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Assessing efficiency in prices and trading volumes of cryptocurrencies before and during the COVID-19 pandemic with fractal, chaos, and randomness: evidence from a large dataset

Salim Lahmiri[1,2*]

*Correspondence:
salim.lahmiri@concordia.ca

[1] Department of Supply Chain and Business Technology Management, John Molson School of Business, Concordia University, Montreal, Canada
[2] Chaire Innovation et Économie Numérique, ESCA École de Management, Casablanca, Morocco

Abstract

This study examines the market efficiency in the prices and volumes of transactions of 41 cryptocurrencies. Specifically, the correlation dimension (CD), Lyapunov Exponent (LE), and approximate entropy (AE) were estimated before and during the COVID-19 pandemic. Then, we applied Student's *t*-test and *F*-test to check whether the estimated nonlinear features differ across periods. The empirical results show that (i) the COVID-19 pandemic has not affected the means of CD, LE, and AE in prices, (ii) the variances of CD, LE, and AE estimated from prices are different across pre-pandemic and during pandemic periods, and specifically (iii) the variance of CD decreased during the pandemic; however, the variance of LE and the variance of AE increased during the pandemic period. Furthermore, the pandemic has not affected all three features estimated from the volume series. Our findings suggest that investing in cryptocurrencies is advantageous during a pandemic because their prices become more regular and stable, and the latter has not affected the volume of transactions.

Keywords: Market efficiency, Cryptocurrency price, Cryptocurrency volume, COVID-19 pandemic, Correlation dimension, Lyapunov exponent, Approximate entropy

Introduction

The COVID-19 pandemic has seriously affected the world economy as it caused the lockdown of various business, industrial, and financial activities, resulting in a severe downturn in economic growth worldwide. In this regard, a large number of studies have been conducted to estimate the effect of the COVID-19 pandemic on stocks (Wu et al. 2022; Caporale et al. 2022; Hsu and Tang 2022; Jin et al. 2022; Zhang et al. 2022a, b; Szczygielski et al. 2023; Zeng et al. 2022; Guven et al. 2022), oil (Ren et al. 2021; Chen et al. 2021; Ahundjanov et al. 2021; Espinosa-Paredes et al. 2022; Li et al. 2022; Narayan 2022a; Niu et al. 2022; Zhang et al. 2022a, b), gold (Depren et al. 2021; Salisu 2021; Liu et al. 2022; Drake 2022; Baur and Trench 2022), energy markets (Chen et al. 2022; Tong et al. 2022; Lahmiri 2023a; Sun et al. 2023), and exchange rate markets (Aloui 2021; Zhou et al. 2021; Shahrier 2022; Hung et al. 2022; Aquilante et al. 2022; Beckmann and Czudaj

2022; Narayan 2022b). Additional studies focused on the impact of the COVID-19 pandemic on cryptocurrencies, which are drawing plentiful consideration because of their ability to generate high profits and their role in portfolio diversification and hedging.

