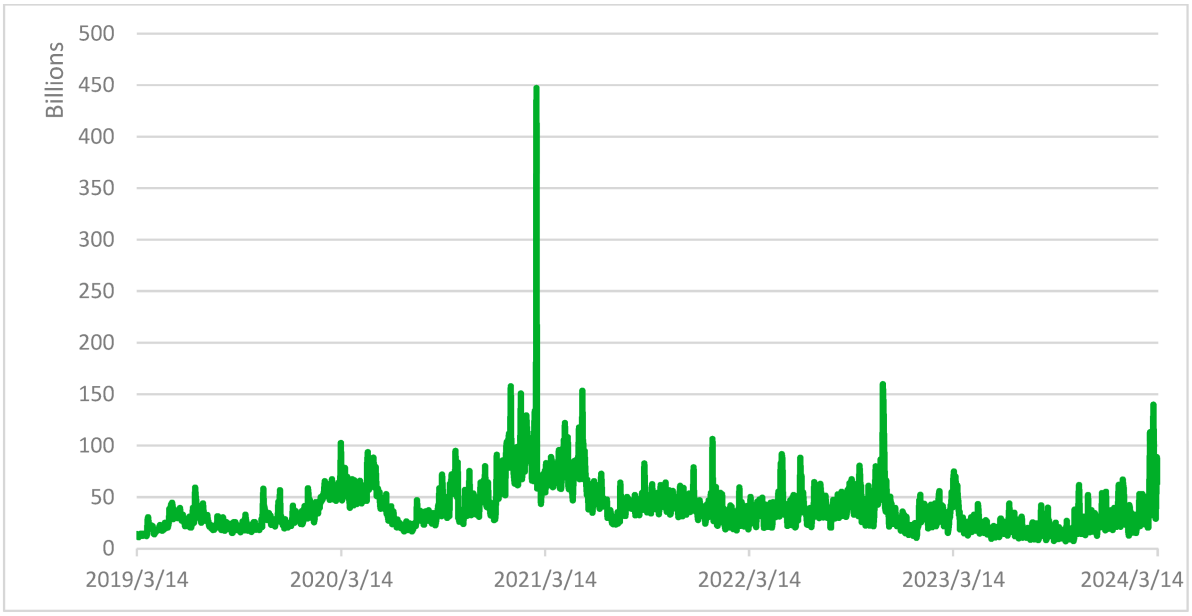


(**a**)

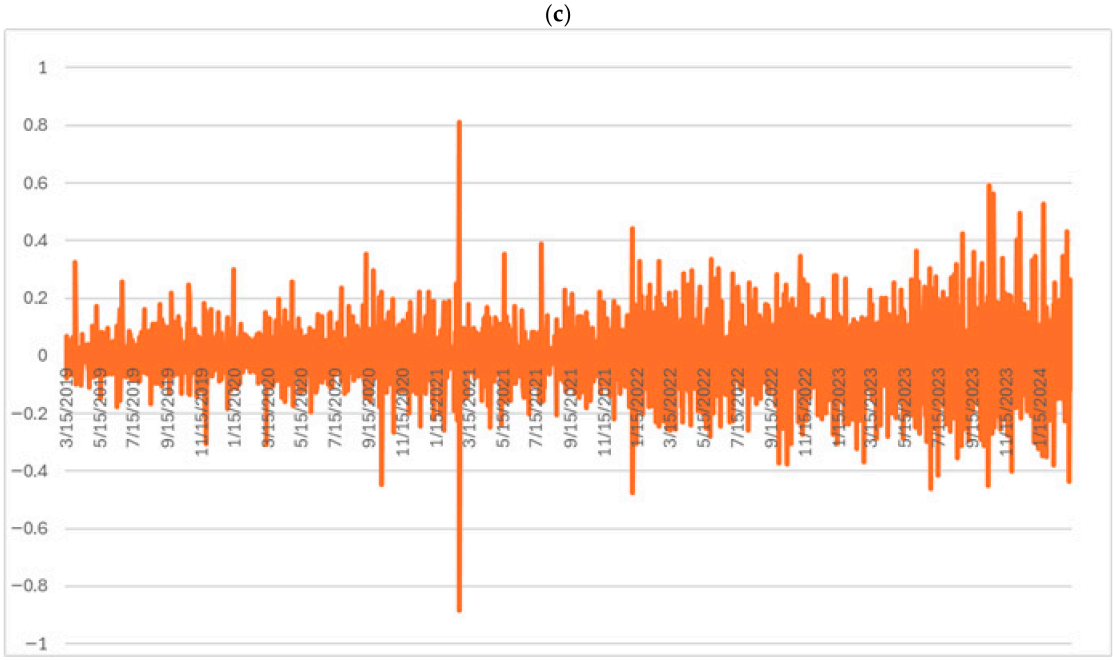


(**b**)

