© AUG 2026 | IRE Journals | Volume 10 Issue 2 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I2-1720306

A Study on Randomness of the Cryptocurrency Market

ZEBA KOUSAR[1], MALLESHA L[2]
[1]*MBA 2nd Year Student, Ballari Institute of Technology and Management, Ballari, Karnataka*
[2]*Assistant Professor, Department of Management Studies, Ballari Institute of Technology & Management (Autonomous), Ballari, Karnataka, India*
ORCID: https://orcid.org/0000-0001-6518-5665

Abstract- Cryptocurrencies have emerged as a prominent asset class characterized by rapid price fluctuations, growing institutional participation, and continuing debate over whether their price movements are random or predictable. This study examines the randomness and weak-form market efficiency of the top ten cryptocurrencies by market capitalization—Bitcoin, Ethereum, Tether, Binance Coin, XRP, USD Coin, Solana, TRON, Dogecoin, and Hype liquid—using daily closing price data from April 2016 to March 2026 (subject to data availability for each coin). Daily log returns were tested using Descriptive Statistics, the Jarque–Bera test of normality, the Wald–Wolfowitz Run Test, and the Autocorrelation Test. The results show that daily returns for all selected cryptocurrencies are non-normally distributed, exhibiting excess kurtosis and skewness. The Run Test results indicate that seven of the ten cryptocurrencies—Bitcoin, Ethereum, Tether, Binance Coin, XRP, USD Coin, and Dogecoin—do not follow a random walk, while Solana, TRON, and Hype liquid exhibit randomness consistent with weak-form efficiency. However, the Autocorrelation Test reveals strong positive serial correlation across all ten cryptocurrencies, indicating that the market falls short of weak-form efficiency. The study concludes that the cryptocurrency market provides mixed and largely inefficient evidence with respect to the Random Walk Hypothesis, implying that historical price information may retain some predictive value for investors.

Keywords: Cryptocurrency, Random Walk Hypothesis, Market Efficiency, Run Test, Autocorrelation, Jarque–Bera Test, Bitcoin

I. INTRODUCTION

Cryptocurrency is a form of digital currency that enables secure online transactions without reliance on banks or other central authorities. Built on blockchain technology, it records transactions in a transparent and immutable manner. Since the introduction of Bitcoin in 2009, the cryptocurrency market has expanded rapidly, with thousands of digital assets now traded across global exchanges. Given their pronounced price volatility and growing popularity among investors, understanding whether cryptocurrency price movements are random or exhibit predictable patterns has become an important area of financial research.

The Random Walk Theory holds that future price changes cannot be reliably predicted from past prices, since publicly available information is already reflected in current prices. Consequently, price movements are expected to occur randomly, limiting the ability of investors to consistently earn abnormal returns through analysis of historical price patterns. This theoretical foundation underlies the weak form of the Efficient Market Hypothesis (EMH), which this study uses to evaluate the cryptocurrency market.

The study focuses on the top ten cryptocurrencies by market capitalization during the study period: Bitcoin (BTC), Ethereum (ETH), Tether (USDT), Binance Coin (BNB), XRP, USD Coin (USDC), Solana (SOL), TRON (TRX), Dogecoin (DOGE), and Hype liquid (HYPE). These assets collectively represent the major segments of the cryptocurrency ecosystem, including store-of-value assets, smart-contract platforms, stablecoins, payment-focused tokens, and high-performance trading platforms.

II. REVIEW OF LITERATURE

A substantial body of research has examined the randomness and weak-form efficiency of cryptocurrency markets, with mixed conclusions. Aggarwal (2019) applied a battery of robust tests, including unit root and breakpoint unit root tests, the BDS test and a GARCH-based volatility measure, to Bitcoin prices from July 2010 to March 2018, and concluded that Bitcoin does not follow the Random Walk Hypothesis. Palamalai (2020) tested the top ten cryptocurrencies using the Runs test, the Kolmogorov-Smirnov test, unit root tests, the Multiple Variance

Ratio test and GARCH-type models and likewise found that leading cryptocurrencies do not follow a random walk.

Other studies report more mixed results. Ajith et al. (2022) used the Variance Ratio test, the BDS test, the Runs test and the Breusch-Godfrey LM test on major cryptocurrencies from January 2016 to March 2021, finding that some coins support the Random Walk Hypothesis while others do not. Apopo and Phiri (2021) similarly found that daily returns of major cryptocurrencies were more consistent with randomness than weekly returns. Aslam et al. (2023) and Tran and Leirvik (2020) both applied time-varying methods — Multifractal Detrended Fluctuation Analysis and Rolling Window Analysis, and the Generalized Spectral, Automatic Portmanteau and Domínguez-Lobato tests respectively — and concluded that cryptocurrency market efficiency changes over time, consistent with the Adaptive Market Hypothesis.