Numerous works have been conducted on various aspects of cryptocurrency markets to determine the driving reasons behind the price formation of cryptocurrencies during the COVID-19 pandemic. These studies include examining the return-volume and return-volatility relationships (Foroutan and Lahmiri 2022), long memory in returns and volatility (Lahmiri and Bekiros 2021; Belén et al. 2022), information-sharing with energy, precious metals, and equity markets (Lahmiri and Bekiros 2020a), the evolution of the informational efficiency (Lahmiri and Bekiros 2020b), the influence of social media sentiment (Kyriazis et al. 2023), dynamic spillovers among the major cryptocurrencies (Al-Shboul et al. 2022), extreme and erratic behavior (James et al. 2021), and multifractal in price and volume variations (Lahmiri 2023b). Specifically, Foroutan and Lahmiri (2022) found a significant return-volatility relationship during the pandemic for most cryptocurrencies; however, no significant relationship was found before the pandemic for all cryptocurrencies. Furthermore, they found a significant return-volume relationship for cryptocurrencies before and during the pandemic, concluding that gold is suitable for portfolio hedging during the pandemic. Lahmiri and Bekiros (2021) found that the COVID-19 pandemic significantly affected long-term memory in return and volatility of cryptocurrency and international stock markets. Belén et al. (2022) concluded that the COVID-19 pandemic slightly affected the long memory of cryptocurrency returns and produced a temporary severe impact on the long memory of volatility. Lahmiri and Bekiros (2020a) found that the information-sharing network among energy, precious metals, and equity markets was modified during the COVID-19 pandemic. Additionally, Lahmiri and Bekiros (2020b) showed that cryptocurrencies embed higher instability and irregularity, and investing in digital assets during big crises could be considered riskier than common equities. In their recent study, Kyriazis et al. (2023) concluded that Twitter-derived sentiment significantly influenced cryptocurrency markets during the pandemic. Al-Shboul et al. (2022) showed that the COVID-19 pandemic significantly affected the relationship between cryptocurrency policy, price, and dynamic connectedness across all market conditions. James et al. (2021) found that cryptocurrency behavior is more self-similar in variance than returns, both before and during the pandemic. Finally, Lahmiri (2023b) showed that price returns and trading volume variations exhibited multifractal properties before the COVID-19 pandemic and tended to exhibit non-fractal behavior during the pandemic.

Regarding standard equity markets, the predictability of cryptocurrency markets is a fundamental problem in price forecasting for better trading; thus, understanding the nonlinear dynamics of cryptocurrencies is needed to assess the predictability of these markets. For instance, this idea is highly related to cryptocurrency market efficiency. If such a market is efficient, prices reflect all relevant information about the traded assets. Considering this, the primary purpose of the current study is to evaluate efficiency in a large set of cryptocurrency markets before the COVID-19 pandemic and during the pandemic. Specifically, we seek to evaluate the information content in prices and volume of transactions with fractal, chaos, and randomness all measured in each period, for instance, before the COVID-19 pandemic and during the pandemic. We examine prices and volumes as they are expected to reveal information that interests investors, managers, and scholars alike. Indeed, because of the importance of information content in volume of cryptocurrencies, recent works have examined the effectiveness of machine learning models in predicting volume (Lahmiri et al. 2020, 2022), relationship with returns (Fousekis and Tzaferi 2021; Foroutan and Lahmiri 2022; Yarovaya and Zięba 2022), effect of liquidity provision (Bianchi et al. 2022), and multifractal properties (Stosic et al. 2019). Specifically, an ensemble predictive system could reduce the trading volume forecasting errors compared to its components and the baseline reference model (Lahmiri et al. 2020). Furthermore, support vector regression tuned with Bayesian optimization and trained with the polynomial kernel helps predict the next-week trading volume of cryptocurrencies (Lahmiri et al. 2022), and traders utilizing volume information in technical analysis can obtain higher profit (Fousekis and Tzaferi 2021). Moreover, a significant return-volatility relationship exists during the pandemic for most cryptocurrencies (Foroutan and Lahmiri 2022), and significant bidirectional causalities occur between trading volume and returns (Yarovaya and Zięba 2022). Additionally, trading volume contains significant predictive information for the dynamics of cryptocurrency returns (Bianchi et al. 2022), and price changes and volume changes follow different multifractal dynamics (Stosic et al. 2019). In this regard, comprehensive surveys on blockchain and cryptocurrencies can be found respectively in Min et al. (2019) and Fang et al. (2022).

This study uses correlation dimension (CD) (Grassberger and Procaccia 1983a, 1983b), Lyapunov exponent (LE) (Rosenstein et al. 1993), and approximate entropy (AE) (Pincus 1991) to estimate fractal, chaos, and randomness in price and volume data, respectively. Fractal, chaos, and entropy are nonlinear statistics used to assess complexity in the dynamics of time series, and they are widely used in econophysics to evaluate the efficiency of equity markets. CD can reveal structure in a nonlinear signal based on phase space reconstructions, LE is suitable for quantifying divergence in the underlying signal, and AE measures regularity/irregularity within a nonlinear signal. In this regard, CD, LE, and AE were successfully employed in economic and financial data analysis.