Figure 1. *Cont.*



(**c**)



(**d**)

Figure 1. (**a**) Plots of Bitcoin (BTC) price P(t). (**b**) Plots of Bitcoin (BTC) return R(t). (**c**) Plots of Bitcoin (BTC) trading volume V(t). (**d**) Plots of Bitcoin (BTC) trading volume change VC(t).

The boxplots of the computed Lyapunov exponent λ from price (P(t)), return (R(t)), and trading volume change (VC(t)) time series are exhibited in Figure 2. With respect to Figure 2, we performed Student-t test to check if (1) H_0: $\lambda = 0$ (two-sided), (2) H_0: $\lambda \geq 0$ (one-sided, right), and (3) H_0: $\lambda \leq 0$ (one-sided, left). The results are provided in Table 3. Accordingly, the computed Lyapunov exponent λ from price (P(t)) time series of all 50 cryptocurrencies is statistically larger than zero since the null hypothesis $\lambda = 0$ is rejected (p-values = 2.5955×10^{-4}), the null hypothesis $\lambda \geq 0$ is accepted (p-values = 0.9999), and the null hypothesis $\lambda \leq 0$ is rejected (p-values = 1.2978×10^{-4}). Therefore, prices of cryptocurrencies are chaotic and could be predicted in the short run. Also, the computed Lyapunov exponent λ from return (R(t)) time series of all 50 cryptocurrencies is statistically larger than zero since the null hypothesis $\lambda = 0$ is rejected (p-values = 2.9818×10^{-31}), the null hypothesis $\lambda \geq 0$ is accepted (p-values = 1), and the null hypothesis $\lambda \leq 0$ is

rejected (p-values = 1.4909×10^{-31}). Hence, returns of cryptocurrencies are chaotic and could be forecasted in the short run. Finally, the computed Lyapunov exponent λ from trading volume change (VC(t)) time series of all 50 cryptocurrencies is statistically larger than zero since the null hypothesis $\lambda = 0$ is rejected (p-values = 2.6353×10^{-30}), the null hypothesis $\lambda \geq 0$ is accepted (p-values = 1), and the null hypothesis $\lambda \leq 0$ is rejected (p-values = 1.3176×10^{-30}). Thus, trading volume changes in cryptocurrencies are chaotic and could be predicted in the short run.

Table 1. Summary of descriptives statistics from price and return series of cryptocurrencies (cryptos).

