International Journal of Advances in Engineering and Management (IJAEM)
Volume 4, Issue 5 May 2022, pp: 1328-1335 www.ijaem.net ISSN: 2395-5252

Examining the Weak-Form Market Efficiency in Cryptocurrency Market

Dr. Rachna Mahalwala
Associate Professor
Bhagini Nivedita College (University of Delhi)

Submitted: 10-05-2022 Revised: 19-05-2022 Accepted: 22-05-2022

ABSTRACT
Having a virtual existence based on blockchain technology and independent of any central authority, the cryptocurrencies are gaining popularity as a new investment option because their transactions are fast, secure, and global. However, the cryptocurrencies are still at its infancy stage and are considered to be highly speculative in comparison to traditional investment assets like stocks, bonds, and mutual funds. The objective of the present study is to examine the validity of the Efficient Market Hypothesis (EMH) and Random Walk Hypothesis (RWH) in cryptocurrency market taking daily closing price data of three cryptocurrencies, namely, Bitcoin, Ethereum and USD Tether for the period January 1st, 2018 to December 31th, 2021. The study employs various tests, namely, the 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 to find out the evidence of market efficiency in its weak form. The results of the study did not find support for the existence of random walk and weak-form market efficiency for cryptocurrency market indicating that the cryptocurrencies' prices are predictable and provide opportunity to earn abnormal returns.

Keywords: Cryptocurrency, Random Walk, Efficient Market Hypothesis, Unit Root, Variance Ratio Test

I. INTRODUCTION

Unlike government-backed currency, the values of cryptocurrencies are determined by market mechanism i.e., prices are determined purely on the basis of supply and demand. This can lead to dramatic swings in the prices of cryptocurrencies, resulting in substantial gains or losses for investors. Also, unlike traditional investment instruments like stocks, bonds, and mutual funds, cryptocurrency investments are not subjected to significant regulatory supervision. Still, the cryptocurrency industry is growing at an astounding rate because it serves dual purposes, a store of value and a medium of exchange.In emerging economies, the cryptocurrencies usage is increasing due to changing demographics, intensifying consumerism, and readiness to adopt new technologies among young generation such as IoT, Blockchain, and others. A growing number of companies across a wide range of sectors and industries are allowing their customers to use cryptocurrencies as an acceptable means of payment for their goods and services. "The global cryptocurrency market size was valued at $1.49 billion in 2020, and is projected to reach $4.94 billion by 2030, growing at a CAGR of 12.8% from 2021 to 2030" (Goswami, Borasi& Kumar, July, 2021). Being an operationally efficient, transparent and secured payment alternative, many financial analysts believe that cryptocurrencies are going to give tough fight to government-controlled legal tender in near future.

The efficient market hypothesis (EMH) contends that the arrival of new information into the market is instantaneously reflected in stock prices and both technical analysis and fundamentalanalysis will fail to help an investor earn returns superior than return on portfolio of randomstocks. EMH is extensively used in finance to study the behaviour of prices of financial assets. Various authors, namely, Bachelier (1900), Cootner (1962), Mandelbrot (1963), Samuelson (1965) and Fama (1965, 1970) contributed to EMH. Fama (1970) proposed three types of market efficiency: (i) Under **Weak form** of efficiency, stock prices reflect all past information; (ii) Under **Semi-strong form** of efficiency, stock prices reflect both the past/historical and publicly available information and (iii) Under **Strong form** of efficiency, current stock prices reflect all existing information i.e., historical, public and private information. Researchers in the field of finance have mainly examined weak-form of efficiency which proposes that stock prices are unpredictable as prices movements occur arbitrarily following a martingale model or a random walk model.

Though investing in cryptocurrencies is still at its nascent stage, it offers great alternative to grab hefty returns than traditional investment alternatives like stocks and bonds and are a good option to diversify the investment portfolio. If we consider cryptocurrency as different asset class for diversifying portfolio, the question arises whether EMH, which is applicable on stocks, is applicable on cryptocurrencies' prices as well? Do the prices of cryptocurrencies predictable?

In the backdrop of above discussion, the focus of present study is primarily on examining whether cryptocurrencies prices follow a random walk as suggested by the weak-form of Efficient Market Hypothesis (EMH).