Indeed, because of their usefulness in analyzing nonlinear time series, the complexity mentioned above measures were successfully employed in examining various economic and financial data. For instance, the correlation dimension was applied to examine chaos in oil products for the Rotterdam and Mediterranean petroleum markets (Panas and Ninni 2000), equity markets in China and the United States (US) (Nie 2017), chaos in variations of cryptocurrency trading volume (Lahmiri et al. 2022), and trading of the Korean–US exchange rate (Lim et al. 2022). Furthermore, the Lyapunov exponent was found to be effective in examining chaos in the US–Polish exchange rate (Brzozowska-Rup and Orłowski 2004), Rotterdam and Mediterranean petroleum markets (Panas and Ninni 2000), stock returns in the US, United Kingdom, Switzerland, Netherlands, Germany, and France (Tsionas and Michaelides 2017), short- and long-term dynamics of Moroccan exchange rates (Lahmiri 2017a), crude oil markets before and after 2008 international financial crisis (Lahmiri 2017b), Moroccan family business stock returns and volatility (Lahmiri 2017c), and Bitcoin and Ethereum cryptocurrencies (Partida et al. 2022). Other studies employed the entropy measure to investigate randomness in Moroccan family business stock returns (Lahmiri 2018), forecast various international stock markets (Karaca et al 2020), assess market efficiency in the art markets (Assaf et al. 2021), evaluate stability in variations of cryptocurrency trading volume (Lahmiri et al. 2022), examine portfolio selection (Brito 2023), and inspect regularity in energy markets under the effect of the COVID-19 pandemic (Lahmiri 2023a).

The complexity measures are estimated from the prices and volumes of the 41 most liquid cryptocurrencies. Then, formal statistical tests are applied to each population of estimated nonlinear parameters to check if it is statistically different between the two periods: before the COVID-19 pandemic and during the pandemic. The battery of statistical tests included the Student's *t*-test for equality of means and the *F*-test for equality of variances. For example, we performed the Student's *t*-test for equality of means and the *F*-test for equality of variances to the estimated sample populations of the CD, LE, and AE to determine if the impact of the COVID-19 pandemic significantly altered the distributions of the estimated complexity measures from prices and volumes of 41 cryptocurrencies.

Our study's contributions can be summarized as follows.

i. We study the efficiency of cryptocurrency markets in terms of predictability, stability, and information disorder using nonlinear statistical measures before and during the COVID-19 pandemic.
ii. We enrich the literature on the effect of the COVID-19 pandemic on cryptocurrencies (Foroutan and Lahmiri 2022; Lahmiri and Bekiros 2021, 2020a, 2020b; Belén et al. 2022; Kyriazis et al. 2023; Al-Shboul et al. 2022; James et al. 2021; Lahmiri 2023a, b) by evaluating its effect on the fractal, chaos, and randomness of these digital assets based on a very recent sample.
iii. We consider a large dataset comprising the 41 most traded cryptocurrencies to draw general conclusions.
iv. Nonlinearity characteristics in volume of transactions are examined to shed light on the information content and behavior of volume to enrich recent studies on volume of transactions of cryptocurrencies (Lahmiri et al. 2020, 2022; Foroutan and Lahmiri 2022; Fousekis and Tzaferi 2021; Yarovaya and Zięba 2022; Bianchi et al. 2022; Stosic et al. 2019; Lahmiri 2023a, b).
v. A battery of statistical tests is applied to draw robust conclusions statistically on the effect of the COVID-19 pandemic on the complexity of the prices and volumes of cryptocurrencies.

This paper is organized as follows. Section "Methods" introduces the methods. Section "Data and results" describes the data and presents the empirical results, and section Conclusion concludes.

