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EVOLVING EFFICIENCY OF CRYPTOCURRENCY MARKET: EVIDENCE FROM LEADING CRYPTOCURRENCIES

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Abstract. The article investigated the efficiency of the cryptocurrency market, with a focus on Bitcoin (BTC), Ethereum (ETH), Tether (USDT), and Binance Coin (BNB-USD), based on their substantial market capitalization. For this purpose, we observed the daily closing prices spanning from January 2018 to December 2023 and employed a set of robust tests, including the generalized spectral test, automatic portmanteau test, and automatic variance ratio test. The findings of the study reveal a random pattern in price fluctuations, indicating weak form efficiency. Furthermore, we adopted the rolling window approach to investigate whether market efficiency is dynamic or static over time. The empirical result illustrated that the crypto market efficiency remains static over time, except for USDT. In conclusion, the overall empirical results support the notion of the random walk hypothesis, indicating that past price movements offer no predictive insight into future prices. These findings have significant implications for investors, emphasizing the lack of predictive insight from past price movements. Policymakers are urged to establish a robust framework for market integrity and reliable price discovery.

1. Introduction

In recent years, cryptocurrencies have garnered significant global attention, piquing the interest of investors, regulators, and scholars alike (Aggarwal 2019). Having witnessed substantial growth over the past decade, the cryptocurrency market's capitalization has now surpassed a remarkable 3 trillion USD, according to data from the CoinMarketCap website (as of December 2023). Fuelled by blockchain technology, these digital assets offer swift, secure, and globally accessible transactions, making them increasingly popular as an emerging investment option (Anamika, Chakraborty, and Subramaniam 2023; Lupu and Popa 2022). Noteworthy is the unique decentralized nature of the crypto market, setting it apart from traditional financial markets governed by centralized regulation (Liu and Tsyvinski 2021). The distinct characteristics of the cryptocurrency market make it a compelling subject of study for both academia and the investment community (Alexiadou et al. 2023; Mallesha and Archana 2023). As debates surrounding the financial viability versus speculative nature of crypto assets persist among investors (Kang, Lee, and Park 2022), the relatively nascent nature of the cryptocurrency market prompts a need for comprehensive research to assess its efficiency under Fama's efficient market hypothesis (EMH) (Kayal and Balasubramanian 2021). The heightened volatility and significant risk associated with the crypto market may be attributed to its limited connections with traditional financial assets (Kayal and Balasubramanian 2021). The EMH posits that

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market efficiency is the degree to which financial market prices accurately reflect all available information (Fama 1970). This theoretical framework has sparked extensive discussions, particularly in the context of cryptocurrencies, where the market operates independently and is influenced by supply and demand dynamics on a global scale (Verma, Sharma, and Sam 2022). Fama proposed a three classification forms of market efficiency: weak form, semi-strong form, and strong form. The weak form of efficiency states that past prices have no impact on the future prices. The semi-strong form asserts all public information is in stock prices, and the strong form implies both public and private information is reflected (Fama 1965). In this study, we examine weak form of market efficiency, also referred to as the random walk hypothesis. Hence, this article evaluates the market efficiency of cryptocurrencies by contributing to existing literature in three different ways. Firstly, it evaluates the weak form efficiency of the top four cryptocurrencies based on market capitalization, considering their direct impact on the rapidly expanding encrypted market. Secondly, it employs robustified random walk tests rather than relying solely on traditional tests of the random walk hypothesis. Thirdly, we determine whether the crypto market efficiency is time-varying or static using the rolling window technique. The findings serve as valuable indicators for investors, traders, and policymakers, facilitating informed decision-making.

The structure of this article discloses as follows: Section two delves into a review of cryptocurrency market efficiency research, with a focus on the random walk hypothesis. Section three outlines the research methodology and data collection, followed by empirical results and discussion in section four. The final section concludes the article by summarizing the findings.

2. Literature Review

The increasing global acceptance of cryptocurrencies for trading, speculation, and investment has captured the attention of practitioners and researchers (Verma, Sharma, and Sam 2022). Recent empirical studies have investigated the presence or absence of a random walk theory in the cryptocurrency market, as summarized in Table 1.

