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Inspecting the efficiency of cryptocurrency markets: New evidence

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ABSTRACT

The purpose of this study is to examine the market efficiency of cryptocurrencies, specifically at a weak level. The study focuses on six prominent cryptocurrencies selected based on their significant market capitalization: Bitcoin (BTC), Tether (USDT), Ethereum (ETH), Binance Coin (BNB-USD), Ripple (XRP-USD), and Cardano USD (ADA-USD). The analysis utilizes unit root, Ljung–Box, variance ratio, runs, and the Brock–Dechert–Scheinkman (BDS) tests to assess different aspects of market efficiency. The data spans from September 2017 to April 2023, encompassing a wide time frame to capture potential shifts in market behavior. The results of all the tests, except the BDS test, indicate that the tested cryptocurrencies' markets are inefficient. However, the BDS test yielded different results, suggesting that BTC and ETH exhibit market efficiency compared to the other cryptocurrencies. This discrepancy indicates that the BDS test may be capturing different aspects of the time series behavior. The practical implication is that investors and market participants should exercise caution and consider the varying levels of efficiency when making decisions regarding these cryptocurrencies. Also, investors should consider a range of factors, including technical and fundamental analyses, when making investment decisions in a dynamic and evolving market.

Contribution/Originality: This research provides a valuable addition to the existing literature by providing valuable insights into the market efficiency of prominent cryptocurrencies and introducing novel insights via the BDS test. It advises investors to consider findings alongside expert opinions, diverse analyses, and personal risk tolerance for a well-informed investment approach.

1. INTRODUCTION

In the realm of finance, the efficient market hypothesis (EMH) has fueled spirited debates. Scholars, including the renowned Eugene F. Fama, have dedicated their efforts to refining this concept over the years. At its core, market efficiency gauges how prices reflect available information. However, it has become more complicated since the introduction of cryptocurrencies. These digital assets that are traded globally have become a captivating research topic regarding market efficiency. Conflicting findings have emerged, with some suggesting inefficiency and enticing opportunities, while others argue for a highly efficient market. This paper navigates the interplay between finance, the EMH, and the ever-evolving landscape of cryptocurrencies.

The EMH is a concept that has been thoroughly examined and refined by numerous scholars. At the same time, it is commonly associated with Eugene F. Fama, who made significant contributions to the theory in the 1960s

(Fama, 1991, 1998; Fama, 1965, 1970). Other notable economists have made valuable contributions to the development of the EMH, such as Malkiel (1989) and Mandelbrot (1963). Market efficiency is the extent to which prices in a financial market accurately reflect all information available (Fama, 1970). Fama argued that the definition of efficiency presented a broad conceptual framework lacking specific and empirically testable implications. To address this challenge, it became imperative to establish a clear understanding of the meaning behind the available information. In response, Fama proposed a classification system consisting of three distinct levels of efficiency. The first level, known as the weak form, is characterized by prices that solely reflect historical data and information. The second level, referred to as the semi-strong form, entails prices that incorporate both historical and current information. Finally, a strong level of efficiency is achieved when prices accurately incorporate not only current and historical data but also unique or privileged information. The EMH caused a lot of discussions, particularly in conjunction with cryptocurrencies. Cryptocurrencies are digital assets that are traded on a number of exchanges around the world, and the supply and demand determine the price of these assets. There has been a lot of research on the efficiency of the cryptocurrency market. The findings of these studies show conflicting results; some contend that the cryptocurrency market is inefficient and offers opportunities for investors to earn abnormal returns, while others hold that the market is highly efficient and that consistently beating the market is virtually impossible (Abreu, Coaguila, & Camargos, 2022; Köchling, Müller, & Posch, 2019; López-Martín, Benito Muela, & Arguedas, 2021). These studies have used a variety of methodologies and approaches to evaluate the effectiveness of the cryptocurrency markets, including tests for both strong and weak forms of market efficiency.

Earlier studies had mixed findings regarding the efficiency of the cryptocurrency market. On the one hand, Bouoiyour, Selmi, and Wohar (2019) and Kurihara and Fukushima (2017) demonstrated that the cryptocurrency market is inefficient. In contrast, research by Chu, Zhang, and Chan (2019) and Le Tran and Leirvik (2020) demonstrated the efficiency of the cryptocurrency market.

The markets for cryptocurrencies are known for having a variety of traits, including high volatility, lax regulations, and relatively low liquidity, all of which can create unusual dynamics and hamper the efficiency of the market. Furthermore, it is challenging to make firm judgments about the efficiency of cryptocurrencies due to their short lifespans compared to traditional financial markets.

Research on the efficiency of cryptocurrency markets is growing, and the results are still being formed. To fully comprehend the effectiveness of cryptocurrency markets and their implications for risk management and investment decisions, more investigation and analysis are required. This study expands the existing literature in a number of ways. First, it offers a fresh perspective on the dynamics of the cryptocurrency market, which is of growing interest to both academics and investors. Second, because the cryptocurrency market is a relatively new and rapidly developing market that functions differently to conventional financial markets, it can help us understand the efficiency of financial markets more generally. Third, it can help to identify potential areas for future research, including the analysis of other forms of market efficiency and the development of new trading strategies based on the unique characteristics of the cryptocurrency market.

