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Long Term Memory Effect in Selected Cryptocurrencies

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Abstract

The worth of digital currencies is increasing due to its proposed advantages and profits. Though decentralized, these digital currencies can be bought with digital wallets using cryptocurrency platform. Efficient Market Hypothesis (EMH) suggests fundamentals for understanding of financial markets however the opponents believe that this theory is incompetent in explaining the functioning of the markets. EMH is not a perfect model nevertheless it provides a concrete base for the analysis of capital markets. EMH's weak version is utilized for this study. This research compares three top cryptocurrencies- Bitcoin, Ethereum and Litecoin to analyze their long-range memory effect to check the market efficiency and also to estimate the volatility for further investments in different cryptocurrencies. Generalized Hurst exponent methodology is applied to examine long range memory in selected cryptocurrencies market. Daily data from 17th September 2015 till 17th October 2018 is used in this study. It was found that: (i) Long memory exists in the selected cryptocurrencies; (ii) Ethereum market is more persistent than Bitcoin and Litecoin as its Hurst exponent is more than the other cryptocurrencies. These findings can be a source of assistance for the policy makers and investors while making prudent decisions regarding investment in emerging cryptocurrencies market.

Keywords: Long term memory; Generalized Hurst Exponent; Crypto–currency; Bitcoin; Ethereum; Litecoin

Introduction

The global financial market crash of 2007/2008 has negatively affected the economic policy driven investments for example stock, rates of foreign exchange, gold and oil. The global markets are hugely determined by economic and political activities of the United States therefore the pricing of these assets is trying to adapt an innovative, progressive and unconventional monetary system which will be independent of politics and government policies. The digital currency i.e cryptocurrency has now become the source of investment in global markets (Beer and Weber, 2015). In 2009, this market was propagated by the introduction of the first virtual currency, Bitcoin by Satoshi Nakamoto (2008). Generally, cryptocurrency is an innovative solution to the online supporters as it is the type of digital money which is open source based and has peer-peer network (Weber, B. 2016). After the Satoshi Nakamoto's offer, more private currency platform is allowed for buying and selling where transactions take place without interference of central and commercial banks. The price of Bitcoin at that time was as low as $5 per coin, and now there are more than 2000 types of cryptocurrencies traded on internet 24/7. By the end of 2017, for the first time, there was astronomical rise in the prices of Bitcoin to almost $19,000 per coin, ultimately market crashed and prices of the alternative coins decreaed. (Cointelegraph, 2018).

After the popularity of the Bitcoin, other alternative coins i.e Doge, Dash, Litecoin, Ethereum, Ripple, Monero, Vertcoin, Stellar, etc. were introduced. All virtual currencies are being used due to some specific reason. However, no other currency type has beaten the price of Bitcoin as the process of acceptance and rejection of virtual currencies by regulators and economist is ongoing therefore the awareness continues to grow. The market of crypto currency is also popular for its high volatility, though most researches are not concerned about this advantage. Also, portfolio managers and traders can have interest in the price predictability i.e market efficiency. Consequently, there are many academic studies in finance and economic fields which focus on the effect of other assets like stocks

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and gold on the crypto currency market (Glaser et al. 2014; Bouri et al. 2018; Corbet et al. 2018c; Dyhrberg, 2016) For the evaluation of the investment environment, the level of market efficiency is vital, by which description and further development of the market can be known. For the market players of the crypto currency market, the knowledge of efficiency and inefficiency of market renders beneficial information. Efficiency of market suggests that past prices predict the scheme for the future dynamics, that is, macroeconomic and domestic policies have no influence on the prices in this context. In 1965 Fama gave the standard definition of the efficient market, according to which the actual prices of the security at any point in time, in an efficient market, will provide estimation of its fundamental value. In 1970 Fama presented Efficient Market Hypothesis (EMH), which demonstrates that the asset's prices already reflected past information where as there is quick adjustment of prices, in the event of new information, such that it is priced properly i.e., are the cryptocurrencies' returns predictable? The yields are expected to change so they cannot be predicted, for efficient market hypothesis to hold, whereas the returns are predictable if the market is inefficient (Lim and Brooks, 2011). The predictable returns, in an inefficient market, the predictable returns make it possible for the investors to earn abnormal profits. The hypothesis of random walk infers market efficiency; since returns are evolving like random walk therefore their results cannot be predictable. Consequently, as the investors try more to defeat the market, it tends to become more efficient. The above mentioned EMH of Fama (1970) refers to the weak form of the efficiency, where the present prices of assets are likely to mirror all the market transactional data, and technical data analysis could not help in recognizing the abnormal returns from the respective data set.