Table 1. Previous Studies on Efficiency of Cryptocurrency Market

	Authors (Year)	**Title of the Study**	**Taken Approach/ Statistical Tests**	**Results Obtained**
1	Yi et al. (2023)	Market efficiency of cryptocurrency: evidence from the Bitcoin market	Quantum harmonic oscillator and variance ratio test.	Mixed results from variance ratio test, but significant probability allocation to the ground state suggests Bitcoin market nearing efficiency.
2	Karaömer and Acaravci (2023)	Adaptive Market Hypothesis: Evidence From the Cryptocurrency Market	Jarque-Bera test, unit root tests, automatic portmanteau and wild bootstrap automatic variance ratio tests.	Supported Adaptive Market Hypothesis, indicating cryptocurrency market efficiency fluctuates in response to news/events.

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Table 1 – continued from previous page

	Authors (Year)	**Title of the Study**	**Taken Approach/ Statistical Tests**	**Results Obtained**
3	Mahalwala (2022)	Examining the Weak-Form Market Efficiency in Cryptocurrency Market	Autocorrelation Function and Partial Autocorrelation Function with Lung-Box Q-statistic, Unit Root tests, Variance Ratio Test and Breusch-Godfrey Serial Correlation Lagrange Multiplier Test.	Did not support random walk model for cryptocurrencies, suggesting price predictability.
4	Magner and Hardy (2022)	Cryptocurrency Forecasting: More Evidence of the Meese-Rogoff Puzzle	Meese–Rogoff puzzle, Encompassing t-Test, Wild Clark and West Test and Correlation Test.	Models outperformed random walk, indicating cryptocurrencies are more persistent than traditional exchange rates.
5	Kang et al. (2022)	Information Efficiency in the Cryptocurrency Market:The Efficient-Market Hypothesis	Random walk tests and event study Approach.	Small percentage of cryptocurrencies met weak-form and semi-strong EMH criteria.
6	Aggarwal (2019)	Do bitcoins follow a random walk model?	Durbin Watson (DW), unit root tests, multiple variance ratio, BDS tests, ARCH and GARCH models.	Strong evidence of market inefficiency due to asymmetric volatility clustering in bitcoin returns.
7	Apopo and Phiri (2021)	On the (in)efficiency of cryptocurrencies: have they taken daily or weekly random walks?	KSS nonlinear unit root, flexible fourier functions and BDS test for linear dependence	Found weak-form efficiency in daily returns but not in weekly returns for the top five cryptocurrencies.
8	Keshari Jena et al. (2022)	Are the top six cryptocurrencies efficient? Evidence from time-varying long memory	Hurst exponent methodology.	Ranked top 10 cryptocurrencies based on inefficiency ratios, identifying Bitcoin as the third most inefficient market.
9	Kyriazis (2019)	A Survey on Efficiency and Profitable Trading Opportunities in Cryptocurrency Markets	Rescaled Range (R/S) and Detrended Fluctuation Analysis (DFA).	Most academic papers provide evidence of Bitcoin's inefficiency and other digital currencies.
10	Urquhart (2016)	The Inefficiency of Bitcoin	Ljung-Box test, Runs test, Bartels test, AVR test, BDS test and R/S Hurst.	Bitcoin is significantly inefficient in the full sample but may be moving towards efficiency in later periods.

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Table 1 – continued from previous page

	Authors (Year)	Title of the Study	Taken Approach/ Statistical Tests	Results Obtained
11	Nadarajah and Chu (2017)	On the inefficiency of Bitcoin	Ljung-Box test, runs test, Bartel's test for independence, wild-bootstrapped automatic variance ratio test, spectral shape tests, BDS test, portmanteau test and generalized spectral test.	Bitcoin returns do not initially satisfy efficient market hypothesis but can be transformed to satisfy it using a power transformation method.
12	Kurihara and Fukushima (2017)	The Market Efficiency of Bitcoin: A Weekly Anomaly Perspective	standard OLS and robust least squares (RLS).	Found evidence of inefficiency in the Bitcoin market, but transactions are becoming more efficient over time.
13	Bariviera (2017)	The inefficiency of Bitcoin revisited: a dynamic approach	R/S Hurst and Hurst DFA method.	Varying levels of efficiency, with daily returns exhibiting less persistent behavior after 2014.