This study is organised in five sections including the present section I on Introduction. Section II provides a brief review of literature. Section III describes the data and methodology adopted to empirically examining the issue under consideration. Section IV presents the empirical results and Section V concludes the study.

II. REVIEW OF LITERATURE

Although the existing literature on cryptocurrencies' price predictability and efficiency is not very extensive, still there are several empirical studies that studied the price dynamics, predictability and efficiency of cryptocurrency market with various tests and models applicable for other financial assets.

Urquhart (2016) studied the informational inefficiency of Bitcoin market employing a number of tests, Ljung-Box Test, the runs test, Bartels test, variance ratio test, BDS test and the rescaled Hurst exponent (R/S Hurst) and reported that the Bitcoin market is weak-form inefficient, but it may become more efficient over time with more investors and users participating Bitcoin trading space. Nadarajah & Chu (2017) following the footsteps of Urquhart (2016) investigated the market efficiency of Bitcoin using eight different tests: Ljung-Box test; runs test; Bartels test; wild-bootstrapped automatic variance ratio test; spectral shape tests; BDS test; robust portmanteau test to check serial correlation; the generalized spectral test. Most of the test results confirmed existence of market efficiency in total contrast with the results of Urquhart (2016). Bariviera (2017) revisited the long memory property of the bitcoin market employing the Hurst exponent using two alternatives: R/S method and Detrended Fluctuation Analysis (DFA) method. With R/S method successfully inferred long memory in returns and DFA method reported variations in informational efficiency over a period of time. Volatility clustering turned out to be a feature of Bitcoin returns. Vidal-Tomas & Ibanez (2019) analysed the efficiency of the cryptocurrency market with market portfolios and checked the consequential impact of new cryptocurrencies on the efficiency of the existing market using the same tests as Urquhart (2016) and Nadarajah and Chu (2017) used in their studies. The results indicated that the market is not weak-form efficient and introduction of new digital currencies did not change the degree of weak-form market efficiency. Caporale, Gil-Alana &Plastun (2018) used two different long-memory methods, R/S analysis and fractional integration, to investigate the presence of persistence in cryptocurrency markets. The results of the study revealed that the current prices are dependent on past prices, however, the degree of persistence changed over a period of time. The results did not support EMH. Kristoufek&Vosvrda (2019) conducted a study to test the efficient market hypothesis for the most popular cryptocurrencies (Bitcoin, Litecoin, DASH, Monero, Ripple, and Stellar) in order to rank these according to their efficiency and employed the Efficiency Index consisting of the long-range dependence, fractal dimension and entropy components for the purpose. The results revealed that old currencies were consistently inefficient over the period of study and the most inefficient coins were Ethereum and Litecoin whereas DASH turned out to be the most efficient cryptocurrency. Kyriazis (2019) carried out a survey to establish predictability of cryptocurrencies' prices focussing mainly R/S analysis and DFA method of testing long memory. The results of the survey found favour for existence of market inefficiency for all digital currencies. The survey, however, concluded that long-range dependence leading to inefficiency gets faded with time in the Bitcoin markets and in the other cryptocurrencies' market too. Zhang et. al (2020) investigated patterns of market-efficiency and liquidity during a bull and bear phases of cryptocurrency market applying DFA method for computing Hurst exponent for analysing the returns of Ethereum, Bitcoin and Litecoin. The results indicated that returns of Ethereum, Bitcoin, and Litecoin during a bull market followed random walk, however, in bearish phase, the market started exhibiting the signs of market inefficiency.Kakinaka&Umeno (2021) explored cryptocurrency market efficiency adopting the asymmetric multifractal detrended fluctuation

International Journal of Advances in Engineering and Management (IJAEM)
Volume 4, Issue 5 May 2022, pp: 1328-1335 www.ijaem.net ISSN: 2395-5252

analysis during COVID 19 pandemic period and reported the visible difference in market efficiency for short- and long-term time horizon after the outbreak of coronavirus. The cryptocurrency market was found to be more inefficient during short-term in comparison to long-term. Yaya et. al. (2021) examined the market efficiency and volatility persistence of selected cryptocurrencies applying fractional integration techniques on cryptocurrency returns for testing EMH and using squared returns as proxy for volatility finding evidence on volatility persistence. The results found the market to be inefficient for most of the cryptocurrencies and volatility to be persistent in nature.