This paper tests the efficiency at the weak level for the top six cryptocurrencies based on market capitalization. This research holds importance due to its direct impact on the rapidly expanding encrypted market. By analyzing the efficiency of these major digital currencies, we gain insights into their price movements and responses to economic events. Furthermore, this study serves as a crucial indicator for investors and traders, aiding their understanding of future performance and facilitating informed investment decisions and improved trading strategies. Moreover, studying competency in digital currencies contributes to advancing financial and economic theories regarding digital assets, ultimately enhancing our comprehension of the overall crypto market.

This study uses a set of robust tests (unit root, variance ratio, Ljung–Box, runs, and BDS) to inspect the efficiency of the cryptocurrency market, and the findings indicate that most of the tested cryptocurrencies exhibit no efficiency. This implies that the price movements of these cryptocurrencies may not follow a random or independent pattern, as indicated by the lack of efficiency. However, the BDS test results showed that BTC and ETH were efficient, while the other cryptocurrencies exhibited no efficiency.

The remainder of this paper is presented as follows: Section 2 contains the literature review; Section 3 discusses the methodology; the empirical findings are reported in Section 4; and Section 5 concludes.

2. LITERATURE REVIEW

In recent years, academic literature has focused on the efficiency of cryptocurrency markets. The Bitcoin market was among the first to be examined, and studies have found that it was relatively inefficient in its early years, with significant price deviations from fundamental values. However, as the market has matured and trading volume has increased, several studies (Al-Yahyaee, Mensi, & Yoon, 2018; Köchling et al., 2019; Mnif & Jarboui, 2021) suggest that the efficiency of the Bitcoin market has increased over time. This section discusses the key conclusions of the research on the efficiency of the cryptocurrency markets.

Urquhart (2016) discovered strong evidence of the Bitcoin market's inefficiency, so prices did not accurately reflect all available information. He concluded that the Bitcoin market exhibits both short- and long-term price inefficiencies, which may present opportunities for investors to make a profit by taking advantage of these inefficiencies.

Bariviera (2017) used a detrended fluctuation analysis (DFA) as a computational tool to expand our understanding of market efficiency as it applies to the Bitcoin market. The results showed that the Bitcoin market is not efficient. According to Selmi, Tiwari, and Hammoudeh (2018), the generalized Hurst component and calculated multifractal detrended fluctuation analysis (MFDFA) exponent showed persistent and multifractal behavior, indicating that the Bitcoin market is not efficient at the weak level. This indicates that past price changes in Bitcoin have long-term memory and are not entirely random, pointing to market inefficiencies. The study emphasizes how crucial it is to take market efficiency into account when examining the dynamics of the Bitcoin market and hypothesizes that there may be trading opportunities based on the persistent and multifractal nature of Bitcoin price movements.

Al-Yahyaee et al. (2018) used the MFDFA method to analyze the fractal properties of a time series to examine the efficiency of the Bitcoin market. Comparing Bitcoin returns to those of other financial markets, including stocks, currencies, and gold, they discovered that Bitcoin returns have a high degree of inefficiency and long-term memory. According to Aggarwal (2019), the Bitcoin market exhibits high volatility and fluctuations, which are signs of market inefficiency. He also discovered evidence of price bubbles.

According to Alvarez-Ramirez, Rodriguez, and Ibarra-Valdez (2018), the Bitcoin market displays long-range correlations, which may indicate that recent prices and volume levels have a big influence on subsequent prices and volume levels. The study also discovered that there is a significant amount of predictability in the Bitcoin market, indicating that it is not entirely informationally efficient. According to Nan and Kaizoji (2019), the Bitcoin market is efficient at the weak and semi-strong levels. Zargar and Kumar (2019) conducted a study to examine changes in Bitcoin's informational efficiency over time and demonstrated a continuous divergence from random behavior in the higher frequencies of Bitcoin prices.

Köchling et al. (2019) found the Bitcoin market is efficient at the weak level, as they found evidence of significant autocorrelation in Bitcoin returns, indicating that past price information is not fully incorporated into current prices. They also found evidence of a trend in Bitcoin prices, indicating that prices are not fully random. Le Tran and Leirvik (2020) found that Bitcoin has the highest degree of efficiency among the four cryptocurrencies studied. This means that the Bitcoin market adjusts to new information more quickly and efficiently than the other markets. Ethereum has the second-highest degree of efficiency, followed by Ripple and Litecoin.

Khursheed, Naeem, Ahmed, and Mustafa (2020) investigated the adaptive market hypothesis (AMH) for four cryptocurrencies (Bitcoin, Stellar, Monero, and Litecoin) from 2014 to 2018. The results show that price movements with linear and nonlinear dependency varied over time. Bitcoin, Monero, and Litecoin were found to have the longest efficiency periods, whereas Stellar had the longest inefficient market term.