3. Data and Methodology

3.1. **Data Description.** This research employed a dataset encompassing cryptocurrency price data from January 1, 2018, to December 31, 2023. The dataset consisted of daily closing prices, denominated in US Dollars, for four highly adopted cryptocurrencies with significant market capitalisation: Bitcoin (BTC), Ethereum (ETH), Tether (USDT), and BNB (BNB). These data points, gathered from Yahoo Finance. The overview of the sampled cryptocurrencies displayed in Table 2. Figures 1 and 2 depict time-series plots illustrating the price and return data behavior for the four cryptocurrencies. The daily returns for cryptocurrencies were computed using the following formula:

$$R_c = \ln\left(\frac{X_t}{X_{t-1}}\right)$$

Where R_c represents returns of crypto assets; X_t is the crypto asset's closing price at time t; X_{t-1} is the crypto asset's closing price at time t-1; and the natural logarithm of returns is represented by ln.

3.2. **Methodology.** Random walk tests are employed to assess the randomness of time series data, such as security prices, where each movement is considered to be independent and unpredictable. These tests determine the efficiency of financial markets, which are in line with the principles of the Efficient Market Hypothesis (EMH). In order to investigate random walk behaviour of cryptocurrency market, we used three random walk models suggested by Campbell et al. (1998), including Random Walk1 (RW1), Random Walk2 (RW2), and Random Walk3 (RW3) tests. These models analyse the distribution characteristics of increments. Out of these three forms, the focus was on the RW2 and RW3 tests due to the presence of heteroscedasticity (Campbell et al. 1998). A summary of these models is provided in Table 3. Robustified tests were applied for each model. RW2 underwent testing the generalized spectral test, while RW3 was assessed using the automatic portmanteau test and automatic variance ratio test.

TABLE 2. Overview of Sampled Cryptocurrencies

Cryptocurrency	**Explanation**
Bitcoin (BTC)	Introduced by Satoshi Nakamoto in 2008, Bitcoin is the pioneering and widely adopted cryptocurrency, operating on a decentralized blockchain network.
Ethereum (ETH)	Launched in 2015, Ethereum, conceptualized by Vitalik Buterin in 2013, is a blockchain platform facilitating decentralized applications (DApps) and smart contracts, offering advanced features compared to Bitcoin.
Tether (USDT)	Introduced in 2014 by Tether Limited, USDT stands out for stabilizing its value by linking it to a fiat currency, typically the US dollar.
Binance Coin (BNB-USD)	Created by Binance, one of the largest cryptocurrency exchanges globally, BNB serves as the native cryptocurrency for the platform, providing various functionalities for users.

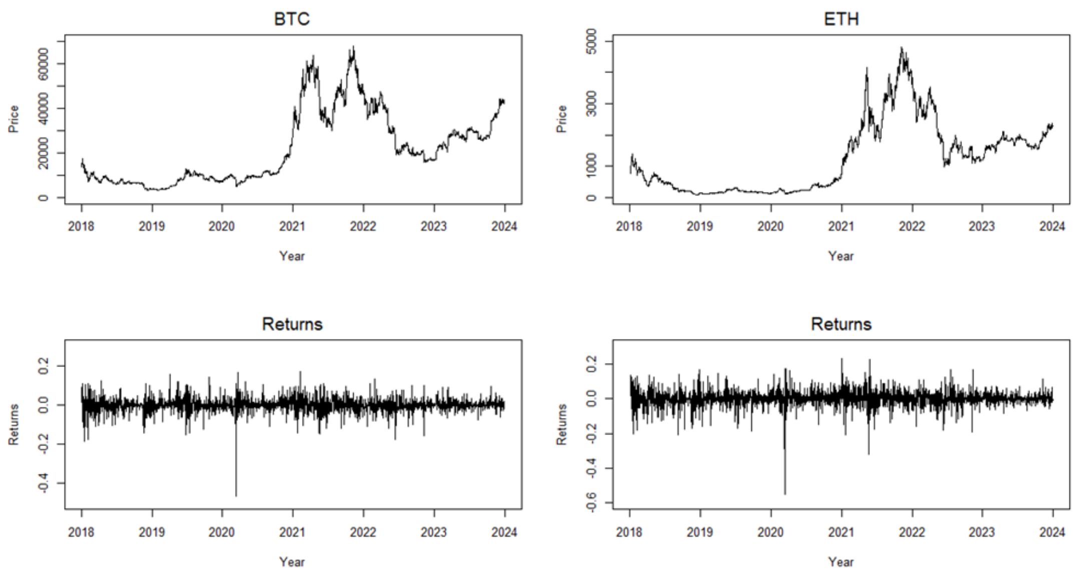

FIGURE 1. Plot of Bitcoin and Ethereum (at Level and Returns)