A quick glance on existing literature indicates that most of the initial studies on the efficiency of cryptocurrency market focussed on Bitcoin in their analyses, however with the evolution of more and more cryptocurrencies, more comprehensive studies on selected sets of cryptocurrencies started surfacing. The present study aims at augmenting the existing literature on the issue by taking Bitcoin, Ethereum and USD Tether as representative for cryptocurrency market and guiding the investors in virtual trading space about existence of opportunities to earn supernormal returns, if any.

III. DATA AND METHODOLOGY

The daily closing prices of three cryptocurrencies, namely Bitcoin (BTC), Ethereum (ETH) and USD Tether (USDT) for the period January 1st, 2018 to December 31th, 2021have been extracted from Yahoo Finance Website (https://finance.yahoo.com/cryptocurrencies) comprising of 1461 observations for each cryptocurrency. For empirical analysis, the closing price data of Bitcoin (BTC), Ethereum (ETH) and USD Tether (USDT) is used by taking first difference of its natural logarithm i.e. R_t= Ln (P_t / P_{t-1}), whereR_t = the logarithmic return of cryptocurrency for day t, P_t = Close Price of cryptocurrency at the end of t, P_{t-1} = Close Price of cryptocurrency at the end of day t-1, t = Day, Ln= Natural log

The preliminary analysis in the study begins with describing the characteristics of data and using Jarque-Bera test of normality. Subsequently, the different tests are employed to find evidences of weak-form of EMH and Random Walk theory. Specifically, auto-correlation function (ACF) and partial auto-correlation function (PACF) with Ljung Box Q-Statistic (Ljung and Box,1978) to check overall randomness based on a number of lags, unit root test using Augmented Dickey Fuller (ADF) test statistic (1979) and Phillip Perron test statistic (1988) to check stationarity property of returns, Variance Ratio test to examine random walk of cryptocurrency prices and Breusch-Godfrey Serial Correlation Lagrange Multiplier (LM) Test (1981) to test for autocorrelation in the residuals of a regression model are used.

ACF provides the values of auto-correlation of a time series with its lagged values and thus explains how well a particular time series is related with its past values. In PACF, rather than examining the correlations of present value of time series with its lagged values as in ACF, correlation of the residuals with the next lag value is considered to model any concealed information in the residuals. The Ljung-Box test is built upon the autocorrelation plot for testing the overall randomness based on a number of lags rather than testing randomness of a time series at each distinct lag. Therefore, it is acknowledged as a "portmanteau" test. The Ljung Box test is specified as follows:

$$Q_{LB} = n(n+2)\sum_{j=1}^{h} \frac{\rho^2(j)}{n-j} \quad (1)$$

Where n is the sample size, ρ_j is the autocorrelation at lag j, and h is the number of lags being considered.

The hypothesis of no serial correlation is rejected at significance level α, if Q_{LB} at critical level is:

$$Q_{LB} = \chi^2_{1-\alpha;h} \quad (2)$$

Where χ2 is the percent point function of the Chi-Square distribution.

Unit Root tests are used to determine whether a time series is stationary having a predictable pattern. ADF test and PP test, belonging to the category of "Unit Root Test" are commonly used to test the null hypothesis of presence of unit root in a time series by regressing the change in a variable on its lagged level. Though ADF test uses a parametric autoregression to estimate the structure of the errors in the test regression, the PP test overlooks any serial correlation in the test regression. A benefit of applying PP test is that a user need not specify a lag length for the test regression.

Lo and MacKinlay (1988) developed a test 'Variance Ratio Test' to investigate the predictability of stock prices under the null hypothesis that a time series follows random walk. This test inspects the predictability of stock price data by comparing variances of differences of the time series returns calculated over different intervals. If returns follow a random walk, the variance of a k-period difference should be k times the variance of the one-period difference. If R_t be a random walk return series of cryptocurrency prices P_t. The variance of (R_t - R_{t-k}) is k times the variance of (R_t - R_{t-1}). The null hypothesis of random walk could be checked by comparing 1/k times the variance of (R_t - R_{t-k}) to the variance of (R_t - R_{t-1}).

