

Testing the Efficient Market Hypothesis: An Empirical Analysis of Cryptocurrency Market Efficiency

V. Richard Paul^{1*}¹Assistant Director, UGC-HRDC, Bharathiar University, Coimbatore, Tamil Nadu**Article History****Received:** 25.07.2020**Accepted:** 21.09.2020**Published:** 23.12.2020**Journal homepage:**<https://www.easpublisher.com>**Quick Response Code**

Abstract: In this paper, we use efficient market testing to investigate the information sharing among the cryptocurrency markets with a view to examining the market efficiency of the cryptocurrencies. In order to analyze and interpret data, ten cryptocurrencies were taken and the study period covers one year from 8th July 2018 to 8th July 2020. The data collected denote daily prices. The following four tools were applied for the present study. Firstly, the unit root test was used in contemplation of finding the stationarity of time series. Secondly, summary statistics, thirdly autocorrelation and finally a run test were used. The empirical findings based on the current study analyze that cryptocurrencies market does not take any random walk as the cryptocurrencies market has a weak-form which is inefficient.

Keywords: cryptocurrencies, random walk, efficient market hypothesis, daily price, unit root test, autocorrelation, runs test.

Copyright © 2020 The Author(s): This is an open-access article distributed under the terms of the Creative Commons Attribution 4.0 International License (CC BY-NC 4.0) which permits unrestricted use, distribution, and reproduction in any medium for non-commercial use provided the original author and source are credited.

INTRODUCTION

The digital currency market, though reasonably novel, is in advance accumulative admiration as a decentralized financial method which could substitute old-fashioned consolidated financial systems and is enticing resources in lieu of the pioneering know-how underneath cryptocurrencies. Protagonists of cardinal bills contend that the growth of cybernetic money bazaars would outcome the additional all-encompassing economic segments aimed at the impending while adversaries recommend the cryptocurrencies fragment is merely being pigeonholed as the hypothetical gurgle. (Sovbetov, 2018). However, the financial circumstance of modest sequestered coinages like virtual bills that are all the same academically convincing, is still limited in its hands-on application. The widespread prevalence of virtual currencies has created a significant argument about the relevance of such currencies, their worth and whether they would provide necessary support as a reorganized monetary system similar to the one which is already centralized. However, the sustaining quality of a centralized or a decentralized system would depend on the efficacy of such a monetary system whether the currency in circulation would lead to maximum fruitful customs.

Unsettled to the element that the procedural viability, lesions of decentralized financial organisms

are motionless on emerging phases of development, the leading prominence about this work is organized about the aptitude of cryptocurrency asset markets information. Efficient market hypothesis (EMH) of notoriety rights depends on well-organized financial markets in relation to the facts. In other words, an investor is not able to reliably attain earnings above the market average (with a certain level of risk), depending merely on the overly obtainable evidence at present.

The present study will discuss the efficiency of the efficient market hypothesis of cryptocurrencies markets in a prescribed manner.

LITERATURE REVIEW

Father of efficient market theory was Gibson (1889), K. Pearson used the term 'random walk' first (in the context of botany) in 1905, and in 1925 it was F. MacCauley applied the same concept 'random walk' to coin-tossing experiments. Later, in 1953, after analyzing 22 stocks, Kendall documented that stock returns were random, which has taken many economists by surprise (Dimson and Mussavian, 2000). While some studies supported the random walk (Roberts, 1967; Larson, 1960; Alexander, 1961), other studies got opposite results (Alexander, 1964). Thus, in the postwar period, the research on EMH remained inconclusive.

Later the proper summary of EMH in the 70s, Grossman had delineated the market competence

inconsistency for the reason that questionable outcomes. (Lehmann, 1990; Jegadeesh, 1990). Despite strong opposition, researchers continued to test EMH on dissimilar stock markets at the domain. In 1997, Chan (1997) reported that global stock markets are weak-form efficient. However the efficient market hypothesis had endured single of the utmost provocative investigation area in money then financial side, rare investigators contend that theory can be considered 'half-true' (Shiller, 2013). While the line of argument is that today's stock prices is cannot be determine the stock prices tomorrow for the reason that instability and evidence disproportionately. During quarrels in favor of efficient market hypothesis and paradoxes in contradiction of efficient market hypothesis. (Malkie, 2003)". Addition, an enquiry by Le Tran and Leirvik (2020) by discovering conceivable relationships among the market competence of eighteen cryptocurrency period sequence. (Urquhart, 2016; Vidal-Tomas and Ibanez, 2018; Charfeddine and Maouchi, 2019; Le Tran and Leirvik, 2020).

Elangovan.R, *et al.* (2020) analysed the efficiency of Indian stock market, they summaries and resulted that is a weak-form inefficient. Drożdż *et al.* (2020) demonstrate the influence of the occurrence within the internal configuration of the market. Further prominently, many reviews emphasize on the foremost investigation issue of the efficient market hypothesis for empathetic cryptocurrency market individualities. All the market productivity competition of the most important operated cryptocurrencies has been intensely rehabilitated. The operative insinuation is the semi-strong form, the depositor cannot have divided the stock to attain cost-effectiveness considerably more complex than they can accomplish in a randomized assortment of assets (Samsa, 2020).

As mentioned in the introduction, several researchers addressed the random walk theory (weak form of EMH), which considers that future prices of stocks cannot be predicted.