Generalized Spectral Test

The generalized spectral test by Escanciano and Velasco (2006) to assess Martingale Difference Hypothesis (MDH), stating that past information does not improve the forecast for future values in a Martingale Difference Sequence (MDS). This generalized spectral test detects both linear and non-linear serial dependencies by analysing the spectral density of the time series (Lazăr, Todea, and Filip 2012), this technique demonstrates robustness against conditional heteroscedasticity and varying lag lengths (Pathak et al. 2020). The null hypothesis posits that adherence to the MDH does not enhance forecasting future values in a Martingale Difference Sequence (MDS) using past information. The MDH is expressed as:

$$H_0 = m_\theta(Z_t) = 0, \theta \geq 1$$
$$varpi_\theta(k) = E\left[(Z_t - \mu)\exp(ikZ_{t-\theta})\right]$$

In this setting, Z_t is a martingale process at time t, where t, $\theta_\epsilon[1, ...T]$. The unforecastable stochastic process and pairwise function is $m_\theta(Z_t) = E(Z_t - \mu Z_{t-\theta})$. Equation (1) introduces

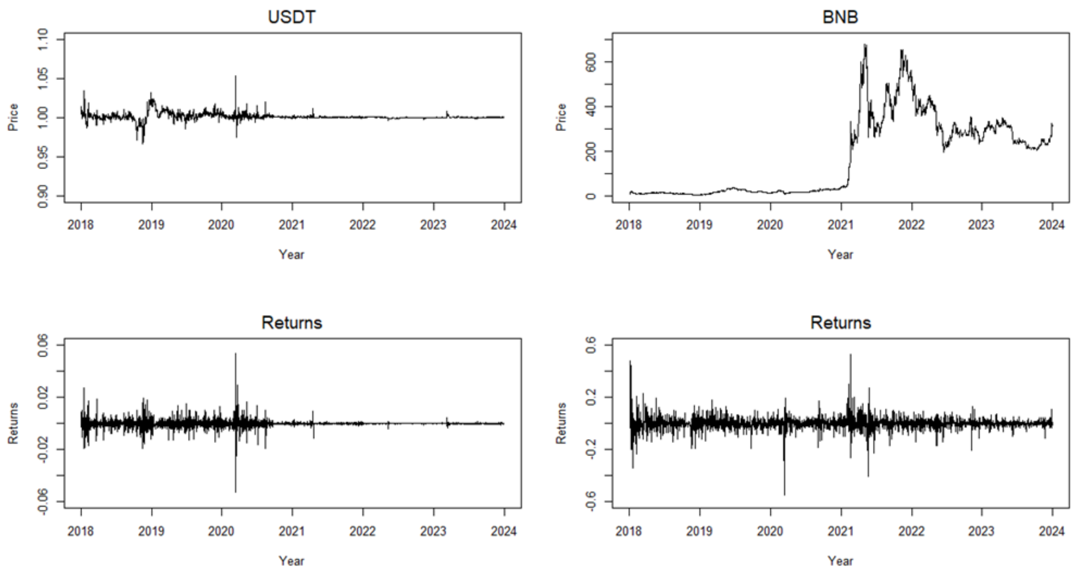

FIGURE 2. Plot of USDT and BNB (at Level and Returns)

a nonlinear dependency gauge function with k and an exponential weight for non-linear dependence. The null hypothesis is succinctly stated as $m_\theta(k) = 0, \theta \geq 1$.

Automatic Portmanteau Test

The statistical evaluation known as the automatic portmanteau test, alternatively referred to as the robustified portmanteau test, serves the purpose of examining the adequacy of a time series model (Escanciano and Velasco 2006). Its primary function is to assess the null hypothesis, the absence of autocorrelation within the time series. This test offers a robust alternative to conventional portmanteau tests (Mallesha and Archana 2024), addressing sensitivity issues to outliers or distributions with heavy tails. The automatic portmanteau test equation is as follows:

$$AQ_k^* = T \sum_{j=1}^{k} \rho_j^2$$

where T represents the total number of observations, $\rho_j$signifies the jth order autocorrelations, and k denotes the optimal lag length, specifically, the first k autocorrelations of a time series that indicate unpredictability.