Methods

Correlation dimension

Consider the original time series $\{x_1, x_2,\ldots, x_N\}$ and the phase space vectors expressed $Y_i=(x_i,\ x_{i+\tau},\ldots,\ x_{i+(m-1)\tau})$ for $i=1,\ 2,\ldots,N\text{-}(m-1)\tau$, where m is the embedding dimension (reconstruction scalar), and τ is the time delay (the delay that separates the occurrence of two observations). The embedding dimension and the time delay are set to two and one, respectively. The associated integral is given by:

$$C(r) = \frac{1}{M^2}\sum_{i,j=1}^{M}\theta\left(r - \left|Y_i - Y_j\right|\right) \tag{1}$$

where M is the number of points in the phase space and $\theta(x)$ is the Heaviside step function. The relationship between (r) and r is given by:

$$\lim_{r\to 0} C(r) \propto r^D \tag{2}$$

where D is computed based on the following equation:

$$D = \lim_{r\to 0}\frac{ln[C(r)]}{ln(r)}. \tag{3}$$

Finally, the CD (Grassberger and Procaccia 1983a, 1983b) is the parameter $D(m)$, which is the slope of the plot of $\ln[C(r)]$ versus $\ln(r)$. CD is one such fractal dimension (McMahon et al. 2017), and the larger the CD value, the larger the complexity of the data dynamics.

Lyapunov exponent

Consider the original time series $\{x_1, x_2,\ldots, x_N\}$ and the phase space vectors expressed $Y_i = (x_i, x_{i+\tau},\ldots, x_{i+(m-1)\tau})$ for $i = 1, 2,\ldots,N-(m-1)\tau$, where m is the embedding dimension (reconstruction scalar), and τ is the time delay (the delay that separates the occurrence of two observations). The embedding dimension and the time delay are set to two and one, respectively. In this framework (Rosenstein et al. 1993), the nearest neighbor of each point in the trajectory is identified after reconstructing the system's dynamics. As the latter changes over time, the distance between each point and its nearest neighbor increases exponentially; hence, the divergence of each point and its neighbor is given by:

$$d(i) \approx Ce^{\lambda(i\Delta t)} \tag{4}$$

where λ is the LE, C is the initial separation between neighbors, i is the time step, and Δt is the sampling. By applying the logarithm to both sides of Eq. 4, the following mathematical expression is obtained:

$$ln(d(i)) \approx ln(C) + \lambda(i\Delta t) \tag{5}$$

Finally, the LE given by λ is approximated as the average rate of divergence across all pairs of points and their corresponding nearest neighbors using a least-squares fit to the average line expressed in Eq. 5. When λ is positive, the system is unstable. Conversely, when it is negative, the system is stable.

Approximate entropy

Consider the original time series $\{x_1, x_2,\ldots, x_N\}$ and the m-vectors $(x_i, x_{i+1},\ldots, x_{N-m+1})$, where for $i = 1, 2,\ldots,N-(m-1)$, and m is the embedding dimension (reconstruction scalar). This study sets the embedding dimension to two. The distance between $x(i)$ and $x(j)$ is given by:

$$d\left[x_i, x_j\right] = \max_{k=0,m-1}\left[\left|x_{i+k} - x_{j+k}\right|\right] \tag{6}$$

Afterward, for i = 1, (N − m + 1), the quantities $C_r^m(i)$ and $\Phi^m(i)$ are calculated as follows:

$$C_r^m(i) = \frac{number\ of\ d\left[x_i, x_j\right] \leq r}{N - m + 1} \tag{7}$$

$$\Phi^m(i) = \frac{1}{N - m + 1}\sum_{i=1}^{N-m+1} ln\left(C_r^m(i)\right) \tag{8}$$

where r is the filter factor. Finally, the AE is computed as follows:

$$\mathrm{AE}(m, r, N) = \Phi^m(r) - \Phi^{m+r}(r) \tag{9}$$

In this framework, a large AE value indicates irregularity in the system (Pincus 1991). Conversely, a small value of AE indicates a regular system.