Hypotheses

H01. The return series of cryptocurrencies are normally distributed.

H02. There is no stationarity in the return series of cryptocurrencies.

H03. The cryptocurrencies return series follow a random walk.

Method: Research design

In examining the weak-form market efficiency in cryptocurrencies, we have selected the cryptocurrencies. Day-to-day departing values of major ten cryptocurrencies, founded on their market capitalization, types (coins and tokens) and information convenience, were collected. Merely cryptocurrencies dispensed and dealt earlier the 2019-2020 cryptocurrency were measured in this study. The nominated 10 cryptocurrencies are like Bitcoin (BTC), Cardano (ADA), Ethereum (ETH), Litecoin (LTC), Tron (TRX), Stellar (XLM), Nem (XEM), Maker (MKR), Loto (LOTO) and EOS [EOS]. The data collected are from 8th July 2018 to 8th July 2020. We selected these ten cryptocurrencies just since merely these ten indices are obtainable, but the information about the other ten cryptocurrencies are not obtainable.

Sample

The fact sun ruffled for the experiential study is the day-to-day closing prices of cryptocurrencies. All the data were gathered from the official website <https://www.coingecko.com/>.

Analytical procedure

Unit root test, the Augmented Dickey-Fuller test, summary statistics and Jarque-Bera Test, autocorrelation and runs test statistical tools were applied in the current study. To calculate the daily returns, the formula could be used $[(LN(\text{Today closing price})/yesterday closing price) \times 100]$.

Abovementioned statistical test has been applied by numerous investigators (Degutis and Novickyte, 2014; Harshita *et al.*, 2018; Titan, 2015). The methods used in the present study are constant based on previous study. The ADF test used in the study must be a negative number. If the negative numbers are more, then the null hypothesis will be rejected, as it is arising a unit root. The runs test, a non-parametric test, mainly looks for the value variations reasonably than the extent of value variations. However, the last checks whether the sequence contains growing values or decreasing prices. The null hypothesis of the run test tells us that the data set is from a random process.

Table 1: Data sources and cryptocurrency overview

Sl. No	Cryptocurrencies symbol	Market capitalization 2020	Data source
1.	Bitcoin BTC	\$395,799,863,746	Coingecko
2.	Cardano ADA	\$5,214,107,174	Coingecko
3.	Ethereum ETH	\$72,436,347,872	Coingecko
4.	Litecoin LTC	\$6,133,693,800	Coingecko
5.	Tron TRX	\$2,234,072,422	Coingecko
6.	Stellar XLM	\$4,174,146,998	Coingecko
7.	Nem XEM	\$2,306,497,457	Coingecko
8.	Maker MKR	\$538,318,094	Coingecko
9.	Loto LOTO	\$910,458,701	Coingecko
10.	Eos EOS	\$2,907,908,027	Coingecko

Summary statistics for cryptocurrencies. In order to find the time-series data, it is significant to check the regularity of the information which is obtainable from the summary statistics. The mean value of BTC cryptocurrency exhibits the maximum mean return of (46665.4). For the purpose of making the distribution normal, the form is that both skewness and kurtosis must be equal to 0 and 3 respectively. From Table1, the value of skewness of the returns is understood to be negative for BTC and ADA cryptocurrencies. The distribution of the daily returns was asymmetrical and likewise, the significance of skewness of the returns was found to be positive for all cryptocurrencies except BTC and ADA and therefore the distribution of the day-to-day earnings stood symmetrical. Kurtosis value is greater than 3 for all the indices except BTC, ADA, ETH, TRX and LOTO. When we analyse these summary statistics, we reject $H01$ and as a result, it is concluded that distribution of returns is not normal.

Outcomes of the study:

Our summary statistics summarizes the data for the sample period. First, we examined the summary

statistics. To test the normality, the Kurtosis value was calculated to measure the Peakedness the distribution of the series. Table 1 depicts the results of summary statistics for cryptocurrencies. In order to find the time-series data, it is important to check the regularity of the information which is obtainable from the summary statistics. The mean value of BTC cryptocurrency exhibits the maximum mean return of (46665.4). For the purpose of making the distribution normal, the form is that both skewness and kurtosis must be equal to 0 and 3 respectively. From Table1, the value of skewness of the returns is understood to be negative for BTC and ADA cryptocurrencies. The distribution of the daily returns was asymmetrical and likewise, the significance of skewness of the returns was found to be positive for all cryptocurrencies except BTC and ADA and therefore the distribution of the day-to-day earnings stood symmetrical. Kurtosis value is greater than 3 for all the indices except BTC, ADA, ETH, TRX and LOTO. When we analyse these summary statistics, we reject $H01$ and as a result, it is concluded that distribution of returns is not normal.