The Breusch-Godfrey LM test is a test for detecting autocorrelation in the errors of a return series under the null hypothesis of no serial correlation in error structure up to a pre-determined order q. The test fits in the category of asymptotic tests, known as Lagrange Multiplier tests and may be used to test for higher order autoregressive moving average (ARMA) errors even in the absence of lagged dependent variables in the regression model for a time series variable.

IV. EMPIRICAL FINDINGS

Before explaining the results relating to existence/absence of weak-form of market efficiency and randomness of price movements of Bitcoin (BTC), Ethereum (ETH) and USD Tether (USDT) representing cryptocurrency market in the present study, descriptive statistics of cryptocurrencies are reported in Table 1 to get a feel of the data. Table 1 shows that mean returns for all the three cryptocurrencies are close to zero, the standard deviation of returns of all cryptocurrencies is away from 1 but pretty larger in comparison to mean, the return series for Bitcoin and Ethereum are negatively skewed and for USD Tether positively skewed, and the kurtosis of returns of all cryptocurrencies is very large indicating all return series are leptokurtic. Therefore, we can conclude that cryptocurrencies' returns demonstrate all typical characteristics of financial asset returns. Further, the Jarque-Bera statistic rejects the null hypothesis of normal distribution of the return in case of all cryptocurrencies' returns.

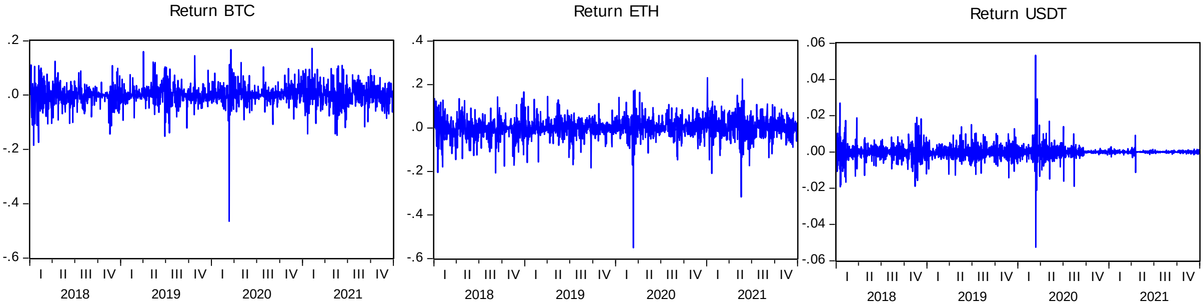
Table 1: Summary of Descriptive Statistics

Statistics	RETURN BTC	RETURN ETH	RETURN USDT
Mean	0.000836	0.001069	-4.84E-06
Median	0.001390	0.001011	-4.00E-05
Std. Dev.	0.040233	0.052068	0.004390
Skewness	-1.149207	-1.104186	0.297320
Kurtosis	17.05592	13.90879	36.63989
Jarque-Bera	12348.59	7541.109	68910.25
Probability (p-Value)	0.000000	0.000000	0.000000
Observations	1461	1461	1461

Source: Authors' Calculation using EViews

Figure 1 shows returns for Bitcoin, Ethereum, and USD Tether from January 1st, 2018 to December 31st , 2021. The figure depicts that all three returns series are mean reverting and that volatility clustering is present.

Figure 1: Line Graph of Cryptocurrencies' Returns



International Journal of Advances in Engineering and Management (IJAEM)
Volume 4, Issue 5 May 2022, pp: 1328-1335 www.ijaem.net ISSN: 2395-5252

Source: Authors' Construction using EViews

The computed values of ACFs, PACFs and Ljung-Box Q-statistics with probability values at lag 1, lag 5 and 10 are given in Table 2. The estimated values of ACFs, PACFs and Q-statistic at lag 1, lag 5 and lag 10 are significant at 5% level of significance with small p-values. This establishes signs of autocorrelation in return series rejecting the null hypothesis of no serial correlation. This suggests that cryptocurrencies' prices do not follow a random walk as these are not independent. Thus, cryptocurrencies' prices or returns are predictable.