Volatility and efficiency are indivisible, efficiency is a significant part of the market-returns, though the variation from such returns is the function of volatility, it fizzles out during the time of persistence. The investigation about the persistence of volatility and efficiency in the cryptocurrency market, interests readers.In this study, we will investigate the efficiency of the market in three crypto currencies i.e., Bitcoin, Ethereum and Litecoin by long range memory effect via Hurst exponent methodology. Highlighting important features of the cryptocurrency market will enable regulators to inform citizens not only of the risks, but also the opportunities, associated with adopting virtual currencies. In addition, modernization and research going on in this field facilitates not only individuals but also institutional investors, as a result they improve and upgrade their risk management and investment policies

Development of the Crypto Currency Market

About forty years ago, the idea of privatizing currency was anticipated by Friedrich Hayek (Lemieux, 2013). In 2009, the largest virtual currency, Bitcoin having highest market capitalization started circulations in 2009 and became globally popular digital currency (Orgera, 2017). Although there is bulk of research related digital currencies in computer sciences but in recent times, economist have started analyzing cryptocurrencies to understand market's functionality (Gandal and Halaburda, 2016). The virtual currency's hypothetical (speculative) nature has fully camouflaged the potential of the schematic frame works that support these digital currencies (Chohan, 2017a). A reasonable but a number of disproportionate researches have been on Bitcoin as compared to other cryptocurrencies (Gkillas and Katsiampa, 2018). This large and unbalanced amount of research on Bitcoin generates the market's myopic view which limits the understanding therefrom (Farell, 2015).

The Most Popular Digital Currencies in 2017

Apart from Bitcoin, other highly demanding digital currencies are: Ethereum, Ripple, Bitcoin Cash, Litecoin, Dash, Byteball Bytes, Monero and Maker (Statista, n.d). During the year of 2017, in digital currencies market, the most dominating digital currencies were: Bitcoin, Litecoin, Ethereum, Ripple, and Bitcoin Cash (Gkillas and Katsiampa, 2018). Among these five currencies, Bitcoin and Litecoin are popular among the professionals (Shehhi et al. 2014) Investment in these two cryptocurrencies is considered safe as compared to Ethereum, Ripple and Bitcoin Cash (Gkillas and Katsiampa, 2018).

Types of Cryptocurrencies:

Bitcoin – In 2008, a white paper published by Satoshi Nakamato, proposed Bitcoin as an open-source, peer-peer digital currency. It utilizes algorithm SHA-256 for the process of mining (Wang and Vergne, 2017). Satoshi Nakamato introduces his research by proposing that "Commerce on the Internet has come to rely almost exclusively on financial institutions serving as trusted third parties to process electronic payments. While the system works well for most transactions, it still suffers from the inherent weakness of the trust based model" (Satoshi Nakamoto, 2008). Bitcoin professed insufficiencies resulted in creation of altcoins to correct the faults of the protocol of Bitcoin (DeVries, 2016; Gandal and Halaburda, 2016). The biggest challenge of Bitcoin is its widespread adaptation on exceptional scale (Orgera, 2017). Other drawbacks of the Bitcoin protocol include the usage of highly dedicated software and low processing speed (Gandal and Halaburda, 2016). However, still Bitcoin is the benchmark against all other digital currencies' analysis (Wang & Vergne, 2017). For a comparative summary of market data, see Table 1.

Ethereum – Vitalik Buterin founded a "Turing-completed" digital currency named as Ethereum (Chen et al. 2017). Both developers and institutions have been attracted by the Ethereum platform (Hileman and Rauchs, 2017). The smart contracts of Ethereum ease the conversion of Bitcoin to other virtual currencies (Nolan et al. 2018). Third parties service providers like Escrow services is also replaced by its smart contract platform (Crosby et al. 2016). Russian government has successfully utilized Ethereum platform as a transparent channel for trading agricultural spots (Baydakova, 2018). For a comparative summary of market data, see Table 1.

Litecoin – Litecoin is introduced by Charles Lee which uses scrypt proof-of-work opposite to the code of Bitcoin SHA-256, hashing function (Chen, Chen et al. 2017). Though its performance is not that much good in 2018 (Sinclair, S. 2018), but it is thought as one of the most established digital currencies (Hileman and Rauchs, 2017). Bitcoin shortcomings are improved in Lietcoin by enhancing security against cyber threats and increasing processing speed (Wang & Vergne, 2017). The vital offering of Litecoin is its application of the peer-to-peer network for pragmatic transaction payments (Orgera, 2017). For a comparative summary of market data, see Table 1.