Table 2: Summary Statistics for the Cryptocurrencies

Cryptocurrencies Symbol	Mean	Max	Min	S.D.	Skew	Kur	Jarque-Ber (J.B)	Prob	obs
BTC	46665.04	67566.83	22803.08	10606.88	-0.11	1.94	17.55	0.00	360
ADA	1.46	2.97	0.13	0.66	-0.06	2.65	2.00	0.36	360
ETH	2653.37	4812.09	583.71	1063.93	0.17	2.06	15.12	0.00	360
LTC	185.27	386.45	101.82	49.48	1.30	5.18	173.04	0.00	360
TRX	0.07	0.16	0.02	0.03	0.16	2.44	6.24	0.04	360
XLM	0.36	0.73	0.12	0.10	0.76	4.04	51.31	0.00	360
XEM	0.24	0.79	0.09	0.13	1.79	6.39	366.61	0.00	360
MKR	2697.30	6012.46	517.86	947.51	0.30	4.03	21.68	0.00	360
LOTO	1.18	2.53	0.26	0.47	0.13	2.84	1.51	0.46	360
EOS	4.66	14.37	2.30	1.62	2.05	9.48	884.01	0.00	360

Note(s): BTC, Bitcoin; ADA, Cardano; ETH, Ethereum; LTC, LITECOIN; TRX, TRON; XLM, Stellar; XEM, Nem; MKR, Maker; LOTO, loto; EOS, Eos;

Source: Compiled from EViews10

Daily Closing Price

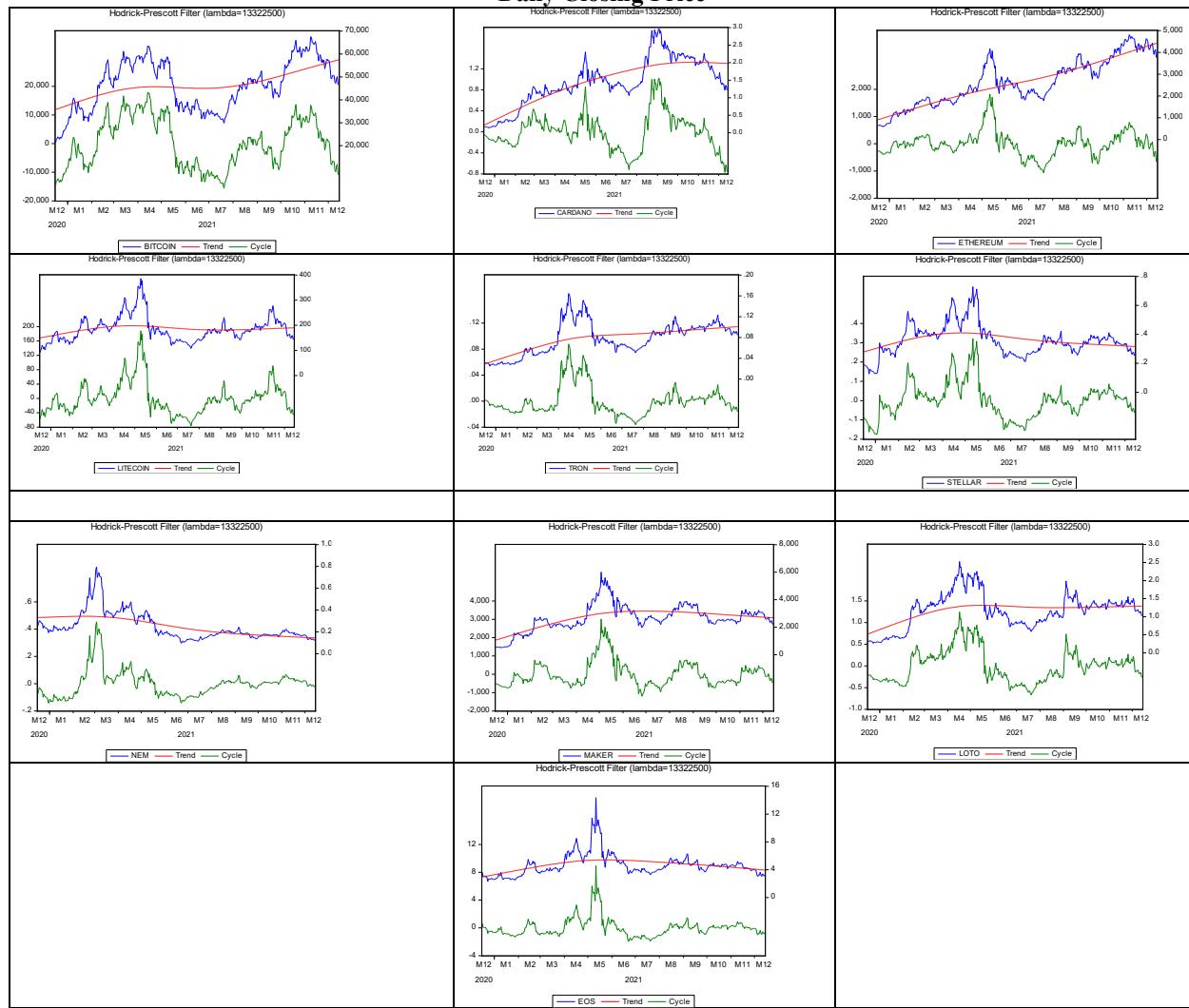


Figure -1

Source: compiled from Eviews7

To test the stationarity in the cryptocurrencies, ADF test was piloted and the table 3 shows the outcomes of the ADF test. The ADF test statistic values of Intercept are less than

critical values at a 1 per cent significance level. Hence, H_0 was rejected and it was determined thereno stationarity in the return series of cryptocurrencies. These results show that data have exhibited stationarity.