Corbet and Katsiampa (2020) examined whether Bitcoin displays comparable asymmetrical reversion patterns across varying time durations and concluded that the Bitcoin price returns are efficient. On the other hand, the price of cryptocurrencies exhibited significant asymmetric multifractality, with upward trends showing more multifractality than negative trends. Naeem, Bouri, Peng, Shahzad, and Vo (2021) indicated that the Covid-19 pandemic had a detrimental effect on the efficiency of Bitcoin, Ethereum, Litecoin, and Ripple due to a marked rise in inefficiency levels during the Covid-19 time frame. The findings showed that Bitcoin and Ethereum were the most negatively impacted cryptocurrencies, but they also showed that these two biggest cryptocurrencies recovered more quickly from their abrupt shift toward inefficiency at the end of March 2020. Their findings support the idea that market efficiency varies over time. Unusual catastrophic events such as the Covid-19 pandemic also have a negative effect on how well the top cryptocurrencies perform. In contrast, the findings by Mnif, Jarboui, and Mouakhar (2020) diverged from the aforementioned conclusions. Their research demonstrated Bitcoin's superior efficiency prior to the pandemic. Nevertheless, subsequent to the COVID-19 outbreak, Bitcoin was discovered to possess lower efficiency than Ethereum. Furthermore, an interesting trend emerged as all examined cryptocurrencies exhibited heightened efficiency after the pandemic.

In addition to the aforementioned studies, there is another group of studies that focus on investigating market efficiency in the weak form across multiple cryptocurrencies (Bitcoin, Ripple, Litecoin, and Dash). For example, Caporale, Gil-Alana, and Plastun (2018) inspected the long-memory behavior in the returns of four cryptocurrencies through employing fractional integration techniques, and their findings indicate that all four cryptocurrencies exhibited long-memory behavior in their returns.

Vidal-Tomás, Ibáñez, and Farinós (2019) examined the efficiency of the cryptocurrency market by looking at the performance of a diverse portfolio of 118 cryptocurrencies. According to their research, some traditional financial markets may be more efficient than the cryptocurrency market, and the development of new cryptocurrencies may not always result in an increase in market efficiency. Noda (2021) examined the time-varying characteristics of the cryptocurrency market using a GLS-based TV-AR model. The results of this study indicate that these markets require more regulatory intervention and that cryptocurrencies are not efficient enough to be regarded as a formal exchange system.

Yaya, Ogbonna, Mudida, and Abu (2021) analyzed market efficiency as well as volatility persistence in 12 cryptocurrencies, and they discovered that the markets for Bitcoin and the majority of the altcoins analyzed in our study are both efficient and volatile. Keshari Jena, Tiwari, Doğan, and Hammoudeh (2022) used a novel time-varying generalized Hurst exponential approach to rank six of the top 10 cryptocurrencies based on their inefficiency ratios. Throughout the examined time frame, all six crypto marketplaces exhibited time-varying efficiency. According to the inefficiency ratio, Bitcoin was the third most inefficient market, with DASH and NEM ranking first and second, respectively.

It is important to note that market efficiency varies across cryptocurrencies and historical periods. Furthermore, the Covid-19 pandemic was found to have a negative impact on market efficiency, temporarily increasing inefficiency levels in major cryptocurrencies.

Overall, while there is evidence of inefficiency and predictability in some aspects of cryptocurrency markets, there are also signs of increasing efficiency as the markets mature. More research is needed to gain a comprehensive understanding of the efficiency dynamics in cryptocurrency markets.

3. METHODOLOGY

This study uses many parametric and nonparametric tests to examine the efficiency of the cryptocurrency market in its weak form. Firstly, we use a unit root test. This test is frequently used to evaluate the efficiency of financial markets, and the most commonly used are the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests.

The formula used for the ADF test is as follows:

$$\Delta CRT_T = \theta_0 + \theta_1 CRT_{T-1} + \theta_2 T + \sum_{T=1}^{N} \theta_i \Delta CRT_{T-i} + \mu_T \qquad (1)$$

The first difference operator is denoted by Δ, the daily currency return is denoted by CRT, and the error term is denoted by μ_T. With the unit root test, the following null hypothesis will be investigated:

$$\text{HO: } \theta_1 = 0 \text{ Versus H1: } \theta_1 < 0$$

The ADF test was modified by the Phillips–Perron test, which employs Z-statistics based on the ADF regression equation. The formula for estimation is as follows:

$$\Delta CRT_T = \theta_0 + \gamma CRT_{T-1} + \mu_T \qquad (2)$$

Equation 2 represents the estimation formula for the ADF test, which calculates the probability of a unit root in a time series data set, showing non-stationarity. It claims that if the coefficient of the lag difference term is close to zero and the p-value is greater than a specific threshold, the null hypothesis of a unit root (non-stationarity) cannot be rejected, implying that the data is non-stationary.

Secondly, we employ the Ljung–Box test, which is a variation of the Box and Pierce test, in order to examine the autocorrelation between returns. The time series up to a specific lag have no significant autocorrelation, which is the null hypothesis for both tests.

$$Q_{LB}(K) = N(N+2) \sum_{K=1}^{h} \delta^2(K) / N - K \sim X^2 h \qquad (3)$$

N refers to the size of the sample, K denotes the number of lags tested, and $\delta^2(K)$ denotes the autocorrelation of order K.