Table 1: Cryptocurrency market capitalizations*(in US dollars) as at 12/09/2018

Cryptocurrency	Market capitalization	Volume(24h)	Circulating supply of coins	Maximum supply of coins
Bitcoin	108,955,587,484	3,925,705,349	17,263,825	21,000,000
Ethereum	17,627,290,682	1,834,831,739	101,913,942	N/A
Litecoin	2,867,248,642	275,956,395	58,260,278	84,000,000

Source: Coinmarketcap, 2018. *Excludes tokens

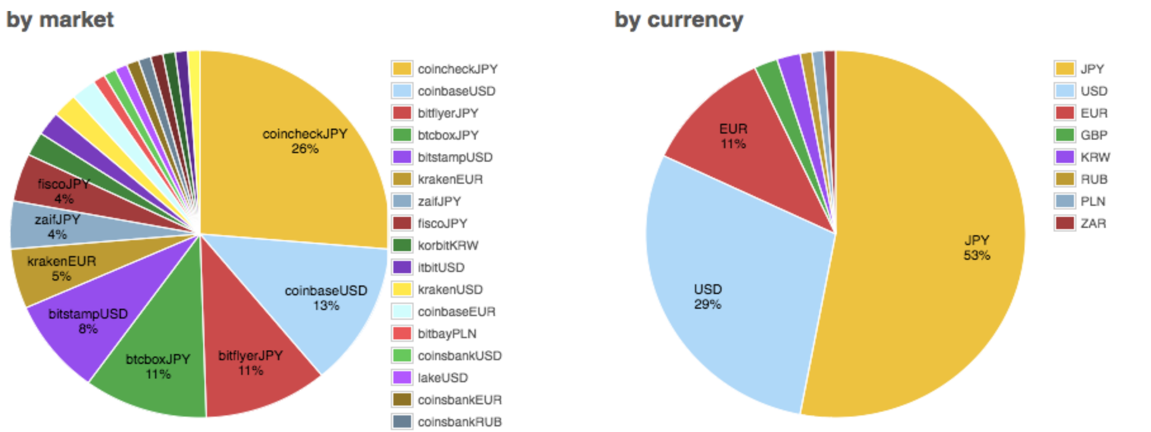

Figure 1: Distribution of the Bitcoin trading by market and currency (Source: Bitcoin chart 2018)

Literature Review

In his paper Nakamoto introduced Bitcoin as a peer-to-peer electronic cash system. Without any financial intermediary, it allows electronic cash transfer to other party. Bitcoin, a crypto currency came into light in 2009, as first decentralized digital currency which manages online payments by sending money through banks, online buying goods and services from one party to another without any financial institution (Raymaekers, 2015). Speed and security of transaction, convenience and cost are several advantages of using Bitcoin currency (Raymaekers, 2015). In the block-chain startups, $1.2 billion has been invested in this technology (Bhosale and Mavale, 2018). Robb (2017) studied that the financial clearing process, financial and security settlements, transparency and efficiency of governance is increased by blockchain technology. Therefore, business legitimately involved in the Bitcoin eco space has valuable interest in blockchain. The blockchain data is segregated into blocks, as its origin is in distributed databases thus continuously adding new sequential blocks of data (Swan, 2015). Using cryptographic signatures, blocks are linked together resulting in time-stampped and temper-proof transactions. In a recent research, it was predicted that in next five years, blockchain could minimize $16 billion of cost savings by simplifying audit and accounting processes.

Recently Bitcoin has become a topic of interest for research in economics, though it was already a topic of interest in computer sciences. Few publications by computer scientists served as incentives. Eyal and Sirer, (2014) concluded that "selfish mining" can generate higher revenue for miners who conspire against one another as mining is not incentive-compatible. The criteria for selfish mining to be profitable is less than for double-spending attacks. Babaioff et al. (2012) analyzed that an incentive for nodes to broadcast transactions, is not provided by current Bitcoin protocols. As the system is based on this assumption, this finding is problematic. Further research in the computer science field was conducted by Christin (2013) who studied crypto currency in anonymous online market place. some work about Bitcoin is published in legal journals, but very less is found in economic literature except European Central Bank's (2012) report on virtual currencies. This report mentioned two examples, Bitcoin and Linden dollars to analyze the effect of digital currencies on the usage of fiat money. While analyzing the economics of private digital currencies Gans (2013) clearly focused on platform-based currencies launched by Facebook or Amazon (that retain full control) rather than Bitcoin which is a decentralized currency. Institutional details related to digital currency developments were provided by Dwyer (2014) Bitcoin exchange rate of 40 Bitcoin exchanges was analyzed to assess the risk investors have to face from these exchanges (Moore and Christin, 2013). Glaser et al. (2014) examined whether interest of users in crypto currencies is due to the interest in the currencies or the prospect of a new investment asset. The findings showed that mostly interest was due to the aspect of the asset. Jena et al (2020) studied the time varying effect in top six cryptocurrencies and conclude that all the six crypto markets exhibit a time-varying efficiency throughout the studied period, However, the most efficient crypto markets are Ethereum and Ripple.

