

Should You Invest or Trade in Cryptocurrency: A Perspective from Weak Form Efficiency

Dr. Santosh Kumari

Associate Professor
Department of Commerce
Shri Ram College of Commerce
University of Delhi
Delhi (India)
Email (O): dr.santoshkumari@srcc.du.ac.in

Ritabrata Majumder

B.Com.(Hons)-II Year,
Batch 2020-2023
Shri Ram College of Commerce
University of Delhi
Delhi (India)

Abstract

The idea of efficient market hypothesis is long drawn and stems from the idea of informational efficiency. A large and liquid market where transaction costs are low form the basis of an efficient market- yet the crypto market is often illiquid, exhibit large fluctuations and attracts the attention of retail speculators with unreliable information. Thus, this study aims to establish inefficiency in the crypto market through showing presence of serial correlation, non-randomness and volatility clustering. The study assumes significance as it indicates that positive developments, like introduction of Bitcoin and Ethereum futures and options or ETFS, can be used to move the Cryptocurrencies towards being efficient in long run. Through finding inefficiency, a prima-facie advantage is found in trading crypto-rather than investing.

Keywords: GARCH (1,1), Serial Correlation, Efficient Market Hypothesis, Random Walk, Autocorrelation Function, Efficiency.

Introduction

Cryptocurrency, although existing on paper for long, rose to prominence after Satoshi Nakamoto's white paper detailing Bitcoin and its cryptograph. Cryptocurrencies have varied uses and promised utilities, however, the most revolutionary of its aspect is its use of a decentralized architecture to generate, transfer, store and verify currency; Crypto-and more specifically, Bitcoin, aims to disrupt the financial sector through acting both as a medium of exchange and a store of value.

From then, the crypto market has grown exponentially; attracting investors and traders due to its unmatched returns. Yet, unlike stocks or bonds, its value is not derived from any underlying fundamentals. Thus, it makes sense for an investor or trader to value cryptocurrency based on past price movements, returns and volatilities. Finding whether the cryptocurrency market is weak form efficient assumes significance from both the trader's and investor's point of view. Whilst an inefficient market would allow a speculator to make abnormal returns through trading, it can serve as a detriment for an investor- who would be better off buying

and selling the assets periodically, instead of simply holding the asset for long.

The results indicated presence of autocorrelation among returns along with volatility clustering. In addition, returns were not random. Thus concluding that Bitcoin, Ethereum and Litecoin markets are inefficient and present trading opportunities.

Theoretical Basis

Efficient Market Hypothesis forms the backbone of modern financial economics and contains keys to deciphering the potential gains from an active style of portfolio management. Depending upon rate of digestion of information into the market, the price of an asset can be used for making various economic decisions. In an efficient market, prices of securities assimilate and reflect information about them. But, in illiquid and thinly traded markets, wide fluctuations might occur due to asymmetrical information.

Formal classifications of the efficiency of the market can be in three broad categories:

- (a) Weak form Efficiency or a random walk; such a market is denoted by lack of autocorrelation among returns and makes technical analysis redundant.
- (b) Semi-Strong Market Efficiency, implying that all publicly available information is reflected in the prices; this form of market efficiency eschews the principles of fundamental analysis.
- (c) Strong form Market Efficiency, which claims that both public and privately held information is already factored into the price. In such forms of market, even insider trading is unable to profit consistently.

The idea of EMH is strongly rooted in the fact that irrational or biased investors-betting on singular assets and not the entire market at large, would be unable to be profitable consistently and leave. However, in the crypto space, entry of amateur speculators might indicate that in an inefficient market, there could be many profitable trading strategies based on the collective and shared irrationality. This can be exploited by actively trading in cryptos, which, due to inefficiency, may be momentarily mispriced.

Review of Literature

The notions of random walk or alternatively, the Efficient market hypothesis was studied as far back as 1933, where predictability of stock markets was studied by Cowles 3rd, A. (1933). Very importantly, he found that no matter the expertise, traders were unable to generate better performance than the market on a consistent basis.

Although first studied by Cowles, the formal definition and division of the Efficient Market Hypothesis was established by Roberts, H.(1967) where he introduced the now common-place forms of efficiency- including weak, semi strong and strong form of efficiency.

The theoretical implication of the Efficient Market Hypothesis Fama, E. F. (1970) and Fama, E. F. and French, K. R. (1988) is the inability of trader to consistently generate risk adjusted excess returns.