Thirdly, we utilize the variance ratio test, introduced by Lo and MacKinlay (1988), to examine the null hypothesis of a random walk with drift in the financial time series. We apply this test assuming that the time series is a random walk or that its returns are independent and identically distributed over time.

The variance ratio VR(K) can be expressed mathematically as:

$$VR_K = \sigma_c^2(K)/\sigma_d^2(1) \qquad (4)$$

The $\sigma_c^2(K)$ unbiased estimators refer to the variance of the K^{th} differences series, the variance of the first-difference series was pointed out of $\sigma_d^2(1)$.

Two statistical tests developed by Lo and MacKinlay (1988) were used. The first standard normal test statistic under the homoscedasticity assumption is:

$$Z_Q = (VAR_Q - 1) / \sqrt{\theta_Q} \backsim N(0,1). \qquad (5)$$

$$\text{Where } \theta_Q = 2(2Q-1)(Q-1) / 3_Q\ (NQ)$$

The second standard normal test statistic under the heteroscedasticity assumption is:

$$\theta_Q = \sum_{M=1}^{Q-1} [2(Q-M)^2/Q]\, \sigma^M M$$

Under the null hypothesis (H0), the variance ratio is equal to one for all chosen periods (Q).

Fourthly, the runs test is employed. This is a non-parametric test used to assess the randomness of a sequence of data, and specifically for detecting autocorrelation in data and checking whether the data is distributed randomly or not. Based on the assumption that the time series independently and randomly fluctuates, this test assumes that the observed number of runs in the series should closely align with the predicted number of runs.

The following equation can be used to determine the overall number of runs:

$$E = N(N+1) - \sum_{i=1}^{n} n_i^2 / N \qquad (6)$$

The total number of runs is denoted by E, the total number of observations is denoted by N, and n_i refers to the number of observations in each category.

The following formula can be used for normal Z-statistics to test the hypotheses:

$$Z = {}^{(Q \mp 0.05 - \theta)}/_{\sigma_\theta} \quad (7)$$

Where Q stands for the actual number of runs, and θ is the expected number of runs.

Fifthly, we apply the BDS test by Brock, Dechert, and Scheinkman (1987), a non-parametric method for identifying nonlinear dependence in time series. The test compares distances between observed pairs in the actual series with those in a surrogate (simulated) series, assuming independence in the distribution patterns.

The test is based on the examination of the autocorrelation function of the squared values of a time series. The formula for the BDS test statistic, also known as $Q_{n\,m}(\mu)$, is as follows:

$$Q_{n\,m}(\mu) = \left\{\frac{m-n+1}{2(n-1)}\right\} * \Sigma\,\Sigma\{\vartheta(\mu - |Y_i - Y_j|) - \vartheta(\mu)\} \quad (8)$$

$Q_{n\,m}(\mu)$ refers to the BDS statistic, the sample size is denoted by m, the embedding dimension is denoted by n, and (μ) is the metric bond, $\vartheta(\mu)$ refers to the standard normal cumulative distribution function, and Y_i, and Y_j refer to the observations in the time series.

The test statistic Q_ (n m) (μ) quantifies the correlation between different time lags, indicating similarity in the time series. The BDS test's null hypothesis assumes an independent and identically distributed time series, while rejecting it suggests non-randomness or dependence in the series.

4. EMPIRICAL FINDINGS

4.1. Data

Six cryptocurrencies are used in this study, which now constitute more than 80% of the total market value of cryptocurrencies, namely Bitcoin (BTC), Ethereum (ETH), Tether (USDT), Binance Coin (BNB-USD), Ripple (XRP-USD), and Cardano USD (ADA-USD). All currencies are represented in US dollars. Daily closing prices were used for the period spanning from September 2017 to April 2023 and were taken directly from the Yahoo Finance website (https://finance.yahoo.com/cryptocurrencies).

Here a brief explanation for every cryptocurrency:

Bitcoin (BTC): This is the first and most well-known cryptocurrency. It was launched in 2009 by Satoshi Nakamoto, the name used by the mysterious individual or group who developed Bitcoin in Nakamoto (2008), and it runs on the decentralized blockchain network. Since Bitcoin was the first cryptocurrency, it has paved the way for the creation of thousands of others and has emerged as a major player in the cryptocurrency market.

Ethereum (ETH): Decentralized blockchain platform Ethereum (ETH) is where the idea of smart contracts and decentralized applications (DApps) was first introduced. Buterin (2014) made the initial suggestion in 2013 and it was formally introduced in 2015. While Ethereum and Bitcoin have some similarities, Ethereum provides a more sophisticated and adaptable platform for creating and running decentralized applications.

Tether (USDT): This was first introduced in 2014 by a company called Tether Limited. What sets Tether apart from other cryptocurrencies is that it is designed to maintain a stable value by pegging its price to a specific fiat currency, typically the US dollar (hence the ticker symbol USDT).