	Prices				Returns			
Cryptos	**Average**	**Standard Deviation**	**Skewness**	**Kurtosis**	**Average**	**Standard Deviation**	**Skewness**	**Kurtosis**
AAVE	183.1688	127.0304	1.4307	1.2414	−0.0004	0.0243	−0.3844	5.2749
ADA	1.0224	0.7818	1.4255	1.2029	−0.0003	0.0199	−0.0043	4.5221
ALGO	0.7233	0.6790	1.3202	0.6529	−0.0006	0.0229	−0.1763	7.9866
AR	24.0802	21.4372	1.5052	1.2032	0.0002	0.0304	0.7142	5.2234
ATOM	20.1171	11.1413	1.3123	0.4970	−0.0002	0.0249	−0.5125	7.9070
AVAX	44.1847	36.0773	1.3326	0.7261	0.0002	0.0260	−0.4933	6.0172
AXS	36.4421	45.3032	1.7872	2.2463	0.0003	0.0291	0.9431	11.7503
BCH	370.1821	241.7353	1.5028	3.3347	−0.0004	0.0210	0.4772	18.4089
BNB	432.6202	117.6890	1.1719	1.0525	0.0000	0.0170	−1.3451	15.8031
BSV	101.3561	62.2146	1.4859	2.9540	−0.0005	0.0219	0.3641	18.6192
BTC	44,449.6033	15,364.1893	0.6732	0.0190	0.0001	0.0134	−0.4004	3.8798
CHZ	0.2308	0.1268	1.0355	0.7292	−0.0004	0.0256	−0.4785	8.8330
CRO	0.2146	0.1928	1.8932	2.9587	0.0000	0.0207	0.0299	5.8479
DAI	1.3104	0.0472	−0.3046	−1.1445	0.0000	0.0018	−0.1146	4.4761
DODGE	0.1618	0.0992	1.6946	2.8980	−0.0003	0.0229	−0.3576	12.8375
DOT	16.7354	13.4956	1.5200	1.5754	−0.0004	0.0222	−0.9002	9.8650
EGLD	120.5333	101.8954	1.7973	3.1481	−0.0003	0.0223	−0.2261	6.2431
ETC	39.2971	18.9298	1.3829	1.8359	−0.0004	0.0227	0.1661	9.2628
ETH	2948.4547	1067.4621	0.8880	−0.0287	0.0000	0.0174	−0.6475	6.7705
FET	0.4912	0.4316	3.7447	23.0645	0.0008	0.0297	−0.0184	5.1147
FIL	26.1125	31.8598	1.5827	1.5796	−0.0010	0.0251	−0.2144	8.3213
FLOW	6.4549	8.2026	1.5724	1.4218	−0.0011	0.0248	0.1024	6.0425
FTM	0.8751	0.8864	1.7353	1.9096	0.0001	0.0311	−0.7464	7.6666
GRT	0.4003	0.3664	1.2537	0.4977	−0.0004	0.0273	−0.3488	10.6039
HBR	0.1725	0.1315	1.1923	0.3143	−0.0003	0.0221	−0.1424	7.7010
HNT	13.7716	13.6732	1.3703	1.3464	−0.0002	0.0284	0.9269	7.8023
ICT	25.8154	41.0941	5.4692	44.7201	−0.0014	0.0267	0.0394	6.2405
LINK	17.4330	10.0549	1.0095	0.2917	−0.0003	0.0230	−0.7526	7.4417
LTC	131.8918	58.6798	1.5459	2.9885	−0.0005	0.0197	−1.0607	11.9289
MANA	1.3169	1.1871	1.9321	2.9803	−0.0002	0.0288	2.8374	42.7627
MATIC	1.4057	0.5516	1.1043	1.2264	0.0002	0.0260	0.5581	9.1067

Table 1. *Cont.*

	Prices				Returns			
Cryptos	**Average**	**Standard Deviation**	**Skewness**	**Kurtosis**	**Average**	**Standard Deviation**	**Skewness**	**Kurtosis**
MKR	2064.3424	1109.0066	0.8508	0.1669	−0.0002	0.0215	0.5960	8.6308
QNT	166.2591	73.9347	1.7396	3.7584	0.0005	0.0237	0.7270	7.6964
RUNE	5.6918	4.4278	1.1435	0.9292	−0.0002	0.0307	−0.4352	6.0352
SAND	1.5924	1.7737	2.2035	4.3828	0.0002	0.0293	0.4634	9.2470
SHIB	0.0000	0.0000	2.3752	6.5553	0.0000	0.0313	0.5902	13.6869
SNX	5.9379	4.1713	1.6952	2.6917	−0.0005	0.0282	0.0292	6.0991
SOL	82.9473	70.7954	1.2863	0.7297	0.0006	0.0270	−0.8760	10.1840
STX	1.2773	0.8474	1.0914	0.7037	0.0003	0.0271	0.6320	9.3047
THETA	3.2602	2.9537	1.2259	0.1822	−0.0004	0.0244	−0.9693	8.3548
TRX	0.1025	0.0265	1.2046	1.1096	0.0001	0.0161	−1.4367	16.8382
TUSD	1.3093	0.0468	−0.2801	−1.0805	0.0000	0.0018	0.8843	9.2951
UNI	13.5007	9.2454	1.3888	0.7510	−0.0004	0.0236	0.2541	10.3079
USDC	1.3104	0.0475	−0.3099	−1.1402	0.0000	0.0017	−0.2846	4.0116
USDT	1.3106	0.0476	−0.2923	−1.1398	0.0000	0.0017	−0.0021	1.8979
VET	0.0615	0.0480	1.3826	0.9659	−0.0006	0.0223	−0.7131	7.1781
XLM	0.2225	0.1246	1.6407	3.1886	−0.0006	0.0191	0.2302	19.0493
XMR	234.9750	55.9509	1.5122	3.0481	−0.0004	0.0201	−2.2437	30.7300
XRP	0.8036	0.2973	0.9930	0.4908	−0.0003	0.0206	0.8898	23.9784
XTZ	2.8349	2.1445	1.3348	0.9159	−0.0006	0.0229	−0.6297	8.5986

Table 2. Obtained *p*-values from ADF, Phillips–Perron (P-P), and KPSS tests applied to price, return, and volume change.