Data and results

The dataset is composed of 41 cryptocurrencies collected from the Yahoo Finance website, and the sample period ranges from January 1, 2018, to October 24, 2022. This sample period is constrained because of data availability to obtain a large set of cryptocurrencies. Then, to examine the effect of COVID-19 on the estimated nonlinear statistics of the cryptocurrencies, the total sample is split into two periods: before the COVID-19 period from January 1, 2018, to December 31, 2019, and during the pandemic period from January 1, 2020, to October 24, 2022. The list of cryptocurrencies with their acronyms in parentheses includes 0x (ZRX), Basic Attention Token, Bitcoin Cash (BCH), Bitcoin Gold (BTG), Chainlink (LINK), Civic (CVC), Dash (DASH), Decred (DCR), DigiByte (DGB), Dogecoin (DOGE), Enjin (ENJ), Ergo (ERG), Ethereum (ETH), Filecoin (FIL), Gnosis (GNO), Golem (GLM), Horizen (ZEN), Huobi Token, Icon (ICX), Iost (IOST), Lisk (LSK), Litecoin (LTC), Loopring (LRC), Medibloc (MED), Monero (XMR), Nem (XEM), Neo (NEO), OMG network (OMG), Qtum (QTUM), Siacoin (SC), Stellar (XLM), Storj (STORJ), Syscoin (SYS), Tether (USDT), Tezos (XTZ), Tron (TRX), Voyager Token (VGX), Waves (WAVES), Wax (WAXP), XRP (XRP), and Zilliqa (ZIL). We selected this set of cryptocurrencies because they are highly traded and because of the availability of their historical data during the period considered for the empirical investigation.

For illustration purposes, Fig. 1 displays the evolution of Bitcoin cryptocurrency price and volume of transactions before and during the pandemic. Figure 2 shows the boxplots of the CD, LE, and AE estimated from the price time series, and Fig. 3 shows the boxplots of the CD, LE, and AE estimated from the volume of transactions time series. The distributions of the estimated nonlinear measures for both price and volume series initially appear to differ between the pre- and post-COVID-19 pandemic periods. Two

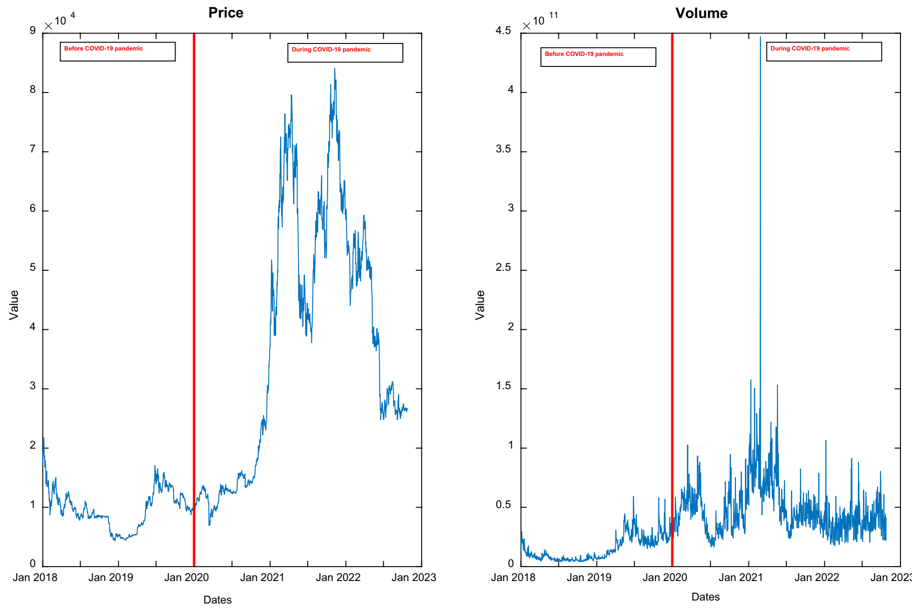

Fig. 1 Plots of evolution in price and volume of transactions for bitcoin cryptocurrency. The red line indicates separation between the period prior to the pandemic and period of the pandemic