Binance Coin (BNB-USD): This was developed by Binance, one of the biggest and most well-known cryptocurrency exchanges in the world. The native cryptocurrency of the Binance platform, BNB performs a number of useful services for exchanges.

Ripple (XRP-USD): This is a digital cryptocurrency that operates on Ripple, which is a real-time gross settlement system, currency exchange, and remittance network. The technology firm Ripple Labs Inc., which focuses on transforming cross-border payments and financial transactions, released it in 2012.

Cardano (ADA-USD): This runs on Cardano blockchain technology. It was developed by a group of scientists, researchers, and engineers led by Charles Hoskinson, co-founder of Ethereum. Cardano aims to offer a secure, scalable, and sustainable platform for the creation of decentralized applications (DApps) and the execution of smart contracts.

The daily cryptocurrency returns are calculated as follows:

$$RC_T = LN(PC_T) - LN(PC_{T-1})$$

Where $LN(PC_T)$ refers to the natural logarithm of the cryptocurrency closing price at time T.

Our model differs from prior research in many ways.

First, this study specifically focuses on six cryptocurrencies that collectively represent more than 80% of the total market value of cryptocurrencies. Second, we employ daily closing prices for the period from September 2017 to April 2023. This specific time frame enables the examination of long-term trends and potential shifts in market efficiency over a significant duration.

Table 1. Descriptive statistics.

Statistic	BTC	ETH	USDT	BNB-USD	XRP-USD	ADA-USD
Mean	7E-04	9E-04	-4.04E-06	0.003	4E-04	0.0013
Median	0.001	0.001	0.000	0.001	-0.001	0.000
Max.	0.225	0.234	0.056	0.529	0.606	0.862
Min.	-0.464	-0.550	-0.053	-0.543	-0.551	-0.504
Std. dev.	0.040	0.050	0.004	0.057	0.062	0.066
Skew	-0.806	-0.916	0.729	0.380	0.842	1.947
Kurtosis	15.039	12.818	51.101	18.369	19.828	27.921
Jarque–Bera	12129.08	8201.88	190385.9	19467.94	23585.57	52410.83
Prob.	0	0	0	0	0	0
Sum	1.37236	1.783	-0.008	5.062	0.866	2.498
Sum sq. dev.	3.125	5.034	0.038	6.531	7.734	8.631
Observations	1973	1973	1973	1973	1979	1977

The descriptive statistics for the daily returns of the six cryptocurrencies are shown in Table 1. The mean daily return for each cryptocurrency ranges from -4.04E-06 for USDT to 0.002566 for BNB-USD. The median daily returns are generally lower than the mean, ranging from -0.00078 for XRP and USDT to 0.001036 for BNB-USD. USDT has the highest daily return of 0.056606, while BTC has the lowest daily return of -0.46473.

The standard deviations of the daily returns range from 0.03981 for BTC to 0.066089 for ADA-USD, indicating that the daily returns for these cryptocurrencies are relatively volatile. The skewness of the daily returns is negative for ETH and BTC, indicating that their returns are skewed to the left, while the skewness is positive for the other cryptocurrencies, indicated by skewness to the right.

The kurtosis values for all the cryptocurrencies are higher than 3, indicating that the distributions of the daily returns are leptokurtic (i.e., they have heavier tails than a normal distribution).

The Jarque–Bera test is used to test the normality of the daily returns. The test statistic is high for all the cryptocurrencies, indicating that the null hypothesis of normality is rejected at a high significance level. In terms of the sum and the sum of the squared deviations, BNB-USD has the highest values, indicating that it has the highest total return and the highest volatility among the six cryptocurrencies.

In conclusion, the descriptive statistics suggest that the daily returns of these cryptocurrencies are relatively volatile and have non-normal distributions, which is not compatible with weak form efficiency.

Table 2. Estimates of the Ljung–Box Q-statistics.