	Prices		Returns		Volume Change	
	ADF	**KPSS**	**ADF**	**KPSS**	**ADF**	**KPSS**
AAVE	0.0267	0.0100	0.0010	0.1000	0.0010	0.1000
ADA	0.1524	0.0100	0.0010	0.1000	0.0010	0.1000
ALGO	0.0835	0.0100	0.0010	0.1000	0.0010	0.1000
AR	0.2632	0.0100	0.0010	0.0327	0.0010	0.1000
ATOM	0.1583	0.0100	0.0010	0.1000	0.0010	0.1000
AVAX	0.3629	0.0100	0.0010	0.0250	0.0010	0.1000
AXS	0.2821	0.0100	0.0010	0.0100	0.0010	0.1000
BCH	0.0010	0.0100	0.0010	0.1000	0.0010	0.1000
BNB	0.4458	0.0100	0.0010	0.1000	0.0010	0.1000
BSV	0.0010	0.0100	0.0010	0.1000	0.0010	0.1000
BTC	0.8188	0.0100	0.0010	0.1000	0.0010	0.1000
CHZ	0.0564	0.0100	0.0010	0.1000	0.0010	0.1000
CRO	0.2755	0.0100	0.0010	0.0100	0.0010	0.1000

Table 2. *Cont.*

	Prices		Returns		Volume Change	
	ADF	**KPSS**	**ADF**	**KPSS**	**ADF**	**KPSS**
DAI	0.8707	0.0100	0.0010	0.1000	0.0010	0.1000
DODGE	0.0094	0.0100	0.0010	0.1000	0.0010	0.1000
DOT	0.0496	0.0100	0.0010	0.1000	0.0010	0.1000
EGLD	0.1647	0.0100	0.0010	0.1000	0.0010	0.1000
ETC	0.0056	0.0100	0.0010	0.1000	0.0010	0.1000
ETH	0.4767	0.0100	0.0010	0.1000	0.0010	0.1000
FET	0.9990	0.0100	0.0010	0.0886	0.0010	0.1000
FIL	0.0010	0.0100	0.0010	0.1000	0.0010	0.1000
FLOW	0.0024	0.0100	0.0010	0.1000	0.0010	0.1000
FTM	0.2104	0.0100	0.0010	0.0737	0.0010	0.1000
GRT	0.0039	0.0100	0.0010	0.1000	0.0010	0.1000
HBR	0.1470	0.0100	0.0010	0.1000	0.0010	0.1000
HNT	0.2067	0.0100	0.0010	0.0183	0.0010	0.1000
ICT	0.0010	0.0100	0.0010	0.1000	0.0010	0.1000
LINK	0.0144	0.0100	0.0010	0.1000	0.0010	0.1000
LTC	0.0022	0.0100	0.0010	0.1000	0.0010	0.1000
MANA	0.1342	0.0100	0.0010	0.1000	0.0010	0.1000
MATIC	0.3124	0.0100	0.0010	0.1000	0.0010	0.1000
MKR	0.0445	0.0100	0.0010	0.1000	0.0010	0.1000
QNT	0.4012	0.0100	0.0010	0.1000	0.0010	0.1000
RUNE	0.0287	0.0100	0.0010	0.1000	0.0010	0.1000
SAND	0.1859	0.0100	0.0010	0.0426	0.0010	0.1000
SHIB	0.1035	0.0100	0.0010	0.1000	0.0010	0.1000
SNX	0.0098	0.0100	0.0010	0.1000	0.0010	0.1000
SOL	0.7231	0.0100	0.0010	0.0100	0.0010	0.1000
STX	0.6715	0.0100	0.0010	0.1000	0.0010	0.1000
THETA	0.0066	0.0100	0.0010	0.1000	0.0010	0.1000
TRX	0.5281	0.0100	0.0010	0.1000	0.0010	0.1000
TUSD	0.8734	0.0100	0.0010	0.1000	0.0010	0.1000
UNI	0.0136	0.0100	0.0010	0.1000	0.0010	0.1000
USDC	0.8776	0.0100	0.0010	0.1000	0.0010	0.1000
USDT	0.8820	0.0100	0.0010	0.1000	0.0010	0.1000
VET	0.0021	0.0100	0.0010	0.1000	0.0010	0.1000
XLM	0.0010	0.0100	0.0010	0.1000	0.0010	0.1000
XMR	0.0330	0.0100	0.0010	0.1000	0.0010	0.1000
XRP	0.0920	0.0100	0.0010	0.1000	0.0010	0.1000
XTZ	0.0395	0.0100	0.0010	0.1000	0.0010	0.1000

ADF and Phillips–Perron tests are used to test the null hypothesis of the presence of a unit root, meaning the time series is non-stationary. KPSS tests the null hypothesis of stationarity. All tests are performed at the 5% significance level.