In the crypto currency space, Efficiency has been studied by Urquhart, A. (2016), Vidal-Tomás, D., Ibáñez, A. M., & Farinós, J. E. (2019), Wei, Q., Li, S., Li, W., Li, H., & Wang, M. (2019), Hu, A. S., Parlour, C. A. & Rajan, U. (2019), Caporale, G. M. & Gil-Alana, L. & Plastun, A. (2017), and Nan, Z. & Kaizoji, T. (2019). In the above studies, Bitcoin was found to be weak form inefficient.

Lahmiri, S. & Bekiros, S. (2018) undertook a study across 7 exchanges, finding high degree of randomness in the series.

Unlike volatility clustering Urquhart, A. (2016) studied price clustering at round numbers in Bitcoin and round-number effect in volume distribution and market liquidity.

The novelty in this paper lies in the fact that in addition to employing traditional means of finding autocorrelations, like the Ljung-Box test, the study also finds volatility clustering through GARCH effect. In addition, Mcleod-Li test was carried out to find evidences of ARCH effect. Also, the Run's test serves as a robust counter balance to autocorrelation test. Thus, this study provides a novel complement to existent literature by providing greater insight into the issue of Bitcoin,

Ethereum and Litecoin's efficiency. Due to the sample period covering both bull runs of 2017 and 2020, this study might also provide greater insight into the crypto market which has grown significantly since the conduct of past studies.

Research Methodology

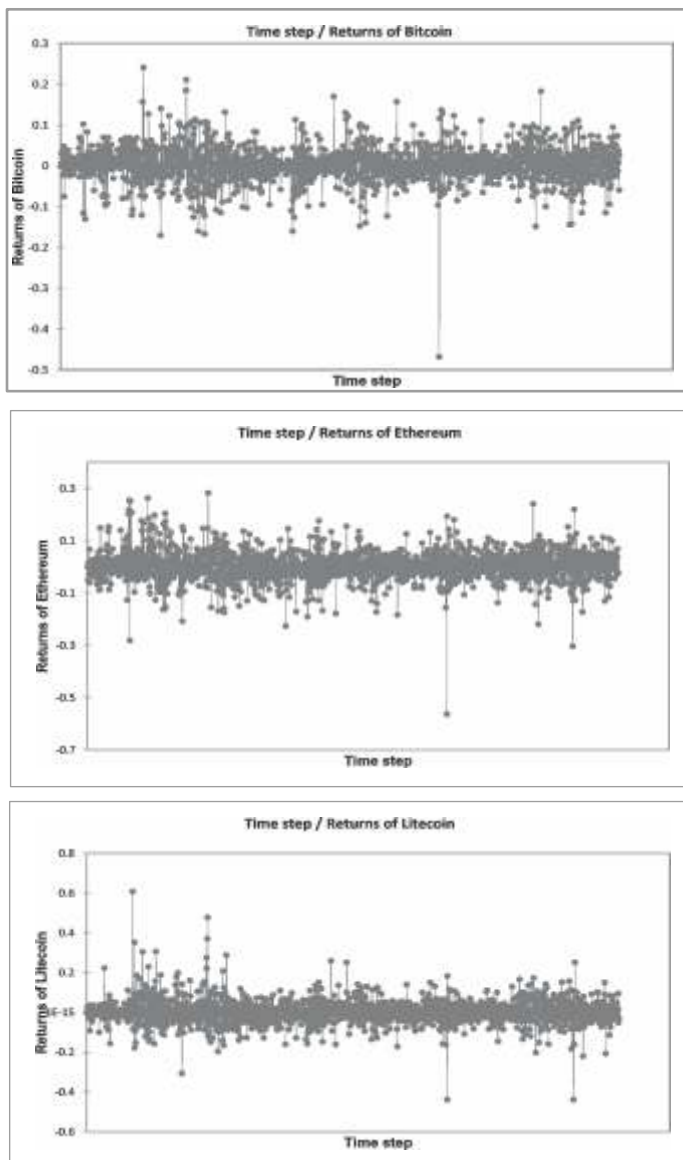
The study aimed to investigate the efficient market hypothesis in its weak form in the context of the emerging cryptocurrency market. For this purpose, the 3 oldest

cryptocurrencies were selected. The sample period under consideration spans from 20th October 2016 to 22nd October 2021. The data was obtained from Federal Reserve Economic Data, Bank of St. Louis.