Lag	Order of estimates	BTC	ETH	USDT	BNB-USD	XRP-USD	ADA-USD
1	AC Q-stat Probability	-0.026- 1.355 0.244	-0.042- 3.460 0.063	-0.377- 280.373 0.000	-0.009- 0.174 0.676	-.003- 0.016 0.898	-0.019- 0.753 0.386
2	AC Q-stat Probability	0.040 4.549 0.103	0.057 9.924 0.016	-0.053- 285.907 0.000	0.074 11.052 0.004	0.043 3.684 0.158	0.113 26.088 0.000
3	AC Q-stat Probability	0.003 4.569 0.206	0.015 10.378 0.007	-0.046- 290.135 0.000	-0.006- 11.132 0.011	0.006 3.762 0.288	0.048 30.752 0.000
4	AC Q-stat Probability	0.025 5.782 0.216	0.034 12.632 0.004	0.025 291.353 0.000	-0.003- 11.154 0.011	0.038 6.620 0.157	0.034 33.042 0.000
5	AC Q-stat Probability	0.027 7.221 0.205	0.001 12.633 0.027	-0.017- 291.943 0.000	-0.043- 14.865 0.025	.009 6.769 0.238	0.002 33.053 0.000
6	AC Q-stat Probability	0.183 8.833 0.029	0.058 19.234 0.013	-0.027- 293.387 0.000	0.045 18.797 0.005	0.051 11.928 0.064	0.007 33.144 0.000
7	AC Q-stat Probability	-0.037- 11.552 0.116	-0.016- 19.725 0.006	0.062 300.937 0.000	-0.021- 19.669 0.006	0.038 14.758 0.039	-0.022- 34.076 0.000
8	AC Q-stat Probability	-0.014- 11.953 0.153	-0.031- 21.582 0.006	-0.044- 304.750 0.000	0.027 21.094 0.007	0.030 16.529 0.035	-0.013- 34.420 0.000
9	AC Q-stat Probability	0.018 12.580 0.183	-0.010- 21.779 0.010	-0.008- 304.873 0.000	0.041 24.410 0.004	0.031 18.382 0.031	0.012 34.707 0.000
10	AC Q-stat Probability	0.050 17.587 0.062	0.040 24.988 0.005	-0.060- 312.091 0.000	0.094 0.000 42.079	-0.037- 21.042 0.021	-0.011- 34.929 0.000
11	AC Q-Stat Probability	0.010 17.771 0.087	-0.005- 25.047 0.009	0.110 336.323 0.000	0.031 43.957 0.000	-0.007- 21.138 0.032	0.016 35.432 0.000
12	AC Q-stat Probability	-0.006- 17.847 0.120	0.001 25.051 0.015	0.041 339.625 0.000	0.016 44.472 0.000	-0.049- 25.832 0.011	0.010 35.627 0.000
13	AC Q-stat Probability	0.006 17.924 0.160	0.022 25.973 0.017	-0.083- 353.446 0.000	0.040 47.663 0.000	0.029 27.490 0.011	0.023 36.689 0.000
14	AC Q-stat Probability	-0.012- 18.214 0.197	-0.023- 27.061 0.019	-0.051- 358.596 0.000	-0.033- 49.885 0.000	-0.018- 28.130 0.014	0.046 40.862 0.000
15	AC Q-stat Probability	0.009 18.381 0.243	0.024 28.190 0.020	0.032 360.680 0.000	-0.012- 50.164 0.000	0.039 31.244 0.008	0.046 45.072 0.000
16	AC Q-stat Probability	-0.015- 18.818 0.278	0.018 28.858 0.025	0.024 361.856 0.000	-0.002- 50.175 0.000	0.034 33.554 0.006	0.089 61.010 0.000

4.2. Empirical Findings

Table 2 provides the estimates of the Ljung–Box Q-statistics for the six different cryptocurrencies at different lags. The Q-statistic tests whether a group of autocorrelations of a time series are jointly zero or not. If the Q-statistic is larger than the critical value at a given significance level, the null hypothesis of no autocorrelation is rejected. The Ljung–Box test rejects the null hypothesis at the standard level of confidence for all examined lags, indicating significant inefficiency in all cryptocurrencies except BTC.

The Q-statistic values are statistically significant for XRP-USD from lag 6. This suggests that there is some dependence between the values of this cryptocurrency at the current time and the values of the previous two time periods. Overall, these results suggest that the values of these cryptocurrencies, except BTC, are not independent and exhibit some degree of autocorrelation or persistence over time. This finding agrees with those of Bariviera (2017); Bariviera, Basgall, Hasperué, and Naiouf (2017); Tiwari, Jana, Das, and Roubaud (2018); Köchling et al. (2019) and López-Martín et al. (2021).

Table 3 shows the results of unit root tests conducted for the six cryptocurrencies. The tests were conducted using the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests with different specifications. Looking at the ADF test results, all six cryptocurrencies exhibit negative test statistics, indicating that they are stationary at the 1% level of significance regardless of the specification used. This suggests that their prices do not follow the random walk hypothesis (RWH) and are not driven purely by a long-term trend.

On the other hand, the PP test results show that the cryptocurrencies are non-stationary at the 1% level of significance when the intercept and trend are included in the specification. However, when the intercept and trend are removed, BTC, ETH, and XRP-USD remain non-stationary at the 1% level, while USDT and ADA-USD are non-stationary at the 5% level, and BNB-USD is non-stationary at the 10% level. Overall, the unit root test results point to the possibility that persistence or mean reversion, as well as a long-term trend, are also factors that influence cryptocurrency prices. However, the precise nature of their behavior may vary depending on the particular cryptocurrency and test specification.

Table 3. Unit root test results.

Statistics	BTC	ETH	USDT	BNB-USD	XRP-USD	ADA-USD
ADF						
With intercept	-45.606*	-46.304*	-15.855*	-29.325*	-44.517*	-28.014*
With intercept and trend	-45.594*	-46.294*	-15.850*	-29.346*	-44.508*	-28.023*
Without intercept and trend	-45.601*	-46.299*	-15.859*	-29.242*	-44.526*	-28.004*
PP						
With intercept	-45.611*	-46.350*	-136.728*	-44.841*	-44.857*	-45.713*
With intercept and trend	-45.600*	-46.341*	-136.727*	-44.856*	-44.848*	-45.712*
Without intercept and trend	-45.608*	-46.350*	-136.746*	-44.772*	-44.866*	-45.733*

Note: * indicates the 1% level of significance.