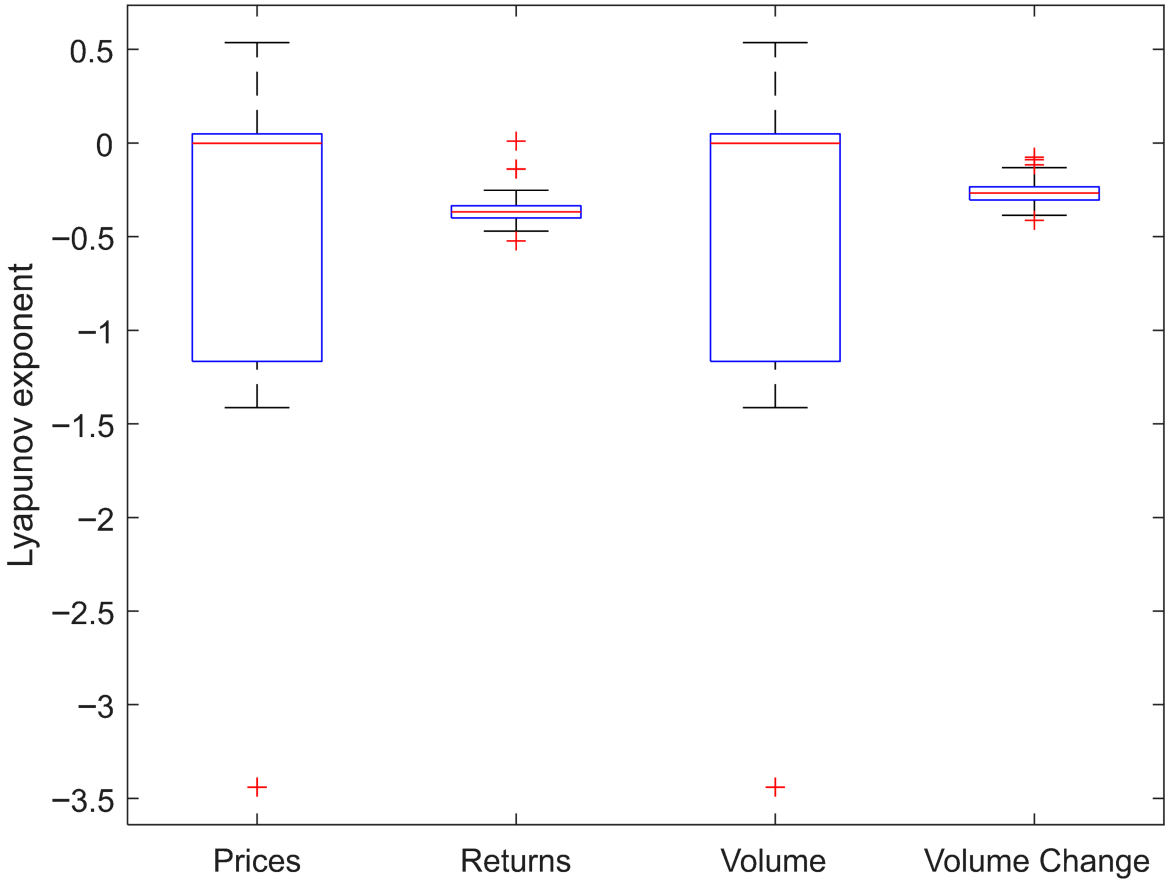


Figure 2. Boxplots of computed Lyapunov exponent λ from all 50 cryptocurrencies.

Table 3. Results from Student-*t* test applied to Lyapunov exponent λ under the null hypothesis H_0.

	***p*-Value**	***t*-Statistic**
Prices P(*t*)		
H_0: $\lambda = 0$	2.5955×10^{-4}	−3.9384
H_0: $\lambda \geq 0$	0.9999	−3.9384
H_0: $\lambda \leq 0$	1.2978×10^{-4}	−3.9384
Returns R(*t*)		
H_0: $\lambda = 0$	2.9818×10^{-31}	−27.2369
H_0: $\lambda \geq 0$	1	−27.2369
H_0: $\lambda \leq 0$	1.4909×10^{-31}	−27.2369
Volume change VC(*t*)		
H_0: $\lambda = 0$	2.6353×10^{-30}	−25.9737
H_0: $\lambda \geq 0$	1	−25.9737
H_0: $\lambda \leq 0$	1.3176×10^{-30}	−25.9737

The Student-*t* test is applied to the population of computed Lyapunov exponent; for instance, λ in Equation (2). The degree of freedom is 49 and statistical significance level is set to 5%.