`Table 2: Results of ACF, PACF and Ljung-Box Q-Statistics

Lag	ACF	PACF	LB Q-Stat	Probability
Return BTC				
1	-0.057	-0.057	4.7958	0.029
5	0.041	0.040	10.516	0.033
10	0.043	0.040	19.254	0.037
Return ETH				
1	-0.063	-0.063	5.8940	0.015
5	0.002	0.007	15.604	0.008
10	0.076	0.074	34.367	0.000
Return USDT				
1	-0.418	-0.418	255.57	0.000
5	-0.074	-0.092	276.81	0.000
10	-0.018	-0.023	292.47	0.000

Source: Authors' Calculation using EViews

Table.3 and Table.4 depict the findings of the unit root tests on cryptocurrencies' returns. The ADF test results given in Table 3 show that the value of t-statistic is less the critical values at all levels of significance and p-value (0.0000) is less than 0.05 in case of all three cryptocurrencies. This rejects the null hypothesis "Return series has a unit root." This implies that there is memory in return data generation process and thus cryptocurrency market is inefficient in weak-form.

Table 3: Augmented Dickey Fuller Test Results

Null Hypothesis: RETURN has a unit root		Return BTC		Return ETH		Return USDT	
		t-statistic	Prob.	t-statistic	Prob.	t-statistic	Prob.
ADF test statistic		-40.43261	0.0000	-40.68812	0.0000	-23.72500	0.0000
Test Critical Values	1% level	-3.434621		-3.434621		-3.434621	
	5% level	-2.863313		-2.863313		-2.863313	
	10% level	-2.567763		-2.567763		-2.567763	

Source: Authors' Calculation using EViews

International Journal of Advances in Engineering and Management (IJAEM)
Volume 4, Issue 5 May 2022, pp: 1328-1335 www.ijaem.net ISSN: 2395-5252

Similarly, the results of the PP test shown in Table 4 show that the value of adjusted-t-statistic is less than the critical values at all levels of significance with p-value (0.0000) less than 0.05 for all the three cryptocurrencies. This too rejects the null hypothesis "Return series is non-stationary." This implies that there is no systematic pattern in return series and thus cryptocurrencies' prices/ returns are predictable.

Table 4: Phillips Perron Test Results

Null Hypothesis: RETURN has a unit root		Return BTC		Return ETH		Return USDT	
		Adj. t-stat	Prob.	Adj. t-stat	Prob.	Adj. t-stat	Prob.
PP test statistic		-40.37431	0.0000	-40.65269	0.0000	-129.8922	0.0001
Test Critical Values	1% level	-3.434621		-3.434621		-3.434621	
	5% level	-2.863313		-2.863313		-2.863313	
	10% level	-2.567763		-2.567763		-2.567763	

Source: Authors' Calculation using EViews

Table 5 displays the results of variance ratio test applied on cryptocurrencies' returns to check the null hypothesis "Return follows a martingale model". For all the three cryptocurrencies, the "Joint Tests" z-statistics is significant at 1 percent and strongly rejects the null hypothesis. Similarly, the individual variance ratio z-statistics for period 2, 4, 8 and 16 reject the null hypothesis with p-value less than 0.05. This implies that return series for all cryptocurrencies are not random and the knowledge of the past prices will aid in predicting future prices**.**