Name	Symbol	Frequency	Reporter
Bitcoin	BTC	Daily	Coinbase
Ethereum	ETH	Daily	Coinbase
Litecoin	LTC	Daily	Coinbase

Daily stock prices and returns were observed to study the volatility of the cryptocurrencies (Figure - 1,2, and 3)

Figure-1, 2 & 3: Returns of Bitcoin, Ethereum and Litecoin



If the Cryptocurrency returns are to be weak form efficient, consequent price changes (returns) are to be uncorrelated implying that past patterns of price changes should not be repeated in the future. This key criterion automatically makes technical analysis redundant. For this purpose, autocorrelation or serial correlation must be studied for the returns. The study uses Autocorrelation function and the Ljung-Box test for this purpose. The Ljung-Box test maybe formulated as below

$$q_m = n(n+2) \sum_{j=1}^m r_j^2 / (n-j^2) \dots \dots \dots (1)$$

Here, r_j represents accumulated autocorrelation and m represents the time lag

The null hypothesis of absence of autocorrelation is rejected if,

$$Q > \chi^2_{1-\alpha, h} \dots \dots \dots (2)$$

Furthermore, GARCH modelling was carried out to establish presence of Volatility clustering which might indicate inefficiency in the market.

GARCH(1,1) was formulated by Bollerslev(1986) and can be specified as:

$$\text{Mean Equation: } R_t = \mu + \phi R_{t-1} + \varepsilon_t \dots \dots \dots (3)$$

$$\text{Variance Equation: } \sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \dots \dots \dots (4)$$

If the $\alpha + \beta$ term is very close to 1, it might indicate high persistence of volatility clustering. The implication of this finding is that high volatility periods are followed by high volatility period and lower volatility periods, are likewise, followed by lower volatility periods.

The idea that past volatilities can affect present ones show that information is not instantaneously digested into the market – thus allowing one to conclude that price of a security at any point might not accurately display all available information.

Finally, Randomness of the price changes (returns) was studied using the Wald-Wolfowitz Run test. A “Run” can be defined as two consecutive positive or negative values (calculated from the average). The test can be modelled as -

$$Z = \frac{R - R(\text{dash})}{\text{Standard Deviation of } R} \dots \dots \dots (5)$$

$$R(\text{dash}) = \frac{2n_1n_2}{n_1 + n_2} + 1 \dots \dots \dots (6)$$

$$s_R^2 = \frac{2n_1n_2(2n_1n_2 - n_1 - n_2)}{(n_1 + n_2)^2(n_1 + n_2 - 1)} \dots \dots \dots (7)$$

Hypothesis of the Study

Hypothesis 1:

H0: The selected variables are not Autocorrelated.

H1: The selected variables are Autocorrelated.

Hypothesis 2:

H0: The selected variables feature no volatility clustering.

H1: The selected variables feature volatility clustering.

Hypothesis 3:

H0: The selected variables are produced from a random process.

H1: The selected variables are not produced from a random process.

Objectives of the Study

The paper strives to identify weak form efficiency of the three oldest and most prominent cryptocurrencies. For performing the requisite task, the study aimed to fulfil requirements by two methodologies (a) Is there presence of Serial Correlation in the returns of Bitcoin, Litecoin and Ethereum? If so, it might indicate that past returns can be accurately used for prediction of current returns. (b) Are

there any clustering of volatilities? Persistence of past volatilities means that the market may not be following a random walk- instead being affected by previous disturbances.

Empirical Results and Discussion

Figure - 4, 5 and 6 presents the time series plot of Bitcoin, Ethereum and Litecoin. Accordingly, descriptive statistics is provided in Table-1.