Automatic Variance Ratio Test

The original variance ratio test by (Lo and MacKinlay 1989) to assumes a random walk for the price process, with variance parameters q and p determined (Urquhart 2016). However, selecting q and p is challenging. To address this, an automatic variance test (AVR) by Choi (1999) employs a data-dependent approach for robustly determining q and p, enhancing reliability in testing the random walk hypothesis. The null hypothesis implies no autocorrelation. The AVR test statistics are formulated as:

$$AV(k) = \sqrt{T/k[VR(k) - 1]/\sqrt{2}}$$

With the Variance Ratio (VR) computed is as follows

TABLE 3. Overview of Random Walk Models

Random Walk Model	Explanation
Random Walk 1 (RW1)	Although RW1 may not align with theoretical principles, its testing can provide valuable insights into random walk behaviour. It is important to properly consider the drift of a random walk as it can be misconstrued as predictability (Campbell et al. 1998). Before delving into these concerns, let us first briefly revisit traditional statistical tests for the assumption of independent and identically distributed data (Campbell et al. 1998). These tests, which do not rely on any specific distribution family, are often categorised as non-parametric tests. The Pt process can be expressed as: $P_t = \mu + P_{t-1} + \epsilon_t, \quad \epsilon_t \sim \text{iid}(0, \sigma^2)$
Random Walk 2 (RW2)	The Random Walk 2 (RW2) model is a more general framework than the RW1 model. It allows for independent but not identically distributed increments, which means the price movements can still be independent, but their distributions may differ (Campbell et al. 1998). The RW2 model can also capture time-varying volatility. Thus, the RW2 model permits the inclusion of heteroscedasticity in ϵ_t. The estimation procedure for RW2 is outlined as follows: $P_t = \mu + P_{t-1} + \epsilon_t, \quad \epsilon_t \sim \text{inid}(0, \sigma^2)$
Random Walk 3 (RW3)	The assessment of serial correlation, indicating the correlation between two instances within a time series but at distinct time points, serves as a straightforward method for evaluating the random walk and martingale hypotheses (Campbell et al. 1998). The random walk hypothesis (RW3) asserts that the initial differences in the random walk's level exhibit no correlation across various time leads and lags. This uncomplicated method underlies several examinations of the random walk.

$$VR(k) = 1 + 2\sum_{i=1}^{T-1} m(i/k)_{\rho i}$$

In this context, ρi represents the sample autocorrelation of order i, and m(.) denotes a weighting function with positive and decreasing weights.

4. Results and Discussion

The study computed several measures to examine cryptocurrency market efficiency using the top four leading crypto assets. It is crucial to comprehend the qualities of the data being analysed before executing the tests (Challa, Malepati, and Kolusu 2020). The data was analysed using RStudio 2023.06.2+561, a statistical software. The Jarque-Bera normality test stands out as a widely used method. This test serves as one of the diagnostic tools for assessing the distribution of observed returns, helping to determine whether they adhere to a normal distribution pattern (Jarque and Bera 1980).

Table 4. Summary of Descriptive Statistics

Cryptocurrency	**BTC**	**ETH**	**USDT**	**BNB**
Mean	0.0003	0.0004	0.0000	0.0016
Std. Dev.	0.0375	0.0486	0.0037	0.0542
Skewness	-1.0526	-1.0126	0.3510	0.2786
Ex. Kurtosis	13.8487	10.7952	48.4023	18.1547
Minimum	-0.4647	-0.5507	-0.0526	-0.5431
Maximum	0.1718	0.2307	0.0534	0.5292
Jarque Bera	16922	10405	202034	28450
P-value	0.0000*	0.0000*	0.0000*	0.0000*

Note: * Denotes significant @ 5 % level

The data presented in Table 4 provides an overview of the descriptive statistics. In the random walk model context, an assumption is made regarding the normal distribution of observed returns. However, the data reveals that the skewness and kurtosis values for cryptocurrency returns differ from the ideal values of 0 and 3, respectively. These disparities suggest that cryptocurrencies do not conform to a normal distribution pattern. Furthermore, the Jarque-Bera statistic for cryptocurrency returns significantly exceeds the expected value under a standard normal distribution, leading us to reject the null hypothesis that all cryptocurrencies, such as BTC, ETH, USDT, and BNB, adhere to a normal distribution.