Table 3: Results of Augmented Dickey-Fuller Test for Cryptocurrency

Cryptocurrency symbol	t-value	Critical Value		
		1%	5%	10%
BTC	-2.486880	-3.448161	-2.869285	-2.570963
ADA	-2.016874	-3.448161	-2.869285	-2.570963
ETH	-1.759974	-3.448161	-2.869285	-2.570963
LTC	-2.823170	-3.448161	-2.869285	-2.570963
TRX	-2.125134	-3.448161	-2.869285	-2.570963
XLM	-2.573931	-3.448161	-2.869285	-2.570963
XEM	-1.778290	-3.448161	-2.869285	-2.570963
MKR	-2.448623	-3.448211	-2.869307	-2.570975
LOTO	-2.399705	-3.448262	-2.869329	-2.570987
EOS	-2.403535	-3.448211	-2.869307	-2.570975

Note(s): BTC, Bitcoin; ADA, Cardano; ETH, Ethereum; LTC, LITECOIN; TRX, TRON; XLM, Stellar; XEM, Nem; MKR, Maker; LOTO, loto; EOS, Eos;

Source: Compiled from EViews10

Autocorrelation: In the table no.4 to 11, shown the sixteen lag periods accompanying through autocorrelation for all the indices. The results of autocorrelation for Bitcoin are presented in Table 4.

Table 4: Results of Autocorrelation Test for Bitcoin

Autocorrelation	Partial Correlation		Autocorrelation AC	Partial Autocorrelation PAC	Q-Stat	Prob
. *****	. *****	1	0.977	0.977	350.53	0.000
. *****	. .	2	0.957	0.038	687.43	0.000
. *****	. .	3	0.936	-0.013	1010.8	0.000
. *****	. .	4	0.916	0.000	1321.2	0.000
. *****	. .	5	0.894	-0.057	1617.5	0.000
. *****	. .	6	0.870	-0.043	1899.1	0.000
. *****	. .	7	0.846	-0.030	2166.1	0.000
. *****	. .	8	0.823	0.017	2419.6	0.000
. *****	. .	9	0.802	0.028	2660.9	0.000
. *****	. .	10	0.779	-0.044	2889.3	0.000
. *****	. .	11	0.755	-0.031	3104.6	0.000
. *****	. .	12	0.731	-0.025	3307.1	0.000
. *****	. .	13	0.711	0.058	3498.8	0.000
. *****	. .	14	0.689	-0.043	3679.3	0.000
. *****	. .	15	0.667	-0.008	3848.9	0.000
. *****	. .	16	0.646	0.034	4008.8	0.000

Source: Compiled from EViews 10

The initial lag denotes an autocorrelation of 0.977 (Q-Statistic = 350.53, $p < .05$), signifying the cryptocurrencies do not follow random walk. And also fascinating to note that the autocorrelation values for

the Lags were positive ($p < .05$) and these outcomes support that the stock earnings are not random. The results of autocorrelation for Cardano are shown in Table 5.

Table 5: Results of Autocorrelation Test for Cardano

Autocorrelation	Partial Correlation		Autocorrelation AC	Partial Autocorrelation PAC	Q-Stat	Prob
*****	*****	1	0.984	0.984	355.70	0.000
*****	..	2	0.971	0.060	702.71	0.000
*****	..	3	0.957	-0.017	1040.8	0.000
*****	..	4	0.946	0.069	1371.7	0.000
*****	..	5	0.932	-0.053	1694.4	0.000
*****	..	6	0.920	0.022	2009.6	0.000
*****	..	7	0.908	-0.004	2317.3	0.000
*****	..	8	0.895	-0.029	2617.2	0.000
*****	..	9	0.883	0.010	2909.6	0.000
*****	*..	10	0.867	-0.115	3192.6	0.000
*****	*..	11	0.850	-0.067	3465.4	0.000
*****	..	12	0.833	-0.012	3728.1	0.000
*****	..	13	0.818	0.045	3982.2	0.000
*****	..	14	0.803	-0.022	4227.5	0.000
*****	..	15	0.786	-0.036	4463.5	0.000
*****	..	16	0.770	-0.005	4690.5	0.000

Source: Compiled from EViews 10

As presented in Table 5, the initial lag has an autocorrelation of 0.984 (Q-Statistic = 355.70, $p < .05$) which suggests that returns in cryptocurrency do not follow random walk. Further, the

lags showed positive autocorrelations ($p < .05$) corroborating that the returns are not random. The effects of autocorrelation for Ethereum are obtainable in Table 6.

Table 6: Results of Autocorrelation Test for Ethereum

Autocorrelation	Partial Correlation		Autocorrelation AC	Partial Autocorrelation PAC	Q-Stat	Prob
*****	*****	1	0.942	0.942	325.46	0.000
*****	.. **	2	0.916	0.262	634.58	0.000
*****	..	3	0.881	-0.021	921.29	0.000
*****	*..	4	0.840	-0.109	1182.2	0.000
*****	..	5	0.803	-0.013	1421.7	0.000
*****	*..	6	0.754	-0.123	1633.1	0.000
*****	*..	7	0.705	-0.078	1818.6	0.000
*****	..	8	0.656	-0.043	1979.5	0.000
*****	*..	9	0.629	0.207	2127.9	0.000
****	..	10	0.588	-0.030	2257.9	0.000
****	..	11	0.551	-0.040	2372.5	0.000
****	..	12	0.517	-0.014	2473.6	0.000
****	*..	13	0.497	0.154	2567.4	0.000
***	..	14	0.476	0.003	2653.8	0.000
***	*..	15	0.467	0.079	2736.9	0.000
***	..	16	0.452	-0.015	2815.1	0.000

Source: Compiled from EViews 10

The table 6 reveals that there are sixteen lag periods related to the autocorrelation test. The initial lag represents an autocorrelation of 0.942 (Q-Statistic = 325.46, $p < .05$), the lags had positive

autocorrelations ($p < .05$). These results suggest that returns on cryptocurrency are not random. The results of autocorrelation for Litecoin are presented in Table 7.