A further set of studies point toward inefficiency driven by liquidity and volatility. Al-Yahyee et al. (2020) and Abou Tanos and Badr (2024) both found that higher liquidity improves efficiency while higher volatility reduces it, the latter specifically examining the COVID-19 period. Gunay and Kaskaloglu (2019) used the BDS test, Rescaled Range analysis, MFDFA and the largest Lyapunov exponent to show that cryptocurrency returns exhibit chaotic, non-random behaviour. Closer to the present study, Mallesha and Archana (2023) applied the Ljung-Box test, Run test, Bartels test, Variance Ratio test, EGARCH (1,1) and the R/S Hurst exponent to the top ten cryptocurrencies after the declaration of the COVID-19 pandemic, and found that most cryptocurrencies do not follow the Random Walk Hypothesis. Amirat (2021), using thirteen randomness and correlation tests on eight major coins, likewise found that most cryptocurrencies were inefficient, with Bitcoin as a partial exception.

Table 1: Selected Empirical Studies on Randomness and Market Efficiency of Cryptocurrencies

Author (Year)	Country/Region	Tests Used	Finding
Aggarwal (2019)	India	Multiple robust tests	Inefficient
Palamalai (2020)	India	Runs, KS, Unit root, MVR, GARCH	Inefficient
Ajith et al. (2022)	India	VR, BDS, Runs, Breusch-Godfrey	Mixed
Mallesha & Archana (2023)	India	Ljung-Box, Runs, Bartels, EGARCH, R/S	Inefficient
Amirat (2021)	Saudi Arabia	13 randomness/correlation tests	Mixed
Verma et al. (2022)	Global	VR, ADF, PP, Breusch-Godfrey, ARIMA	Inefficient
Apopo & Phiri (2021)	Global	ADF, PP, KPSS, KSS, FFF unit root	Mixed
Kyriazis (2019)	Greece	R/S, DFA, long-memory tests	Inefficient
Aslam et al. (2023)	Global	MFDFA, rolling window	Mixed
Tran & Leirvik (2020)	Norway	GS, AP, DL tests (AMH)	Mixed
Al-Yahyee et al. (2020)	Global	MF-DFA, quantile regression	Inefficient
Abou Tanos & Badr (2024)	Lebanon	Price delay, liquidity/volatility	Inefficient
Gunay & Kaskaloglu (2019)	Kuwait	BDS, R/S, MFDFA, Lyapunov	Not random
Hairudin & Mohammed (2024)	Malaysia	CWT, MODWT, R/S	Mixed

© AUG 2026 | IRE Journals | Volume 10 Issue 2 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I2-1720306

Source: Compiled by Authors

Taken together, the literature shows that while some studies support the Random Walk Hypothesis for specific coins or time windows, the majority report inefficiency or mixed efficiency, with results varying by the cryptocurrency examined, the sample period used, and the statistical technique applied. Most existing studies, however, focus on a narrow set of coins, shorter sample periods, or specific events such as the COVID-19 pandemic, leaving room for an updated, broader study covering the current leading cryptocurrencies over a longer horizon.

III. STATEMENT OF THE PROBLEM

The cryptocurrency market is characterized by high volatility and rapid price fluctuations, making it uncertain whether price movements are random or predictable. Earlier studies, as summarized above, report inconsistent findings regarding the Random Walk Hypothesis and weak-form market efficiency of cryptocurrencies, with conclusions ranging from full efficiency to full inefficiency to mixed efficiency depending on the coins, period and tests used. Given the growing size of the cryptocurrency market and its increasing integration with mainstream finance, it is essential to examine whether the returns of the currently leading cryptocurrencies follow a random pattern or exhibit predictability, an issue with direct implications for investment decision-making and regulatory policy.

IV. OBJECTIVES AND HYPOTHESIS OF THE STUDY

4.1 Objectives of the study

- To understand the concept of the Random Walk Model.
- To examine whether the returns of selected cryptocurrencies are independent and follow a random pattern using the Run Test.
- To analyze the relationship between current and past returns using the Autocorrelation Test.
- To evaluate the weak-form market efficiency of leading cryptocurrencies.