Table 5: Variance Ratio Test Results

Null Hypothesis: RETURN BTC is a martingale				
Joint Tests		**Value**	**Df**	**Probability**
Max |z| (at period 2)*		7.935591	1460	0.0000
Individual Tests				
Period	**Var. Ratio**	**Std. Error**	**z-Statistic**	**Probability**
2	0.450394	0.069258	-7.935591	0.0000
4	0.227035	0.110902	-6.969786	0.0000
8	0.120778	0.146243	-6.012062	0.0000
16	0.058653	0.187146	-5.030014	0.0000
Null Hypothesis: RETURN ETH is a martingale				
Joint Tests		**Value**	**Df**	**Probability**
Max |z| (at period 2)*		8.808834	1460	0.0000
Individual Tests				
Period	**Var. Ratio**	**Std. Error**	**z-Statistic**	**Probability**
2	0.439315	0.063650	-8.808834	0.0000
4	0.223550	0.102668	-7.562707	0.0000
8	0.122239	0.139447	-6.294591	0.0000
16	0.056897	0.180693	-5.219367	0.0000
Null Hypothesis: RETURN USDT is a martingale				
Joint Tests		**Value**	**Df**	**Probability**
Max |z| (at period 2)*		5.554780	1460	0.0000
Individual Tests				
Period	**Var. Ratio**	**Std. Error**	**z-Statistic**	**Probability**
2	0.354160	0.116267	-5.554780	0.0000
4	0.162978	0.184815	-4.528969	0.0000
8	0.090152	0.237168	-3.836306	0.0001
16	0.043899	0.293437	-3.258282	0.0011
*Probability approximation using studentized maximum modulus with parameter value 4 and infinite degrees of freedom				

Source: Authors' Calculation using EViews

International Journal of Advances in Engineering and Management (IJAEM)
Volume 4, Issue 5 May 2022, pp: 1328-1335 www.ijaem.net ISSN: 2395-5252

In Table 6, the results of Breusch-Godfrey Serial Correlation LM Test with 2 lags are reported to check the null hypothesis "No serial correlation in the residuals of Returns." This test is applied on residual series resulting from the regression equation applied on cryptocurrencies' returns series with returns as dependent variable and constant (c) as independent variable. The LM test statistic (Observed R-squared) with p-value less than 0.05 in case of residuals of return series of all cryptocurrencies gives an indication to reject the null hypothesis and confirm presence of serial correlation in the residuals. This implies that cryptocurrency market is weak-form inefficient.

Table 6: Breusch-Godfrey Serial Correlation LM Test Results

LM test on **Residual Series of RETURN BTC**			
F-statistic	4.211090	**Prob. F(2,1359)**	0.0150
Obs*R-squared	8.388783	**Prob. Chi-Square(2)**	0.0151
LM test on **Residual Series of RETURN ETH**			
F-statistic	5.845537	**Prob. F(2,1359)**	0.0030
Obs*R-squared	11.61694	**Prob. Chi-Square(2)**	0.0030
LM test on **Residual Series of RETURN USDT**			
F-statistic	3.092363	**Prob. F(2,1358)**	0.0457
Obs*R-squared	6.170287	**Prob. Chi-Square(2)**	0.0457

Source: Authors' Calculation using EViews

V. CONCLUSION

Cryptocurrency is a digital currency which is not backed up with gold as currency and its circulation is not controlled by any central bank. The cryptocurrency market is still highly speculative as cryptocurrencies' prices move quickly without any alarms in the absence of any regulator. Despite of all, the cryptocurrency market is rising rapidly as it provides an alternative to traditional investment instruments, stocks and gold. The purpose of current study is to examine the pattern of cryptocurrency prices in the light of weak-form of Efficient Market Hypothesis to answer the research question: Whether cryptocurrency market is weak-form efficient with cryptocurrencies prices following random walk? For the purpose of empirical analysis, the daily closing prices of three cryptocurrencies, namely Bitcoin, Ethereum and USD Tether are converted to returns for the period January 1st, 2018 to December 31th, 2021. The data characteristics are similar to other financial assets. The autocorrelation function and partial autocorrelation function with Lung-Box Q-statistic confirms the existence of memory in return generation process. Both the unit root tests, augmented dickey-fuller test and Phillip Perron test establish that returns series for the three cryptocurrencies are stationary. The variance ratio test results reveal that returns do not follow random walk. The Breusch-Godfrey Serial Correlation LM Test indicates that even residuals of return series are serially correlated. Overall, the empirical findings suggest that cryptocurrency market is weak-form inefficient and cryptocurrencies' prices are foreseeable. The results relating to rejection of presence of weak-form of Efficient Market Hypothesis are in conformity with most of the previous studies (Urquhart, 2016; Vidal-Tomas & Ibanez, 2019; Kyriazis, 2019; Yaya et. al., 2021). The results are useful for investors in cryptocurrencies as they establish that the information of past prices can be helpful to forecast future prices of cryptocurrencies because current prices do not reflect all past information successfully. It means investors have opportunity to identify available undervalued cryptocurrencies to earn superior returns.