The runs test is a statistical test used to determine the randomness of a data set. The test entails counting the number of runs in a data set, where a run is described as a series of consecutive decreasing or increasing values, as illustrated in Table 4.

The results of the tests provide evidence of non-randomness in all six cryptocurrencies. The test value is a criterion for determining whether a set of data is statistically significant. The test values in this case range from -0.000777747 to 0.00103626.

For each cryptocurrency, the number of cases below and above the test value was counted, as well as the total number of cases. The number of runs in the data was also calculated.

The Z-score measures the distance between the sample mean and the population mean in units of the standard deviation. In this case, the Z-scores range from 2.68 to 9.435, which are all significant, further supporting the evidence of non-randomness.

The p-values for all six cryptocurrencies are less than 0.05, indicating that we can reject the null hypothesis that the data is random. The p-values suggest that there may be patterns or trends in the data of these cryptocurrencies that are not random. This means that all six cryptocurrencies are inefficient at the weak level.

Table 4. Runs test results.

Statistics	BTC	ETH	USDT	BNB-USD	XRP-USD	ADA-USD
Test values	0.001024	0.000882	-6E-06	0.001036	-0.00078	0.000287
Cases < Test value	986	986	986	986	989	990
Cases >= Test value	987	987	987	987	990	991
Total cases	1973	1973	1973	1973	1979	1981
Number of runs	1047	1060	1197	1074	1107	1053
Z	2.68	3.265	9.435	3.896	5.239	2.764
Asymp. sig. (2-tailed)	0.007	0.001	0	0	0	0.006

Table 5. Variance ratio (VR) test results.

Cryptocurrency	Test stat.	Time horizon (q)			
		q = 2	q = 4	q = 8	q = 12
BTC	Var. ratio(q)	0.468	0.238	0.124	0.062
	Z(q)	-9.495*	-8.401*	-7.227*	-5.976*
	Z*(q)	-23.627*	-18.095*	-13.154*	-9.460*
ETH	Var. ratio(q)	0.453	0.232	0.124	0.060
	Z(q)	-10.346*	-8.939*	-7.474*	-6.169*
	Z*(q)	-24.322*	-18.236*	-13.158*	-9.498*
USDT	Var. ratio(q)	0.383	0.178	0.095	0.045
	Z(q)	-5.565*	-4.663*	-3.982*	-3.377*
	Z*(q)	-27.428*	-19.535*	-13.590*	-9.643*
BNB-USD	Var. ratio(q)	0.459	0.249	0.121	0.0630
	Z(q)	-9.349*	-7.704*	-6.510*	-5.280*
	Z*(q)	-24.053*	-17.850*	-13.208*	-9.466*
XRP-USD	Var. ratio(q)	0.478	0.240	0.122	0.061
	Z(q)	-9.214*	-8.147*	-6.942*	-5.543*
	Z*(q)	-23.256*	-18.074*	-13.218*	-9.497*
ADA-USD	Var. ratio(q)	0.429	0.236	0.125	0.056
	Z(q)	-7.580*	-6.220*	-5.552*	-4.975*
	Z*(q)	-25.392*	-18.167*	-13.164*	-9.546*

Note: Var. ratio(q) denotes the variance ratio; Z(q) denotes the test statistic for the null hypothesis of homoscedasticity; Z*(q) denotes the test statistic for the null hypothesis of heteroscedasticity; and * denotes the 1% level of significance.

The variance ratio test results for the six cryptocurrencies under consideration are displayed in Table 5. The VR test is used to test for the presence of heteroskedasticity in the time series data, which is a violation of the assumption of homoscedasticity in many statistical models.

The Z(q) test statistics for all cryptocurrencies are negative and significant at the 1% level, indicating evidence against the null hypothesis of homoscedasticity. This suggests that the variance of the time series data is not constant over time, which is consistent with the mean reversion behavior observed in the VR ratios.

The Z*(q) test statistics for all cryptocurrencies are also negative and significant at the 1% level, indicating evidence against the null hypothesis of heteroscedasticity. This suggests that the variance of the time series data is not proportional to the level of the time series, which is another violation of the assumption of homoscedasticity. Based on previous results, the RWH is rejected and all cryptocurrencies under study are inefficient in their weak form.

Table 6 present the results of the BDS test for the six different cryptocurrencies. The test results are presented for different dimensions, ranging from 2 to 6. The BDS statistic and the Z(q) values are provided for each cryptocurrency and dimension. The BDS statistic is a measure of the non-randomness or dependence in the time series, while the Z(q) values indicate the level of statistical significance at which the BDS statistic is significant.

The results in Table 6 show that all the cryptocurrencies exhibit some level of non-randomness or dependence in their time series. However, the degree of non-randomness or dependence varies across the different cryptocurrencies and dimensions. BTC and ETH exhibit relatively lower levels of non-randomness or dependence compared to the other cryptocurrencies, as indicated by their lower BDS statistics and Z(q) values. This suggests that BTC and ETH are relatively more efficient at the weak form in terms of the randomness and independence of their price movements.