4.2 Hypothesis of the Study

Jarque-Bera Test

H0: The daily returns of the selected cryptocurrencies are normally distributed.

H1: The daily returns of the selected cryptocurrencies are not normally distributed.

Run Test

H0: The daily returns of the selected cryptocurrencies follow a random pattern.

H1: The daily returns of the selected cryptocurrencies do not follow a random pattern.

Autocorrelation Test

H0: There is no meaningful autocorrelation in the daily returns of the selected cryptocurrencies.

H1: There is meaningful autocorrelation in the daily returns of the selected cryptocurrencies.

V. DATA AND METHODOLOGY

5.1 Sample Data

The study is descriptive and quantitative in nature. It examines the randomness and weak-form market efficiency of the top ten leading cryptocurrencies selected on the basis of market capitalization : Bitcoin (BTC), Ethereum (ETH), Tether (USDT), Binance Coin (BNB), XRP, USD Coin (USDC), Solana (SOL), TRON (TRX), Dogecoin (DOGE) and Hyper liquid (HYPE). Daily closing price data were used for the period April 2016 to March 2026, subject to data availability for each cryptocurrency, sourced from reliable databases including Investing.com, Capitaline.com and Google Scholar. Closing prices were converted into daily logarithmic returns using the formula:

$$Return = \ln(P_t / P_{t-1})$$

where P_t is the closing price at time t and P_{t-1} is the closing price at time t–1.

5.2 Descriptive Statistics and Jarque Bera Test

Descriptive statistics — mean, minimum, maximum, standard deviation, skewness and kurtosis — summarize the distributional characteristics of daily returns. The Jarque-Bera (JB) test, introduced by Jarque and Bera (1980), examines whether a return

© AUG 2026 | IRE Journals | Volume 10 Issue 2 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I2-1720306

series is normally distributed based on its skewness and kurtosis; under normality, skewness should be close to zero and kurtosis close to three. A p-value below 0.05 leads to rejection of the null hypothesis of normality.

$$JB = \frac{n}{6}\left(s^2+\frac{k2}{4}\right)$$

5.3 Run Test

The Run test, also known as the Wald-Wolfowitz Runs test (Wald and Wolfowitz, 1940), is a non-parametric test used to determine whether a sequence of returns is random. Returns are classified as positive or negative, and the number of runs (unbroken sequences of the same sign) is compared with the expected number of runs under randomness:

$$E(R) = [2\, n1\, n2 / (n1 + n2)] + 1$$

where n1 and n2 are the number of positive and negative returns. The standard deviation of the number of runs and the resulting Z-Statistic are computed as:

$$Z = [R - E(R)] / S.D.$$

If Z-Statistics lies within ±1.96 at the 5% significance level, the null hypothesis of randomness is accepted; otherwise, it is rejected.

5.4 Autocorrelation Test

The autocorrelation coefficient measures the relationship between current returns and their own lagged values. It was computed using the CORREL function between each return series and its one-period lag. A coefficient close to zero indicates no meaningful relationship between current and past returns — consistent with randomness and weak-form efficiency — while a coefficient significantly different from zero indicates predictability and possible weak-form inefficiency.

VI. RESULTS AND DISCUSSION

6.1 Descriptive Statistics and Jarque Bera Test

Table 2 summarizes the descriptive statistics of daily returns.

Cryptocurrency	Mean	Min	Max	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	P-value
Bitcoin	0.0020	-0.3918	0.2556	0.0356	-0.1052	8.2205	10292.50	0.0000*
Ethereum	0.0026	-0.4455	0.2951	0.0492	0.1884	6.0258	5548.27	0.0000*
Tether	0.0000	-0.0558	0.0463	0.0036	0.3597	53.6788	393023.67	0.0000*
BNB	0.0031	-0.4407	0.6999	0.0513	2.0556	29.4750	113145.62	0.0000*
XRP	0.0035	-0.4797	1.7955	0.0700	6.6932	136.6285	2867816.64	0.0000*
USDC	0.0000	-0.2039	0.1327	0.0066	-7.7748	426.4624	20282717.05	0.0000*
Solana	0.0040	-0.4235	0.6486	0.0645	0.9457	9.8674	8756.80	0.0000*
TRON	0.0034	-0.4350	1.1818	0.0657	6.6857	109.6315	1555734.91	0.0000*
Dogecoin	0.0227	-0.9843	61.9151	1.0948	56.1216	3172.8712	1354461075.70	0.0000*
Hyper Liquid	0.0031	-0.1468	0.2398	0.0580	0.4670	1.2412	47.86	0.0000*