REFERENCES

[1]. Bachelier, L. (1900). Théorie de la spéculation. In Annales scientifiques de l'Écolenormale supérieure (Vol. 17, pp. 21-86).
[2]. Bariviera, A. F. (2017). The inefficiency of Bitcoin revisited: A dynamic approach. Economics Letters, 161, 1-4.
[3]. Breusch, T. S., & Godfrey, L. G. (1981). A review of recent work on testing for autocorrelation in dynamic simultaneous models. Macroeconomic Analysis, Essays in Macroeconomics and Economics, 1, 63-100.
[4]. Caporale, G. M., Gil-Alana, L., &Plastun, A. (2018). Persistence in the cryptocurrency market. Research in International Business and Finance, 46, 141-148.
[5]. Cootner, P. H. (1962). Stock prices: Ramdom vs. systematic changes. Industrial Management Review (pre-1986), 3(2), 24.
[6]. Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit

root. Journal of the American statistical association, 74(366a), 427-431.
[7]. Fama, E. F. (1965). The behavior of stock-market prices. The journal of Business, 38(1), 34-105.
[8]. Fama, E. F. (1970). Session topic: stock market price behavior. The Journal of Finance, 25(2), 383-417.
[9]. Goswami, A., Borasi, P., & Kumar, V. (2021, July). Cryptocurrency Market: Global Opportunity Analysis and Industry Forecast, 2021–2030 (No. A01745). Allied Market Research. https://www.alliedmarketresearch.com/crypto-currency-market
[10]. Kakinaka, S., &Umeno, K. (2021). Cryptocurrency market efficiency in short- and long-term horizons during COVID-19: An asymmetric multifractal analysis approach. Finance Research Letters, 102319.
[11]. Kristoufek, L., &Vosvrda, M. (2019). Cryptocurrencies market efficiency ranking: Not so straightforward. Physica A: Statistical Mechanics and its Applications, 531, 120853.
[12]. Kyriazis, N. A. (2019). A survey on efficiency and profitable trading opportunities in cryptocurrency markets. Journal of Risk and Financial Management, 12(2), 67.
[13]. Ljung, G. M., & Box, G. E. (1978). On a measure of lack of fit in time series models. Biometrika, 65(2), 297-303.
[14]. Lo, A. W., &MacKinlay, A. C. (1988). Stock market prices do not follow random walks: Evidence from a simple specification test. The review of financial studies, 1(1), 41-66.
[15]. Mandelbrot, B. (1963). New methods in statistical economics. Journal of political economy, 71(5), 421-440.
[16]. Nadarajah, S., & Chu, J. (2017). On the inefficiency of Bitcoin. Economics Letters, 150, 6-9.
[17]. Phillips, P. C., & Perron, P. (1988). Testing for a unit root in time series regression. Biometrika, 75(2), 335-346.
[18]. Samuelson, P. A. (1965). A theory of induced innovation along Kennedy-Weisäcker lines. The Review of Economics and Statistics, 343-356.
[19]. Urquhart, A. (2016). The inefficiency of Bitcoin. Economics Letters, 148, 80-82.
[20]. Vidal-Tomás, D., Ibáñez, A. M., &Farinós, J. E. (2019). Weak efficiency of the cryptocurrency market: a market portfolio approach. Applied Economics Letters, 26(19), 1627-1633.
[21]. Yaya, O. S., Ogbonna, A. E., Mudida, R., & Abu, N. (2021). Market efficiency and volatility persistence of cryptocurrency during pre-and post-crash periods of Bitcoin: Evidence based on fractional integration. International Journal of Finance & Economics, 26(1), 1318-1335.
[22]. Zhang, Y., Chan, S., Chu, J., & Sulieman, H. (2020). On the market efficiency and liquidity of high-frequency cryptocurrencies in a bull and bear market. Journal of Risk and Financial Management, 13(1), 8.