Table 7: Results of Autocorrelation Test For Litecoin

Autocorrelation	Partial Correlation		Autocorrelation AC	Partial Autocorrelation PAC	Q-Stat	Prob
*****	*****	1	0.960	0.960	337.89	0.000
*****	..	2	0.926	0.066	653.38	0.000
*****	..	3	0.889	-0.056	944.82	0.000
*****	..	4	0.858	0.055	1217.2	0.000
*****	* .	5	0.815	-0.153	1463.8	0.000
*****	..	6	0.775	-0.021	1687.2	0.000
*****	..	7	0.732	-0.040	1887.2	0.000
*****	..	8	0.688	-0.057	2064.5	0.000
*****	.*	9	0.652	0.086	2224.0	0.000
****	..	10	0.612	-0.057	2365.1	0.000
****	..	11	0.576	0.017	2490.4	0.000
****	..	12	0.538	-0.028	2599.9	0.000
****	.*	13	0.511	0.086	2698.9	0.000
****	..	14	0.484	0.022	2787.9	0.000
***	..	15	0.465	0.063	2870.4	0.000
***	..	16	0.447	0.039	2947.0	0.000

Source: Compiled from EViews 10

As presented in Table 7, there are 16 lag periods associated with the autocorrelation test. The first lag depicts an autocorrelation of 0.960, (Q-Statistic = 337.89, $p < .05$), and the

lags had positive autocorrelations ($p < .05$). These results indicate that cryptocurrency are not random. The results of autocorrelation for Tron are presented in Table 8.

Table 8: Results of Autocorrelation Test for Tron

Autocorrelation	Partial Correlation		Autocorrelation AC	Partial Autocorrelation PAC	Q-Stat	Prob
*****	*****	1	0.979	0.979	351.52	0.000
*****	.*	2	0.962	0.088	691.77	0.000
*****	* .	3	0.941	-0.086	1018.4	0.000
*****	..	4	0.922	0.016	1332.8	0.000
*****	..	5	0.900	-0.064	1633.4	0.000
*****	..	6	0.880	0.025	1921.8	0.000
*****	..	7	0.861	0.023	2198.7	0.000
*****	..	8	0.845	0.036	2465.6	0.000
*****	..	9	0.828	0.020	2723.2	0.000
*****	..	10	0.811	-0.059	2970.5	0.000
*****	* .	11	0.790	-0.098	3205.7	0.000
*****	* .	12	0.766	-0.075	3428.0	0.000
****	..	13	0.746	0.047	3639.0	0.000
****	..	14	0.722	-0.053	3837.4	0.000
****	.*	15	0.704	0.117	4026.7	0.000
****	* .	16	0.682	-0.079	4204.9	0.000

Source: Compiled from EViews 10

As given in Table 8, the first lag portrays an autocorrelation of 0.979, (Q-Statistic =351.52, $p < .05$), and the lags showed positive autocorrelations ($p < .05$).

These results corroborate that cryptocurrency do not follow random walk. The results of autocorrelation test for Stellar are presented in Table 9.

Table 9: Results of Autocorrelation Test for Stellar

Autocorrelation	Partial Correlation		Autocorrelation AC	Partial Autocorrelation PAC	Q-Stat	Prob
*****	*****	1	0.964	0.964	341.12	0.000
*****	..	2	0.934	0.069	662.41	0.000
*****	..	3	0.903	-0.030	963.36	0.000
*****	..	4	0.873	-0.001	1245.4	0.000
*****	..	5	0.842	-0.024	1508.7	0.000
*****	..	6	0.810	-0.041	1752.7	0.000
*****	..	7	0.779	-0.002	1979.1	0.000
*****	..	8	0.745	-0.046	2187.0	0.000
*****	..	9	0.716	0.023	2379.2	0.000
*****	* ..	10	0.681	-0.066	2553.9	0.000
*****	* ..	11	0.644	-0.080	2710.5	0.000
***	12	0.611	0.026	2851.6	0.000
***	* ..	13	0.586	0.121	2982.0	0.000
***	14	0.562	0.005	3102.2	0.000
***	15	0.541	0.039	3214.0	0.000
***	16	0.518	-0.050	3316.6	0.000

Source: Compiled from EViews 10

As presented in Table 9, the first lag depicts an autocorrelation of 0.964 (Q-Statistic =341.12, $p < .05$), and the lags had positive autocorrelations ($p < .05$).

These results indicate that the cryptocurrency do not follow a random walk. The results of autocorrelation test for Nemare presented in Table 10.