Figure - 4, 5 and 6: Plots of the Variables

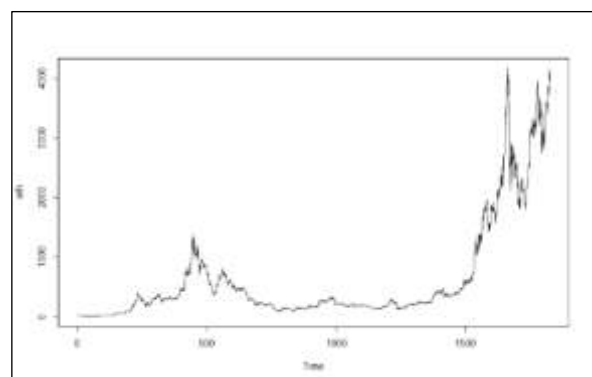
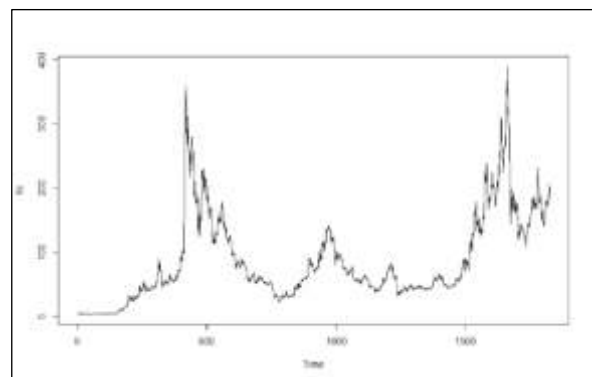
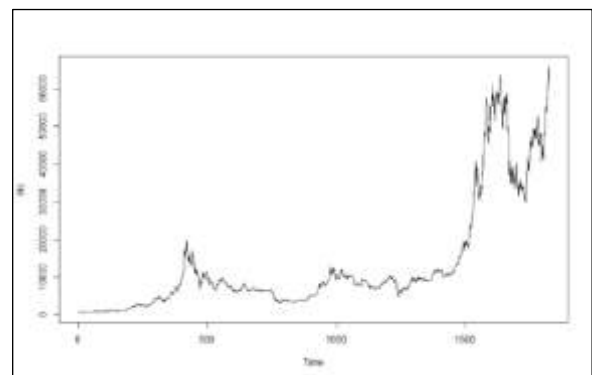


Table - 1: Descriptive Statistics of Variable Prices

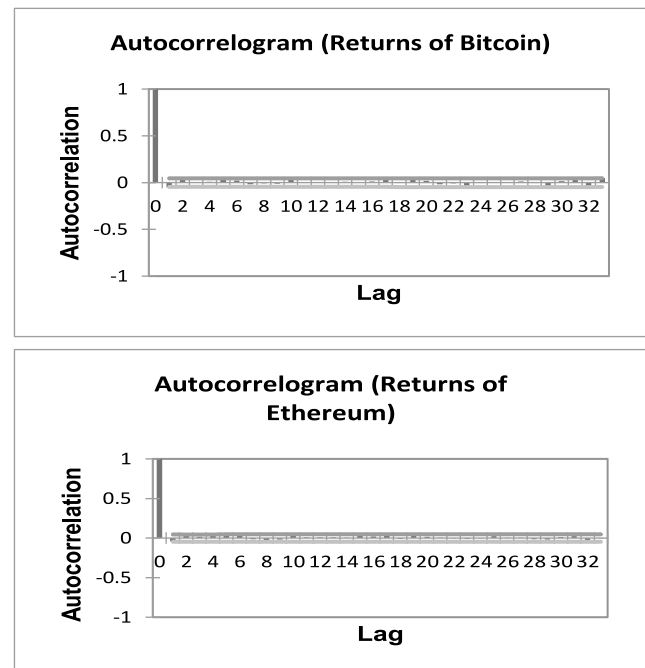
Statistic	Ethereum	Bitcoin	Litecoin
Number of observations	1826	1826	1826
Minimum	6.75	649.98	3.5
Maximum	4172.5	66005.17	389.97
Range	4165.75	65355.19	386.47
1st Quartile	164.64	4307.99	43.66
Median	264.7	8157.15	59.46
3rd Quartile	589.23	11498.99	126.22
Sum	1153626.36	24362504.38	157491.37
Mean	632.124	13349.317	86.297
Variance (n)	774287.093	227960175.4	4645.699
Standard deviation (n)	879.936	15098.35	68.159
Skewness (Pearson)	2.159	1.819	1.303
Kurtosis (Pearson)	3.807	2.137	1.576
Standard error (Skewness (Fisher))	0.057	0.057	0.057
Standard error (Kurtosis (Fisher))	0.115	0.115	0.115
Mean absolute deviation	612.599	10838.316	53.708
Median absolute deviation	137.06	3580.44	27.09

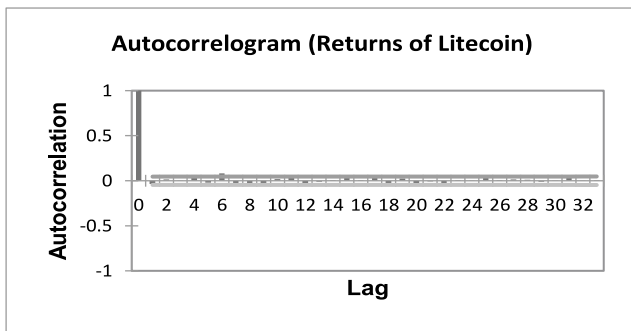
A cardinal assumption of a market being weak form efficient lies in the random walk theory- which suggests that at every instance, the current prices of an asset factors in all available past and present information available- whether publicly available or privately held. Thus, previous events or prices shall not be able to affect future prices, ensuring that future prices exhibit a form of Brownian motion- a random walk that cannot be anticipated. For establishing or disproving autocorrelation or serial correlation, Ljung-Box test is used. A market is said to be weak form efficient when no serial correlation is existent between the returns of the variable.