Note: * denotes significance at the 5% level. Source: Authors' estimation

Most coins show a positive mean daily return, with Dogecoin recording the highest average return (0.0227) and Tether and USDC — both stablecoins — recording means close to zero, consistent with their price-stability design. Dogecoin also displays the widest range of returns and the highest standard deviation (1.0948), indicating the greatest volatility among the sample, while Tether shows the narrowest range and lowest standard deviation (0.0036), reflecting minimal volatility. Skewness is negative for Bitcoin and USDC and positive for the remaining coins, and kurtosis values are well above three for all cryptocurrencies, indicating heavy-tailed return distributions. The Jarque-Bera statistics are significant

© AUG 2026 | IRE Journals | Volume 10 Issue 2 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV10I2-1720306

at the 5% level for every coin, so the null hypothesis of normality is rejected throughout the sample: cryptocurrency returns are not normally distributed, a pattern that departs from the assumption of a purely random, normally distributed return series.

6.2 Run Test

Table 3 : The Test was applied to examine whether daily returns follow a random pattern.

Cryptocurrency	Runs	N1	N2	Total Cases	Z-Statistic	P-value
Bitcoin	1951	1907	1740	3647	4.4386	9.06E-06
Ethereum	1961	1846	1792	3638	4.6907	2.72E-06
Tether	2202	1375	1428	2803	30.2381	0.0000
BNB	1662	1586	1456	3042	5.1878	2.13E-07
XRP	2088	1749	1799	3548	10.5260	0.0000
USDC	1801	1115	1132	2247	28.5593	0.0000
Solana	1048	1038	1041	2079	0.3295	0.7418
TRON	1622	1599	1460	3059	0.0587	0.9532
Dogecoin	1742	1566	1647	3213	4.7858	1.70E-06
Hype liquid	253	235	239	474	1.3818	0.1670

Note: denotes significance at the 5% level. Source: Authors' estimation

The Run test results show that Bitcoin, Ethereum, Tether, BNB, XRP, USDC and Dogecoin all record p-values below 0.05, leading to rejection of the null hypothesis of randomness for these coins. Their daily returns therefore do not follow a random pattern, implying that past price movements may contain information relevant to predicting future returns and that these cryptocurrencies are weak-form inefficient. By contrast, Solana (p = 0.7418), TRON (p = 0.9532) and Hyper liquid (p = 0.1670) have p-values above 0.05, so the null hypothesis of randomness cannot be rejected for these three coins, which are consistent with the Random Walk Hypothesis and weak-form efficiency. Overall, seven of the ten selected cryptocurrencies do not follow a random walk, while three do, provide mixed evidence on market efficiency.

6.3 Autocorrelation Test

Table 4 presents the autocorrelation coefficients for each cryptocurrency's daily returns against their own one-period lagged values.

Cryptocurrency	Autocorrelation	Market Efficiency
Bitcoin	0.9979	Weak-form inefficient
Ethereum	0.9970	Weak-form inefficient
Tether	0.2023	Weak-form inefficient
BNB	0.9928	Weak-form inefficient
XRP	0.9731	Weak-form inefficient
USDC	0.9978	Weak-form inefficient
Solana	0.9948	Weak-form inefficient
TRON	0.9812	Weak-form inefficient
Dogecoin	0.6390	Weak-form inefficient
Hyperliquid	0.9988	Weak-form inefficient

VII. FINDINGS

- Daily returns of the selected cryptocurrencies show positive average returns overall, though the magnitude varies considerably across coins.
- Volatility differs sharply across the sample: Dogecoin exhibits the highest volatility, while Tether exhibits the lowest, consistent with its stablecoin design.
- The Jarque–Bera Test confirms that daily returns of all selected cryptocurrencies are not normally distributed.
- The Run Test shows that Bitcoin, Ethereum, Tether, BNB, XRP, USDC, and Dogecoin do not follow a random walk, indicating weak-form inefficiency, while Solana, TRON, and Hyperliquid display random price movements consistent with weak-form efficiency.
- The Autocorrelation Test shows strong positive autocorrelations for all ten cryptocurrencies,

indicating that past returns are systematically linked to current returns market wide.

- Overall, the study provides mixed evidence on the Random Walk Hypothesis: while a subset of cryptocurrencies shows random behavior under one test, the persistence of positive autocorrelation across the full sample points toward broader weak-form inefficiency.