Table 10: Results of Autocorrelation Test for Nem

Autocorrelation	Partial Correlation		Autocorrelation AC	Partial Autocorrelation PAC	Q-Stat	Prob
*****	*****	1	0.979	0.979	351.66	0.000
*****	..	2	0.959	0.018	690.06	0.000
*****	* ..	3	0.935	-0.108	1012.6	0.000
*****	4	0.910	-0.047	1318.8	0.000
*****	5	0.886	0.045	1610.3	0.000
*****	* ..	6	0.867	0.077	1889.7	0.000
*****	7	0.847	-0.014	2157.3	0.000
*****	8	0.828	0.002	2414.0	0.000
*****	* ..	9	0.807	-0.079	2658.4	0.000
*****	* ..	10	0.781	-0.133	2887.9	0.000
***	* ..	11	0.759	0.096	3105.1	0.000
***	12	0.737	0.038	3310.6	0.000
***	13	0.715	-0.031	3504.6	0.000
***	14	0.696	0.014	3688.8	0.000
***	15	0.678	0.031	3864.4	0.000
***	* ..	16	0.657	-0.101	4029.7	0.000

Source: Compiled from EViews 10

As can be seen in Table 10, there are 16 lag periods related to the autocorrelation test. The first lag depicts an autocorrelation of 0.979, (Q-Statistic = 351.66, $p < .05$), and the lags had positive

autocorrelations ($p < .05$), thus documenting that cryptocurrency are not random. The results of autocorrelation test for Make rare presented in Table 11.

Table 11: Results of Autocorrelation Test for Maker

Autocorrelation	Partial Correlation		Autocorrelation AC	Partial Autocorrelation PAC	Q-Stat	Prob
. *****	. *****	1	0.968	0.968	344.06	0.000
. *****	. *	2	0.946	0.136	673.41	0.000
. *****	.	3	0.922	-0.014	987.26	0.000
. *****	.	4	0.902	0.038	1288.2	0.000
. *****	.	5	0.879	-0.034	1574.8	0.000
. *****	.	6	0.862	0.067	1851.0	0.000
. *****	* .	7	0.833	-0.165	2110.0	0.000
. *****	* .	8	0.804	-0.077	2351.9	0.000
. *****	.	9	0.777	0.010	2578.2	0.000
. ***	.	10	0.750	-0.002	2790.1	0.000
. ***	.	11	0.721	-0.056	2986.4	0.000
. ***	.	12	0.692	-0.051	3167.6	0.000
. ***	.	13	0.664	0.029	3335.0	0.000
. ***	.	14	0.633	-0.051	3487.6	0.000
. **	.	15	0.605	0.013	3627.4	0.000
. **	.	16	0.577	-0.015	3754.9	0.000

Source: Compiled from EViews 10

As can be seen in Table 11, the first lag depicts an autocorrelation of 0.968, (Q-Statistic =344.06, $p < .05$), and the lags had showed positive autocorrelations

($p < .05$). These results reveal that cryptocurrency are not random. The results of autocorrelation test Loto are presented in Table 12.

Table 12: Results of Autocorrelation Test for Loto

Autocorrelation	Partial Correlation		Autocorrelation AC	Partial Autocorrelation PAC	Q-Stat	Prob
. *****	. *****	1	0.972	0.972	346.77	0.000
. *****	. *	2	0.952	0.124	680.08	0.000
. *****	* .	3	0.925	-0.114	995.64	0.000
. *****	.	4	0.901	0.014	1295.9	0.000
. *****	.	5	0.878	0.034	1582.0	0.000
. *****	.	6	0.858	0.044	1856.2	0.000
. *****	.	7	0.841	0.030	2119.9	0.000
. *****	.	8	0.822	-0.028	2372.7	0.000
. *****	.	9	0.802	-0.045	2613.8	0.000
. *****	.	10	0.781	-0.014	2843.3	0.000
. ***	* .	11	0.756	-0.085	3058.9	0.000
. ***	.	12	0.734	0.019	3262.6	0.000
. ***	. *	13	0.715	0.084	3456.6	0.000
. ***	* .	14	0.693	-0.084	3639.3	0.000
. ***	.	15	0.676	0.050	3813.6	0.000
. ***	.	16	0.658	0.000	3979.2	0.000

Source: Compiled from EViews 10

As can be seen in Table 12, the first lag depicts an autocorrelation of 0.972 (Q-Statistic =346.77, $p < .05$), and the lags had showed positive autocorrelations

($p < .05$). The results document that cryptocurrency is not random. The results of autocorrelation test Eos are presented in Table 13.

Table 13: Results of Autocorrelation Test for Eos

Autocorrelation	Partial Correlation		Autocorrelation AC	Partial Autocorrelation PAC	Q-Stat	Prob
*****	*****	1	0.942	0.942	325.46	0.000
*****	**	2	0.916	0.262	634.58	0.000
*****	..	3	0.881	-0.021	921.29	0.000
*****	*..	4	0.840	-0.109	1182.2	0.000
*****	..	5	0.803	-0.013	1421.7	0.000
****	*..	6	0.754	-0.123	1633.1	0.000
****	*..	7	0.705	-0.078	1818.6	0.000
****	..	8	0.656	-0.043	1979.5	0.000
****	.*	9	0.629	0.207	2127.9	0.000
***	..	10	0.588	-0.030	2257.9	0.000
***	..	11	0.551	-0.040	2372.5	0.000
***	..	12	0.517	-0.014	2473.6	0.000
***	.*	13	0.497	0.154	2567.4	0.000
**	..	14	0.476	0.003	2653.8	0.000
**	.*	15	0.467	0.079	2736.9	0.000
**	..	16	0.452	-0.015	2815.1	0.000

Source: Compiled from EViews 10

As can be seen in Table 13, the first lag depicts an autocorrelation of 0.942 (Q-Statistic =325.46, $p < .05$), and the lags had showed positive autocorrelations ($p < .05$). The results document that cryptocurrency are not random.