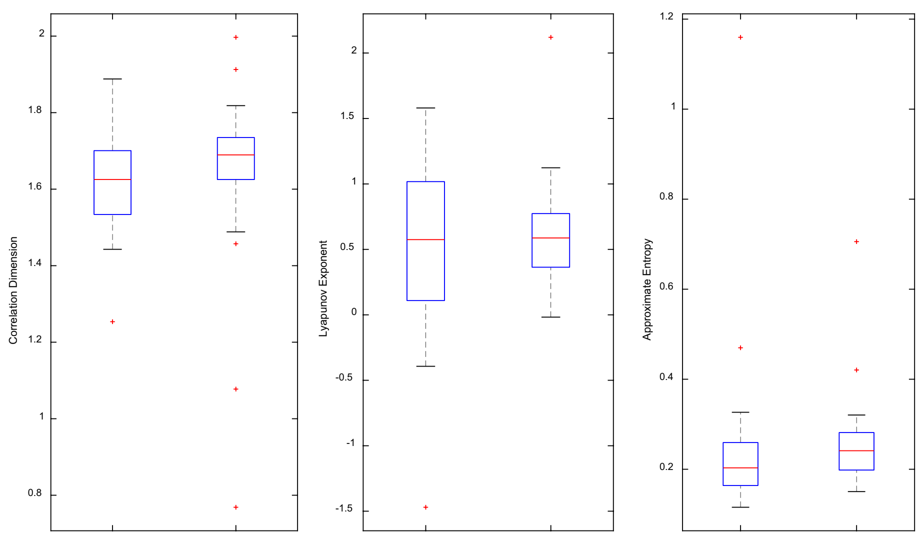

Fig. 2 Boxplots of correlation dimension (CD), Lyapunov exponent (LE), and approximate entropy (AE) all estimated from price time series

statistical tests are performed to verify such assumptions formally: Student *t*-test for equality of means and *F*-test for equality of variances. Both aforementioned statistical tests are performed at a 5% statistical significance level. The probability values (*p*-value) of the statistical tests are presented in Table 1 for the price series and in Table 2 for the volume series.

Table 1 indicates that the Student's *t*-test shows evidence that the means of measured correlation dimension, Lyapunov exponent, and approximate entropy do not differ across the prepandemic and pandemic periods. Thus, the COVID-19 pandemic

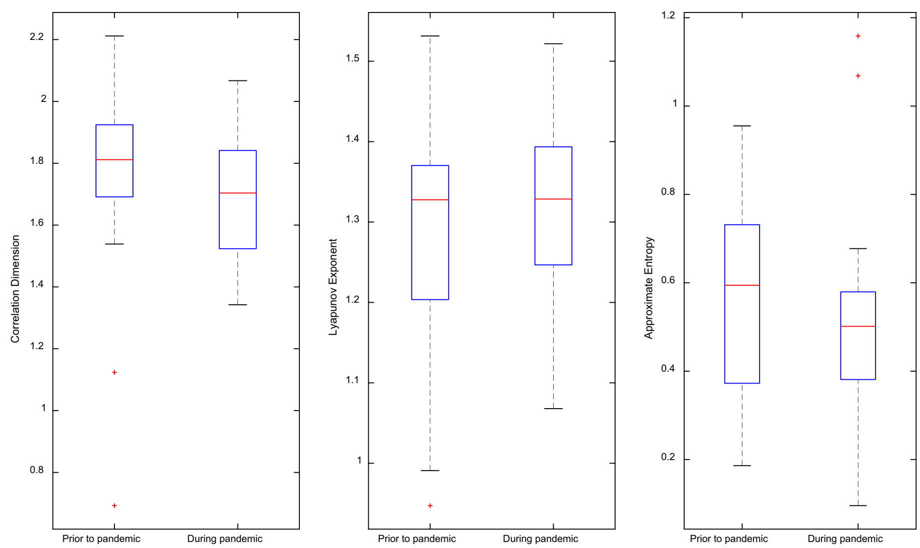

Fig. 3 Boxplots of correlation dimension (CD), Lyapunov exponent (LE), and approximate entropy (AE) all estimated from volume time series