Table 5. Results of Sample Cryptocurrencies (2018-2023)

Cryptocurrency	**BTC**	**ETH**	**USDT**	**BNB**
Generalized Spectral Test	(0.4167)	(0.0660)	(0.9500)	(0.0700)
Auto. Portmanteau Test	2.0952	2.9087	14.6606	0.5642
	(0.1477)	(0.0897)	(0.0001) *	(0.4525)
Auto. Variance Ratio Test	-0.9551	-1.0400	-12.8074	-0.7447
	(0.2920)	(0.2340)	(0.0000) *	(0.5940)

Note: *Denotes significant @ 5 % level

Table 5 displays the outcomes of three statistical assessments: the generalized spectral test, automated portmanteau test, and automatic variance ratio test. In the generalized spectral test, it is noteworthy that all p-values surpass the predetermined significance level. This observation suggests a consistent adherence of cryptocurrencies to the martingale difference process. The results from both the automatic portmanteau and automatic variance ratio tests indicates that the observed series are not autocorrelated, except for USDT. Therefore, our empirical results suggests that the cryptocurrency market predominantly exhibits a random walk behavior, inferring its market efficiency. Overview of empirical results displayed in Table 4. Moreover, to determine whether crypto market efficiency is time-varying or static, we utilized the rolling window technique.

Rolling-Window for Time Series Analysis

A prevalent assumption in time-series modelling is that the coefficients remain constant over time, implying time invariance. The investigation for instability involves scrutinizing whether these coefficients exhibit temporal variations (Pathak et al. 2020). To explore the dynamic aspects of the random walk hypothesis in the context of cryptocurrencies, we apply the rolling window technique described in the relevant section. Our approach involves utilised a fixed-length rolling window with 365 observations (representing a year). Cryptocurrency markets operate continuously, even during public holidays (Patel 2022), whereas conventional financial

Table 6. Summary of Empirical Results (2018-2023)

Cryptocurrency	Generalized Spectral Test	Automatic Portmanteau Test	Automatic Variance Ratio Test	Efficient/ Inefficient
Bitcoin (BTC)	Fail to Reject H0	Fail to Reject H0	Fail to Reject H0	Efficient
Ethereum (ETH)	Fail to Reject H0	Fail to Reject H0	Fail to Reject H0	Efficient
Tether (USDT)	Fail to Reject H0	Reject H0	Reject H0	Inefficient
Binance Coin (BNB-USD)	Fail to Reject H0	Fail to Reject H0	Fail to Reject H0	Efficient