Here, $\text{Returns} = \text{Price}_{t-1} - \text{Price}_t$

Figure - 7, 8 and 9 represents the Auto-Correlogram for Bitcoin, Ethereum and Litecoin across lags.

Figure-7, 8 and 9: Auto-correlogram of Bitcoin, Ethereum and Liteco in Returns





Furthermore, the Ljung Box test is carried out. The hypothesis of the test is as follows:

H_0 = There is no Autocorrelation.

H_1 = There is Auto-Correlation.

Table 2: Ljung Box Autocorrelation Test

	Bitcoin Return	Ethereum Return	Litecoin Return
P value	0.067	0.002	0.001
Remark	Autocorrelation at 10% Interval	Autocorrelation at 1,5,10% Interval	Autocorrelation at 1,5,10% Interval

As noted, Bitcoin exhibited no autocorrelation at 1 and 5% confidence interval. However, serial correlation was observed at 10% confidence interval which might suggest presence of mild autocorrelation. In case of Ethereum and Litecoin, the null hypothesis was rejected at 1, 5 and 10% confidence levels.

To further the narrative of inefficiency of the cryptocurrencies, one must find the evidence of clustering

in volatilities. Before proceeding with the GARCH(1,1) test, McLeod-Li test is carried out to substantiate presence of ARCH effect.

The hypothesis of the test are as follows:

H_0 = No Autoregressive Conditional Heteroscedasticity is found. Residuals are Uncorrelated.

H_1 = ARCH effect present.

Table 3: McLeod-Li Autocorrelation among Residuals Test

	Bitcoin Return	Ethereum Return	Litecoin Return
P value	< 0.0001	< 0.0001	< 0.0001
Remark	ARCH effect present	ARCH effect present	ARCH effect present

Presence of ARCH effects allows one to proceed with GARCH effect. For this particular study, a GARCH (1,1) model was used.

Table 4: GARCH (1,1) Model

	Bitcoin Return	Ethereum Return	Litecoin Return
μ	0.003132	0.00275	0.0012
Ω	0.000113	0.000294	0.000235
α	0.116449	0.134685	0.064724
β	0.832405	0.782490	0.875638
$\alpha + \beta$	0.948854	0.917175	0.940362

The GARCH model can be intuitively explained by interpreting the α term as the short run volatility persistence and the β as volatility persistence in the long run. For all three cryptocurrencies, the reported results showed that the value of $(\alpha+\beta)$ was very close to 1, which allowed interpretation of the above results as presence of persistent volatility clustering.

Further substantiation of the findings was carried out through performing the Wald-Wolfowitz Run Test to examine randomness in the series.

The hypothesis of the test is as follows:

H_0 =Series is Randomly Generated.

H_1 =Series exhibits Non-Randomness.

Table 5: Run Test for Randomness

	Bitcoin Return	Ethereum Return	Litecoin Return
P value	0.039	0.003682	0.02172
Remark	<i>Series is Non-Random</i>	<i>Series is Non-Random</i>	<i>Series is Non-Random</i>

Conclusion

The notion of efficiency in a market remains cardinal for investors, traders and academicians as informational efficiency guarantees highest expected return with necessary adjustment for risk and uncertainty. An informationally efficient market exhibits true randomness- indicating that stock returns are not easy predictable. Thus, this prevents one to profitably trade on a consistent basis. As noted from the results, the Bitcoin, Ethereum and Litecoin markets were found to be informationally inefficient. Mild (Bitcoin) to significant (Ethereum and Litecoin) Serial correlation was exhibited in the returns of the cryptocurrencies. Furthermore, volatility persistence was found through a GARCH framework- indicating that previous volatilities were able to affect the present conditions. Wald-Wolfowitz Run test also served as a robust check to the findings- allowing the study to reach a definitive conclusion regarding non-randomness of Crypto returns.

The implications of this finding suggest that trading activities in cryptocurrencies remain profitable as the returns might be predictable with accuracy. This serves as a detriment to investor's security as speculators are enabled an opportunity to make excess profit.

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