4. Discussion and Conclusions

The presence of chaos has been the subject of a great number of studies in science and engineering [3–18]. In recent years, growing attention has been given to examining predictability in equity markets based on the chaos theory [19–31] where the evidence of

chaos was found. In this study, we evaluated and tested the presence of chaotic dynamics in cryptocurrency markets to check if such markets are unpredictable; if so, they are efficient following the efficient market hypothesis (EMH) [41]. Indeed, we tested the efficiency in cryptocurrency markets to enrich the literature as recent studies focused on the application of machine learning to predict cryptocurrency [52–57]. In this regard the Lyapunov exponent (λ) was computed from a large set composed of 50 cryptocurrencies, and one-sided and two-sided Student-*t* tests were performed to verify if on average the value of computed λ is equal, larger, or less than zero. We used a very recent data period based on daily observations.

It is worth mentioning that there are various approaches to calculate the largest Lyapunov exponent including the Wolf's algorithm [58] and Rosenstein's method [59]. However, in this study, we adopted the method proposed in [45–47] to estimate the largest Lyapunov exponent and test for the presence of chaos. Indeed, tests for chaos are scarce in the literature, and practical implementation is unclear [60]. In this regard, the main advantage of the method we adopted [45–47] is that it can be conducted directly on experimental data without the need to define the generating equations [47].

The findings show clear evidence of chaos, suggesting that the behavior of cryptocurrency markets is nonlinear and deterministic. In particular, strong evidence indicates that the prices, returns, and trading volume changes were all chaotic. As a result, they could be predicted at a daily frequency. This finding is interesting as the sample period covers major US and world economic events, and the COVID-19 pandemic. In this regard, arbitrage opportunities can be implemented to predict cryptocurrencies and generate profits during difficult economic and financial downturns. Our work enriches the literature by showing the presence of chaos in cryptocurrency markets and that these markets are predictable at a daily frequency; hence, they are not efficient in the sense of EMH. For instance, traders and portfolio managers may use prior information on chaos in the dynamics of prices, returns, and trading volume variations to implement predictive systems used to improve forecasting accuracy and generate profits.

Our empirical analysis of fifty cryptocurrency markets based on the chaos theory demonstrates that these markets are not efficient from the perspective of EMH. This could be explained by the theory of behavioral finance [61] used to explain irrational financial and investment decisions made by individuals based on common behavioral biases including loss aversion, herd behavior, overconfidence bias, and confirmation bias.

In addition, we computed the Kolmogorov–Sinai entropy by means of approximate entropy [62,63] across prices, returns, and volume changes. Also, for each series of computed approximate entropy, we calculated the average and standard deviation. For each time series, we used the one-sided Student-*t* test to check if the estimated population of approximate entropy is equal (null hypothesis) or greater than zero (alternative hypothesis). The results indicate that the null hypothesis is rejected for prices (p-value = 3.6447×10^{-5}, t-statistic = 4.3325), accepted for returns (p-value = 0.1611, t-statistic = 1.0000), and rejected for volume changes (p-value = 5.9705×10^{-15}, t-statistic = 10.8648). Therefore, prices and volume changes exhibit chaotic motion, whilst returns exhibit a nonchaotic motion. Hence, approximate entropy and chaos yield the same results with respect to evidence of chaos in prices and volume changes. However, they yield divergent conclusions with respect to returns. The latter can be explained by the choice of parameters used to compute approximate entropy from the returns series.

Several directions for future research emerge from this study. First, the analysis could be extended to the implementation and comparison of different methods used to compute Lyapunov exponent to examine differences between the estimates across the methods. Second, future studies would examine chaos in the post-pandemic period. Third, we will

estimate and compare entropy by using different methods to evaluate how information is carried across price, return, volatility, and change in trading volume. Fourth, another interesting future research direction would be the estimation of fractals to assess long memory in the dynamics of prices, returns, volatility, and trading volume variations. Finally, it would be interesting to investigate in future work the effect of regime shifts on chaos and fractal behavior since some cryptocurrencies can undergo fundamental technological and regime shifts that have the potential to change modeling dynamics [64].

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