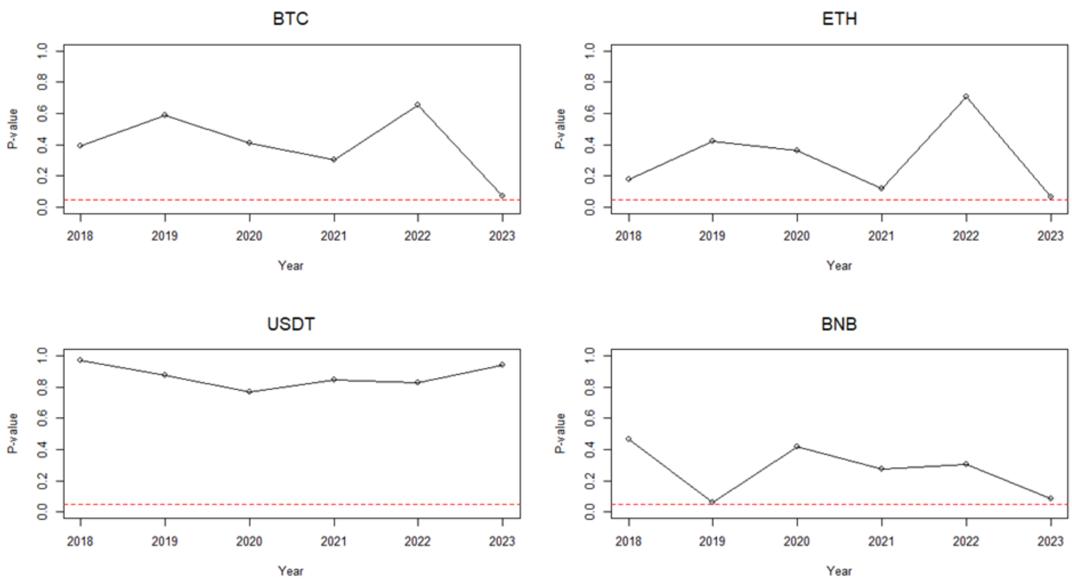

Figure 3. P-values of Generalized Spectral Test over the Rolling Window

Note: Dashed Line Represents 5 % Significance Level

markets operate 250-260 days a year. This 365 window size is chosen to ensure the robustness of the tests' power and size properties and to identify any brief predictability periods (Kayal and Balasubramanian 2021; Khuntia and Pattanayak 2020). Using the fixed-length rolling window method, offset by six observations. We evaluate the magnitude and patterns of fluctuations over time by analysing the respective time series of p-values. The results, presented in Figures 2, 3, and 4, illustrate the outcomes of generalized spectral, automatic portmanteau, and automatic variance ratio tests applied to four prominent cryptocurrencies. A p-value less than or equal to 0.05 leads to the rejection of the null hypothesis of randomness/efficiency at a 5% significance level.

In the analysis of cryptocurrency market efficiency, Figure 3 displays the p-values resulting from a generalized spectral test applied to various cryptocurrencies (BTC, ETH, USDT, BNB) across different window periods. The outcomes reveal consistent market efficiency for all cryptocurrencies throughout the observed periods. Notably, BTC, ETH, and BNB's returns in 2023 hover near the significance level but remain above it. Hence, the generalized spectral test suggests that the randomness of cryptocurrencies remains stable, indicating a sustained market efficiency rather than fluctuating dynamics. Moving on to Figure 4, the p-values from the automatic portmanteau test are depicted for the sample cryptocurrencies (BTC, ETH, USDT, BNB) across various time frames. These p-values assess the autocorrelation of the data, and the