DISCUSSION

This study analyzes the Efficient Market Hypothesis (EMH) in the cryptocurrency market. Given the mixed findings of prior research, this investigation focuses on a recent period of significant financial variation. The results align with most previous studies, revealing weak-form inefficiency even in today's information-rich environment. Empirical analysis of daily returns shows a negatively skewed and irregular distribution. Kurtosis values above 3 confirm a Leptokurtic distribution, deviating from normality and rejecting Hypothesis 1. Autocorrelation tests indicate returns do not follow a random walk. Furthermore, the Augmented Dickey-Fuller (ADF) test rejects the null hypothesis at the 1% significance level, confirming the data's stationarity and rejecting Hypothesis 2. The absence of a unit root means the series does not follow a random walk.

Finally, the runs test confirms that cryptocurrency prices do not move randomly, leading to the rejection of Hypothesis 3. In summary, the evidence skewed and Leptokurtic distributions, stationarity, and non-random runs collectively demonstrates that the cryptocurrency market is weak-form inefficient, contradicting the EMH.

CONCLUSION

Many investors reject the Efficient Market Hypothesis (EMH), leading to divergent trading actions that may not significantly impact prices (Copeland & Weston, 1988). A study analyzing daily cryptocurrency price data from 2011 to 2020, employing unit root, autocorrelation, and runs tests, found results contradicting the random walk theory. This supports the conclusion that the cryptocurrency market is weak-form inefficient. While EMH posits that security prices reflect all available information, critics note this requires asset managers to possess special talent to outperform the market (Brown, 2020). Although information is now more accessible than when Fama (1970) proposed the hypothesis, critics argue EMH ignores transaction costs. Fama himself contended prices reflect information only to the point where the costs of obtaining it do not exceed the benefits. Furthermore, EMH assumes rational, informed agents, a condition behavioral finance scholars challenge as unrealistic in practice.

The 2008 financial crisis is cited as a failure of EMH, demonstrating markets driven by behavioral factors. While financial scholars lack consensus on EMH, many view it as a theoretical benchmark difficult to test empirically. Despite decades of criticism and observed market anomalies, EMH retains its utility as a foundational model, and its study remains vital for financial experts.