Table 1 Results of statistical tests applied to price time series

Statistical tests	Null hypothesis	*p*-value
Student *t*-test	Mean of CD prior pandemic is equal to mean of CD during pandemic	0.3649
Student *t*-test	Mean of LE prior pandemic is equal to mean of LE during pandemic	0.8103
Student *t*-test	Mean of AE prior pandemic is equal to mean of AE during pandemic	0.4473
F-test	Variance of CD prior pandemic is equal to variance of CD during pandemic	0.0033
F-test	Variance of LE prior pandemic is equal to variance of LE during pandemic	0.0345
F-test	Variance of AE prior pandemic is equal to variance of AE during pandemic	5.4535×10^{-04}

CD denotes correlation dimension, LE denotes Lyapunov exponent, and AE denotes approximate entropy. Student *t*-test is applied for equality of means and *F*-test for equality of variances. All statistical tests are performed at 5% significance level. A *p*-value less than 5% significance level implies rejection of the null hypothesis. The results from statistical tests show that the pandemic has not affected the means of CD, LE, and AE across prices of cryptocurrency markets. However, the pandemic significantly affected their variations

Table 2 Results of statistical tests applied to volume of transactions time series

Statistical tests	Null hypothesis	*p*-value
Student *t*-test	Mean of CD prior pandemic is equal to mean of CD during pandemic	0.1172
Student *t*-test	Mean of LE prior pandemic is equal to mean of LE during pandemic	0.3871
Student *t*-test	Mean of AE prior pandemic is equal to mean of AE during pandemic	0.2068
F-test	Variance of CD prior pandemic is equal to variance of CD during pandemic	0.1588
F-test	Variance of LE prior pandemic is equal to variance of LE during pandemic	0.1771
F-test	Variance of AE prior pandemic is equal to variance of AE during pandemic	0.8741

CD denotes correlation dimension, LE denotes Lyapunov exponent, and AE denotes approximate entropy. Student *t*-test is applied for equality of means and *F*-test for equality of variances. All statistical tests are performed at 5% significance level. A *p*-value less than 5% significance level implies rejection of the null hypothesis. The results from statistical tests show that the pandemic has not affected the mean and standard deviation of CD, LE, and AE across volumes of cryptocurrency markets

has not affected the means of CD, LE, and AE measures in cryptocurrencies. On the other hand, the variances of the measured CD, LE, and AE are different across the prepandemic and pandemic periods; hence, the COVID-19 pandemic strongly affected the variability in CD, LE, and AE measured from prices. In sum, the pandemic only statistically and significantly affected the variability in nonlinear dynamics and complexity in the prices of cryptocurrencies.

Furthermore, Table 2 presents the means of measured CD, LE, and AE, all estimated from volume series, which are statistically equal across periods before and during the COVID-19 pandemic. Similarly, the measured CD, LE, and AE variances were statistically equal across periods before and during the COVID-19 pandemic. Therefore, from a statistical perspective, the pandemic did not affect the means and variances of nonlinear measures estimated from the volumes of transactions of cryptocurrencies.

In sum, the statistical tests from Tables 1 and 2 clearly show that the COVID-19 pandemic altered the nonlinear characteristics of the prices of cryptocurrencies but did not affect such features in the volume series; however, to investigate the effect of the pandemic further, we apply one-sided statistical tests to verify how the nonlinear characteristics of the prices of cryptocurrencies changed across periods. The corresponding results are presented in Table 3.