On the other hand, USDT, BNB-USD, XRP-USD, and ADA-USD exhibit higher levels of non-randomness or dependence, as indicated by their higher BDS statistics and Z(q) values. Therefore, we reject the null hypothesis by the applied BDS test, and this mean that the USDT, BNB-USD, XRP-USD, and ADA-USD are not efficient in their weak form.

Table 6. BDS test results.

Cryptocurrency	Test statistics	Dimension				
		2	3	4	5	6
BTC	BDS statistic	0.014	0.029	0.039	0.047	0.050
	Z(q)	6.169*	7.887*	8.800*	10.094*	11.117*
ETH	BDS statistic	0.011	0.024	0.033	0.040	0.041
	Z(q)	5.199*	7.062*	8.209*	9.229*	10.127*
USDT	BDS statistic	0.070	0.001	0.169	0.200	0.221
	Z(q)	23.462*	26.841*	29.683*	33.571*	38.249*
BNB-USD	BDS statistic	0.025	0.050	0.067	0.076	0.080
	Z(q)	11.175*	14.013*	15.652*	17.133*	18.502*
XRP-USD	BDS statistic	0.029	0.054	0.071	0.083	0.086
	Z(q)	12.116*	14.150*	15.640*	17.371*	18.695*
ADA-USD	BDS statistic	0.021	0.040	0.053	0.061	0.064
	Z(q)	9.834*	11.656*	12.862*	14.340*	15.453*

Note: * indicates the 1% level of significance.

Table 7 summarizes the results of all the tests. The results indicate the efficiency or non-efficiency of each cryptocurrency based on the respective tests. Comparing these results to the findings of previous literature can provide insights into the consistency or divergence of the current study's results with earlier research. However, without specific details about the previous literature, it is challenging to make a direct comparison. Nevertheless, a general perspective on the findings can be provided.

Table 7. Summary of results.

Test	BTC	ETH	USDT	BNB-USD	XRP-USD	ADA-USD
Ljung–Box	Efficient	Non-efficient	Non-efficient	Non-efficient	Non-efficient	Non-efficient
Unit root	Non-efficient	Non-efficient	Non-efficient	Non-efficient	Non-efficient	Non-efficient
Runs	Non-efficient	Non-efficient	Non-efficient	Non-efficient	Non-efficient	Non-efficient
Variance ratio	Non-efficient	Non-efficient	Non-efficient	Non-efficient	Non-efficient	Non-efficient
BDS	Efficient	Efficient	Non-efficient	Non-efficient	Non-efficient	Non-efficient

It is important to note that the cryptocurrency market is highly volatile and speculative, with significant price fluctuations and regulatory uncertainties. Investing in cryptocurrencies entails a high level of risk and necessitates careful consideration of one's risk tolerance and investment objectives.

While the findings of this study provide insights into the market efficiency of the tested cryptocurrencies, they should be interpreted in conjunction with other fundamental and technical analyses, as well as market trends and developments. Conducting thorough research, diversifying investments, and consulting with financial professionals can help investors make more informed decisions in the volatile and evolving cryptocurrency market.

5. CONCLUSION

The efficiency of financial markets is a significant subject in finance and has been extensively researched in traditional markets. However, with the rapid expansion of the cryptocurrency market, this study focuses on the market efficiency of cryptocurrencies at a weak level. To conduct this analysis, six cryptocurrencies were carefully chosen based on their market capitalization, collectively representing over 82% of the total market capitalization in the cryptocurrency market. The selected cryptocurrencies are Bitcoin (BTC), Tether (USDT), Ethereum (ETH), Binance Coin (BNB-USD), Ripple (XRP-USD), and Cardano USD (ADA-USD). The statistical tests employed to inspect the efficiency of these cryptocurrencies are the ADF and PP unit root tests, the Ljung–Box test, the variance ratio test, the runs test, and the BDS test.

The results report that most of the cryptocurrencies exhibit no efficiency in terms of the statistical tests conducted except the results of BDS test report different results for BTC, and ETH. This implies that the price movements of these cryptocurrencies may not follow a random or independent pattern, as indicated by the lack of efficiency. This result is in line with those reported by Kurihara and Fukushima (2017); Caporale et al. (2018); Bouoiyour et al. (2019); Kristoufek and Vosvrda (2019); Caporale and Plastun (2019) and Verma et al. (2022).

However, it is worth noting that the BDS test yielded different results. BTC and ETH were found to have a level of efficiency, while the other cryptocurrencies exhibited no efficiency. This discrepancy indicates that the BDS test may be capturing different aspects of the time series behavior compared to the other tests. The field of cryptocurrency research is relatively new and is evolving rapidly. Therefore, it is possible to encounter varying findings in different studies due to differences in methodologies, time periods analyzed, and data sources. Ongoing research and advancements in statistical techniques will continue to contribute to our understanding of cryptocurrency efficiency.

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