VIII. SUGGESTION

- Investors should combine technical and fundamental analysis rather than relying solely on historical price patterns.
- Portfolio diversification is advisable to mitigate the risks associated with cryptocurrency price volatility.
- Caution is warranted when investing in highly volatile cryptocurrencies such as Dogecoin.
- Regulatory authorities should strengthen policy frameworks to improve transparency and investor protection.
- Future research could expand the sample of cryptocurrencies, extend the study period, and apply advanced techniques such as GARCH-family models and long-memory tests for deeper insight.

IX. CONCLUSION

This study examined the randomness and weak-form market efficiency of the top ten cryptocurrencies using Descriptive Statistics, the Jarque–Bera Test, the Run Test, and the Autocorrelation Test over the period April 2016 to March 2026. The findings show that cryptocurrency returns are not normally distributed and that behavior varies considerably across the market. While the Run Test suggests that Solana, TRON, and Hyperliquid follow a random walk, the remaining cryptocurrencies exhibit predictable return patterns, and the Autocorrelation Test reveals strong positive serial dependence across all ten coins. Overall, the study concludes that the cryptocurrency market provides mixed, and on balance largely inefficient, evidence with respect to the Random Walk Hypothesis, suggesting that historical price information may retain some predictive value and that the market does not fully satisfy the conditions of weak-form efficiency.

This study is limited to a selected set of statistical techniques and ten cryptocurrencies; external macroeconomic and regulatory factors were not modelled, and conclusions are based on historical data that may not be held under future market conditions.

REFERENCES

[1] Aggarwal, D. (2019). Do Bitcoin follow random walk? Journal of Behavioral and Experimental Finance, 22, 15–20.

[2] Amirat, A. (2021). Exploring the random walk-in cryptocurrency market. Journal of Risk and Financial Management, 14(3), 1–22.

[3] Aslam, F., et al. (2023). The dynamics of market efficiency of major cryptocurrencies. Finance Research Letters, 51, 103418.

[4] Hairudin, N., & Mohammed, M. (2024). The isotropy of cryptocurrency volatility. Physica A: Statistical Mechanics and its Applications.

[5] Kyriazis, N. A. (2019). A survey on efficiency and profitable trading opportunities in cryptocurrency markets. Journal of Risk and Financial Management, 12(2), 67.

[6] Kyriazis, N. A., et al. (2020). A systematic review of the bubble dynamics of cryptocurrency prices. Research in International Business and Finance, 54, 101254.

[7] Mallesha, L., & Archana, H. N. (2023). Testing of random walk hypothesis in the cryptocurrency market: After declaration of global pandemic.

[8] Palamalai, S. (2020). Testing the random walk hypothesis for leading cryptocurrencies. Borsa Istanbul Review, 20(4), 379–389.

[9] Tran, V. L., & Leirvik, T. (2020). Efficiency in the cryptocurrencies markets. Finance Research Letters, 35, 101382.

[10] Verma, R., et al. (2022). Testing of random walk hypothesis in the cryptocurrency market.

[11] Alexander, C., & Dakos, M. (2020). A critical investigation of cryptocurrency data and analysis.

[12] Lee, D., et al. (2017). Cryptocurrency: A new investment opportunity? Journal of Alternative Investments.

[13] Liu, Y., & Tsyvinski, A. (2021). Risk and returns of cryptocurrency. Review of Financial Studies, 34(6), 2689–2727.

[14] Farell, R. (2015). An analysis of the cryptocurrency industry.

[15] Walter, C. P. (2021). The random walk model in finance: A new taxonomy.

[16] Godfrey, M. D., et al. (1964). Random walk hypothesis of stock market behavior.

[17] Adhikari, R., & Agrawal, R. K. (2014). A combination of ANN and random walk model for financial time series forecasting.

[18] Cheng, P., & Deets, M. K. (1971). Portfolio returns and random walk theory.

[19] Al-Yahyee, K. H., et al. (2020). Why cryptocurrency markets are inefficient: The impact of liquidity and volatility.

[20] Abou Tanos, B., & Badr, G. (2024). Price delay and market efficiency of cryptocurrencies: The impact of liquidity and volatility during the COVID-19 pandemic.

[21] Ajith, et al. (2022). Random walk-in cryptocurrency prices.

[22] Apopo, N., & Phiri, A. (2021). On the (in)efficiency of cryptocurrencies: Have they taken daily or weekly random walks?

[23] Gunay, S., & Kaskaloglu, K. (2019). Seeking a chaotic order in the cryptocurrency market.

[24] Kruckeberg, S., & Scholz, P. (2019). Random walk hypothesis.