Accordingly, in the COVID-19 period, the variance of the correlation dimension decreased. Conversely, the variance of the Lyapunov exponent and the variance of the approximate entropy increased during the pandemic period. In other words, variability in the complexity of prices decreased during the COVID-19 pandemic, variability in the instability of prices increased during the pandemic, and variability in the irregularity of prices decreased during the pandemic; thus, the prices of cryptocurrencies became more regular and stable during the pandemic. This finding indicates the suitability of investing in cryptocurrencies as alternative assets during economic downturns caused by the COVID-19 pandemic.

A previous study (Lahmiri and Bekiros 2020b) used a sample composed of a pre-pandemic period spanning from September 2019 to December 2019 and a pandemic period spanning from January 2020 to April 2020, finding that cryptocurrencies embedded higher instability and irregularity during the pandemic. Compared to our current work, this contradiction can be explained by the effect of sampling. For instance, in the current study, we examine a more extensive period ranging from January 2018 to October 2022, which comprises the period when the worldwide economy began recovering from the COVID-19 pandemic. In this regard, our study is the first to consider a larger period sample to examine nonlinearity characteristics

Table 3 Results of one-sided *F*-test when applied to price time series

Statistical tests	Null hypothesis	*p*-value
F-test	Variance of CD prior pandemic is larger (lower) to variance of CD during pandemic	0.9984 (0.0016)
F-test	Variance of LE prior pandemic is larger (lower) to variance of LE during pandemic	0.0173 (0.9827)
F-test	Variance of AE prior pandemic is larger (lower) to variance of AE during pandemic	2.7267×10^{-04} (0.9997)

CD denotes correlation dimension, LE denotes Lyapunov exponent, and AE denotes approximate entropy. We performed one-sided (right) tests and one-sided (left) tests. All statistical tests are performed at 5% significance level. A *p*-value less than 5% significance level implies rejection of the null hypothesis. Therefore, during the pandemic period, the variance of correlation dimension decreased whilst the variance of Lyapunov exponent and the variance of approximate entropy increased in the dynamics of prices and volumes of 41 cryptocurrencies under the effect of the COVID-19 pandemic.

Conclusion

The current study examined the distributions of these nonlinear statistics before and during the COVID-19 pandemic, estimated from prices and volumes obtained from a large set of cryptocurrencies. We rely on both price and volume for each cryptocurrency as they may reveal information to the market participants. The current study provides further insights into this issue by examining their respective nonlinear dynamics before and during the COVID-19 pandemic. The results from t-tests and F-tests provide strong evidence that the means of the nonlinear statistics are unaffected by the pandemic; however, the latter affected only their variances. Specifically, the variability in prices of cryptocurrencies became more regular and stable during the pandemic. Finally, the pandemic has not altered the nonlinear dynamics in volumes of transactions. As a result, cryptocurrencies may represent an interesting investment during economic downturns as they show regular and stable prices during the pandemic; hence, one could forecast their prices with low error during unstable periods such as the pandemic. In contrast, investors should not invest in assets that show patterns of irregularity and instability during periods of economic crises. Such assets should be risky as they are hard to forecast. In this regard, traders and managers should consider and invest more in cryptocurrencies as they offer a safe investment during downturns in the world economy because of the observed regularity and stability in their dynamics, as indicated by the estimated complexity measures. Indeed, cryptocurrencies are relatively predictable and generate more profits than other assets with irregular and unstable prices during severe economic and financial crises.

Our study helps to understand the effect of the pandemic on cryptocurrencies in terms of shaping nonlinear dynamics in prices and volume to support traders, investors, and portfolio managers seeking opportunities for profits during crises. Certainly, the pandemic has not affected nonlinearities in the dynamics of the volume of transactions and provides evidence that cryptocurrencies remain attractive for traders, investors, and portfolio managers during economic crises.

For future work, we would consider examining connectedness between all cryptocurrencies considered in the current work by examining their complex network and how it evolves through periods of stable and unstable economies.

Abbreviations

CD Correlations dimension
LE Lyapunov exponent
AE Approximate entropy

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Author contributions

S.L.: Conceptualization, Methodology, Programming, Data Analysis, Writing. The author read and approved the final manuscript.

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Competing interests
The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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