REFERENCES

- Alexander, S. S. (1961), "Price movements in speculative markets: Trends or random walks", *Industrial Management Review*, Vol. 2 No 2, pp. 7-26.
- Alexander, S. S. (1964), "Price movements in speculative markets: Trends or random walks", *Industrial Management Review*, Vol.5 No 2, pp.25-46.
- Aren, S. and Aydemir, S.D. (2015), "The factors influencing given investment choices of individuals", *Procedia - Social and Behavioral Sciences*, Vol. 210, pp. 126-135.
- Barber, B.M., Morse, A. and Yasuda, A. (2020), "Impact investing", *Journal of Financial Economics*, Vol. 139 No. 1, pp. 162-185.
- Borden, L. M., Lee, S., Serido, J., and Collins, D. (2008), "Changing college students' financial knowledge, attitudes, and behavior through seminar participation". *Journal of Family and Economic Issues*, Vol.29 No1, pp. 23-40
- Borden, L. M., Lee, S., Serido, J., and Collins, D. (2008), "Changing college students' financial knowledge, attitudes, and behavior through seminar participation". *Journal of Family and Economic Issues*, Vol.29 No1, pp. 23-40.
- Borden, L.M., Lee, S., Serido, J. and Collins, D. (2008), "Changing college students' financial knowledge, attitudes, and behavior through seminar participation", *Journal of Family and Economic Issues*, Vol. 29 No. 1, pp. 23-40
- Chan, K. C., Gup, B. E., and Pan, M.-S. (1997), "International stock market efficiency and integration: A study of eighteen nations", *Journal of Business Finance & Accounting*, Vol. 24 No.6, pp.803-813
- Charfeddine, L., Maouchi, Y., (2019). "Are shocks on the returns and volatility of cryptocurrencies really persistent?" *Finance Res. Lett.* Vol.28, 423-430. <https://doi.org/10.1016/j.frl.2018.06.017>
- Copeland, T., and Weston, J.F. (1988), "Financial Theory and Corporate Policy". 3ed (ed), N.Y. Addison-Wesley Publishing Company.
- Degutis, A. and Novickyte, L. (2014), "The efficient market hypothesis: a critical review of literature and methodology", *Ekonomika*, Vol. 93 No. 2, pp. 7-23.
- Drożdż, S., Kwapień, J., Oświecimka, P., Stanisz, T., Watorek, M., (2020). "Complexity in economic and social systems: Cryptocurrency market at around COVID-19". *Entropy*, Vol.22 (9), 1043. <https://doi.org/10.3390/e22091043>.
- Elangovan.R, Irudayamamy.F.R and Parayitam.S(2020). "Testing the market efficiency in Indian stock market: evidence from Bombay Stock Exchange broad market indices", *Journal of Economics, Finance and Administrative Science*, available at <https://www.emerald.com/insight/content/doi/10.1108/JEFAS-04-2020-0040/full/html>
- Fama, E.F. (1970), "Efficient Capital Markets: A Review of Theory and Empirical Work", *The Journal of Finance*, Vol.25. No 2, pp. 383-417
- Gibson, G. (1889), "The Stock Markets of London, Paris and New York", G.P. Putnam's Sons, New York.
- Grossman, S. (1976), "On the efficiency of competitive stock markets where traders have diverse information", *The Journal of Finance*, Vol. 31 No.2, pp. 573-585
- Hamid, K., Suleman, M. T., Ali, S., Syed, Z., Imdad, A., and Rana, S. (2010), "Testing the Weak Form of Efficient Market Hypothesis: Empirical Evidence from Asia-Pacific Markets", *International Research Journal of Finance and Economics*, Vol. 58 No.1, pp. 121-133
- Hamid, K., Suleman, M.T., Ali, S., Syed, Z., Imdad, A. and Rana, S. (2010), "Testing the weak form of efficient market hypothesis: empirical evidence from Asia-Pacific markets", *International Research Journal of Finance and Economics*, Vol. 58 No. 1, pp. 121-133.
- Harshita, Singh, S. and Yadav, S.S. (2018), "Calendar anomaly: unique evidence from the Indian stockmarket", *Journal of Advances in Management Research*, Vol. 15 No. 1, pp. 87-108.
- Isidore, R. and Christie, P. (2017), "Review of the influence of investor personality (The Big-Five model) on investor behavior", *International Journal of Research in Finance and Marketing*, Vol. 7 No. 7, pp. 23-32.
- Jegadeesh, N. (1990), "Evidence of predictable behavior of security returns", *The Journal of Finance*, Vol.45 No.3, pp. 881-898.
- Larson, A. B. (1960), "Measurement of a random process in futures prices", *Food Research Institute Studies*, Vol.1 No. 3, pp. 313-24.
- Le Tran, V., Leirvik, T., (2020). Efficiency in the markets of crypto-currencies. *Finance Res. Lett.* 35, 10382.
- Lehmann, B. N. (1990), "Fads, martingales, and market efficiency", *The Quarterly Journal of Economics*, Vol.105 No.1, pp.1-28.
- MacCauley, F. R. (1925), "Forecasting security prices", *Journal of the American Statistical Association*, Vol. 20 No. 150, pp. 244-249.
- Malkiel, B. G.(1973), "A Random Walk Down Wall Street". New York: W.W. Norton.
- Malkiel, B. G.(2003), "The Efficient Market Hypothesis and Its Critics", *Journal of Economic Perspectives*, Vol 17 No. 1, pp. 59-82.
- Pearson, K. (1905), "The problem of the random walk", *Nature*, Vol.72 (1865), 294-296

- Roberts, H. (1967), “Statistical versus Clinical Prediction of the Stock Market”, *CRSP. University of Chicago, Chicago*.
- Roll, R. (1994), “What Every CEO Should Know About Scientific Progress in Economics: What is Known and What Remains to be Resolved”, *Financial Management*, Vol. 23 No.1, pp. 69-75.
- Sadiq, M.N. and Khan, R.A.A. (2019), “Impact of personality traits on investment intention: the mediating role of risk behaviour and the moderating role of financial literacy”, *Journal of Finance and Economics Research*, Vol. 4 No. 1, pp. 1-18.
- Samsa, G. (2020). The efficient market hypothesis is usually addressed indirectly: what happens if a direct approach is used instead? *Archives of Business Research*, Vol.9. No.6, pp. 45-50. DOI: <https://doi.org/10.14738/abr.96.2020>
- Shiller, R. (2003), “From efficient markets theory to behavioral finance”, *Journal of Economic Perspectives*, Vol. 17 No.1, pp. 83-104
- Sitkin, S. B., and Weingart, L. R. (1995), “Determinants of risky decision-making behavior: A test of the mediating role of risk perceptions and propensity”, *Academy of Management Journal*, Vol. 38 No. 6, pp.1573-1592
- Sitkin, S.B. and Weingart, L.R. (1995), “Determinants of risky decision-making behavior: a test of the mediating role of risk perceptions and propensity”, *Academy of Management Journal*, Vol. 38.No. 6, pp. 1573-1592.
- Sovbetov, Y., 2018. “Factors influencing cryptocurrency prices: evidence from bitcoin, Ethereum, Dash, litecoin, and monero”. *Journal of Economics and Financial Analysis*\ 2 (2), 1-27.
- Titan, A.G. (2015), “The Efficient Market Hypothesis: review of specialized literature and empiricalresearch”, *Procedia Economics and Finance*, Vol. 32, pp. 442-449.
- Urquhart, A., (2016). “The inefficiency of bitcoin”. *Econ Lett* Vol.148, 80-82. <https://doi.org/10.1016/j.econlet.2016.09.019>.
- Vidal-Tomas, D., Ibanez, A., 2018. “Semi-strong efficiency of Bitcoin”. *Finance Res. Lett.* 27, 259-265. <https://doi.org/10.1016/j.frl.2018.03.013>.