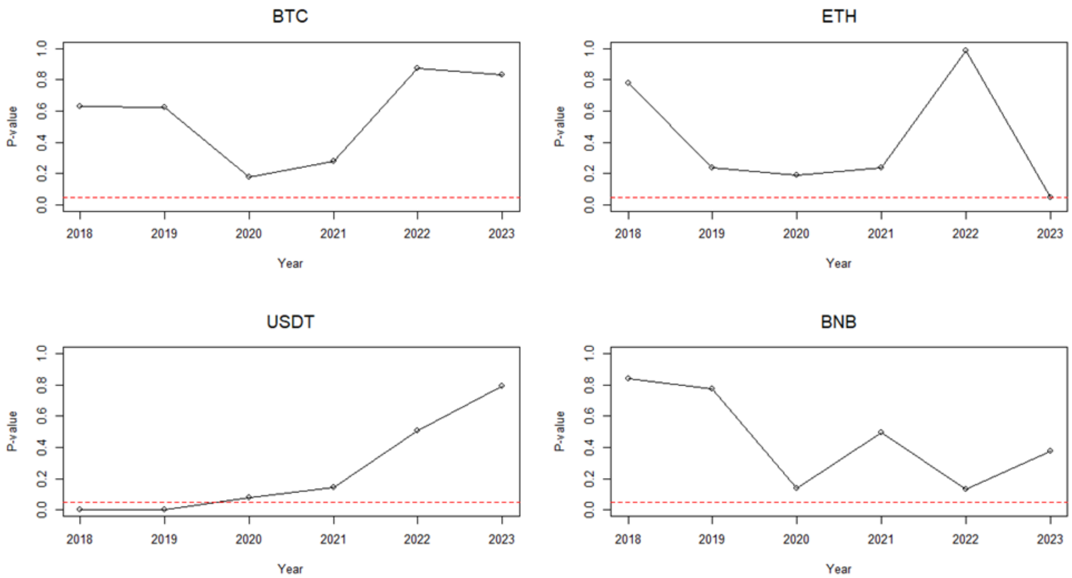

FIGURE 4. P-values of Automatic Portmanteau Test over the Rolling Window

Note: Dashed Line Represents 5 % Significance Level

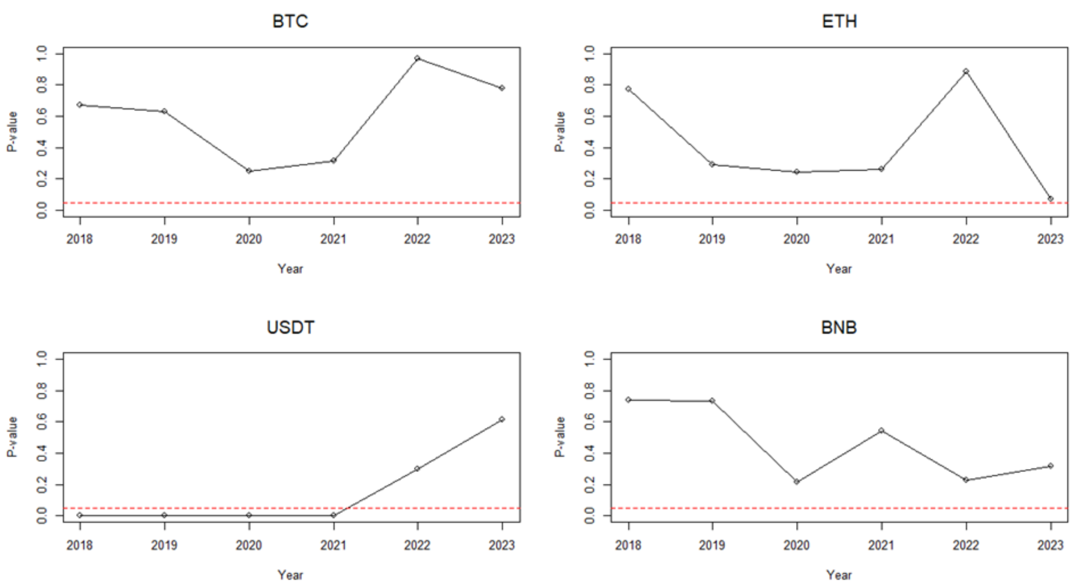

FIGURE 5. P-values of Automatic Variance Ratio Test over the Rolling Window

Note: Dashed Line Represents 5 % Significance Level

majority of cryptocurrencies show insignificance, suggesting no autocorrelation across multiple windows, except for USDT in 2018 and 2019. Thus, the automatic portmanteau test indicates that the cryptocurrency market maintains a constant level of market efficiency, except for USDT in those specific years. Figure 5 presents the p-values resulting from the automatic variance ratio test conducted on sample cryptocurrencies (BTC, ETH, USDT, BNB) across different window periods. The automatic variance ratio test confirms that BTC, ETH, and BNB exhibit market efficiency over the rolling windows. However, USDT is found to be inefficient during several periods (2018, 2019, 2020, and 2021). Overall summary, these systematic analyses using the generalized spectral test, automatic portmanteau test, and automatic variance ratio test provide insights into the overall efficiency of cryptocurrencies across diverse rolling windows. Despite fluctuations in significance levels and occasional deviations, the market appears to predominantly exhibit efficiency, with USDT being an exception during specific periods.

5. Conclusion

The study assesses the random walk behaviour of the cryptocurrency market, inferring its weak form efficiency. We analysed daily prices of four leading cryptocurrencies from January 2018 to December 2019: Bitcoin (BTC), Ethereum (ETH), Tether (USDT), and Binance Coin (BNB-USD). Cryptocurrencies were selected based on market capitalizations. Robustified tests employed, namely generalized spectral test, automatic portmanteau test, and automatic variance ratio test. The study reveals that most prices of leading cryptocurrencies adhere to a random walk behavior, indicating that cryptocurrency price fluctuations occur randomly. Furthermore, to explore whether market efficiency time-varying or static, a rolling window method was used, dividing the timeline into four equal fixed rolling windows. The majority of cryptocurrencies demonstrated consistent parameters in market efficiency, except for USDT (automatic portmanteau and automatic variance ratio tests), suggesting inefficiency across different rolling windows. These findings contribute to a nuanced understanding of cryptocurrency markets' dynamic nature and their alignment with market efficiency. The study concludes that most cryptocurrencies exhibit market efficiency based on statistical tests, implying that their price movements follow a random or independent pattern, indicated by weak form efficiency. This result aligns with prior research by Karaömer and Acaravci (2023), Apopo and Phiri (2021), and Nadarajah and Chu (2017). Caution is advised for investors and market participants, considering the fluctuating levels of efficiency when deciding on these cryptocurrencies. Policymakers are urged to uphold market integrity and protect investors by establishing a robust policy framework for enhanced investor confidence and a reliable price discovery process. The study suggests that a more comprehensive approach, involving a broader range of altcoins, could offer valuable insights for investors, and future research could explore what factors influence market efficiency of crypto market.

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