Objective

To observe the long-term memory effect in the different crypto currencies essentially Bitcoin, Ethereum and Litecoin in current times by using generalized Hurst exponent. This will help to understand whether the market for selected crypto currencies is efficient or not and also to estimate the volatility for further investments in different crypto currencies.

Research Methodology

Various methodologies are used to measure long memory effect in the price series. Two methods are commonly used i.e., R/S analysis and V/S analysis due to its simplicity in calculation. In this paper, we have used R/S analysis to check long range dependence in the log series of the Bitcoin market. The function of Hurst exponent H (q) is used, proposed by Hurst (1951), calculated by q-th order moments of increasing distribution. The equation used to measure the scaling behavior is $\mathrm{Kq}\ (\tau)$ for q=1. Here $\mathrm{Kq}\ (\tau)$ is same like autocorrelation concept $C(t,\tau) = \langle S(t+\tau)S(t)\rangle$(Di Matteo et al, 2005).

$$\mathrm{Kq}\ (\tau) = \frac{\langle |S(t+\tau)-S(t)|q\rangle}{\langle |S(t)|q\rangle} \qquad (1)$$

In the above-mentioned equation, it is possible to change the value τ between τmax and$\langle \ldots \rangle$. For each time scale τ and each parameter q, $H\ (q)$ is used.

$$\mathrm{Kq}\ (\tau) \propto \tau q H(q) \qquad (2)$$

Hurst exponent H (q) is estimated by linear least squares through values of τmax in Eq. (2). The range of the value of Hurst exponent is between 0 and 1. If the value is 0 < H < 0.5 then the series is anti persistence behavior, the value H=0.5 exhibits random walk, while the value 0.5 < H < 1 shows persistence in the series[1],[2].

Calculation of Hurst Exponent

Following steps are included in the calculation of the Generalized Hurst exponent:

1) Hurst exponent is calculated by using original log series of the bitcoin data.
2) Pre-whitening is conducted, estimating AR (p) model with sufficiently high "p" (in this paper we used 1 to 30). Akaike criteria are used for the selection of order.

[1] There are two kinds of scaling behavior process: (i) unifacial processes, in which(q) is independent from q; (ii) multifractal processes in which$H(q)$ is not constant and each moment scales with a different exponent. Most of studies confirm the multi scaling behavior of financial time series (Sensoy and Hacihasanoglu, 2014).

[2] The source code of generalized Hurst exponents can be found at: http://www.mathworks.com/matlabcentral/fileexchange/30076.

3) The residual $\varepsilon(t)$ is obtained from AR (p) model.

4) Residuals are bootstrapped through moving blocks, block length used is 5 [41].

5) Synthetic log series is obtained by first making post blacking, later bootstrap is utilized to that model in which parameters were generated in pre-whitening.

6) Hurst exponent H (b) is calculated for each synthetic series.

7) In the last step, Wald statistics is estimated by $W = (\frac{H(1)-0.5}{S(Hb(1))})^2$, to check the null hypothesis that long range does not exist. The standard error for Generalized Hurst exponent is taken by the standard deviation of $S(Hb\ (1))$.

Data and Results

This study examines long term memory effect in different crypto currencies essentially Bitcoin, Ethereum and Litecoin by using generalized Hurst exponent. Daily data of selected crypto currencies ranging from 17th September 2015 till 17th October 2018 comprising 3375 observations are used for analysis. The returns of Bitcoin price series is found by the formula given below:

$$r_t = \ln\left(\frac{p_t}{p_{t-1}}\right) \cdot 100$$

In the above formula r_t stands for return series of Bitcoin price, p_t is representing the price of Bitcoin at time and p_{t-1} is the price at time $t-1$.

Price fluctuation during the sample period of Bitcoin, Ethereum and Litecoin can be seen in Fig 2, 3& 4 respectively. There is stability in price till 2016, after that there is intense fluctuation in price series especially in first two quarters of 2017. Although there is constant fluctuation, the prices have increased approximately 50,000 times till November 2017. This increase in price continued in the start of 2018, but decreased in March. This price increased shows the persistence behavior of Bitcoin return series. Fig 3 shows the price fluctuations of Ethereum. There is price stability till April 2017, after that there are fluctuations; price becomes high during first quarter of 2018.Same trend is present in the prices of Litecoin that shows stability till 2017, afterwards these prices are increasing till 2018. Descriptive statistics of return is given in the Table 2. The mean of the returns of Bitcoin, Ethereum and Litecoin is not normally distributed rather it shows the fat-tailed behavior. Generalized Hurst exponent gives lowest variance and is less sensitive to the outliers as compared to the traditional Hurst exponent (Barunik and Kristoufek, 2010). It is also best for analyzing heavy tailed, not normally distributed return series (Sensoy and Tabak, 2016). As our dataset of return series shows similar properties so Generalized Hurst exponent is selected for analyzing the long-term memory effect thus ensuring accurate and revered findings.

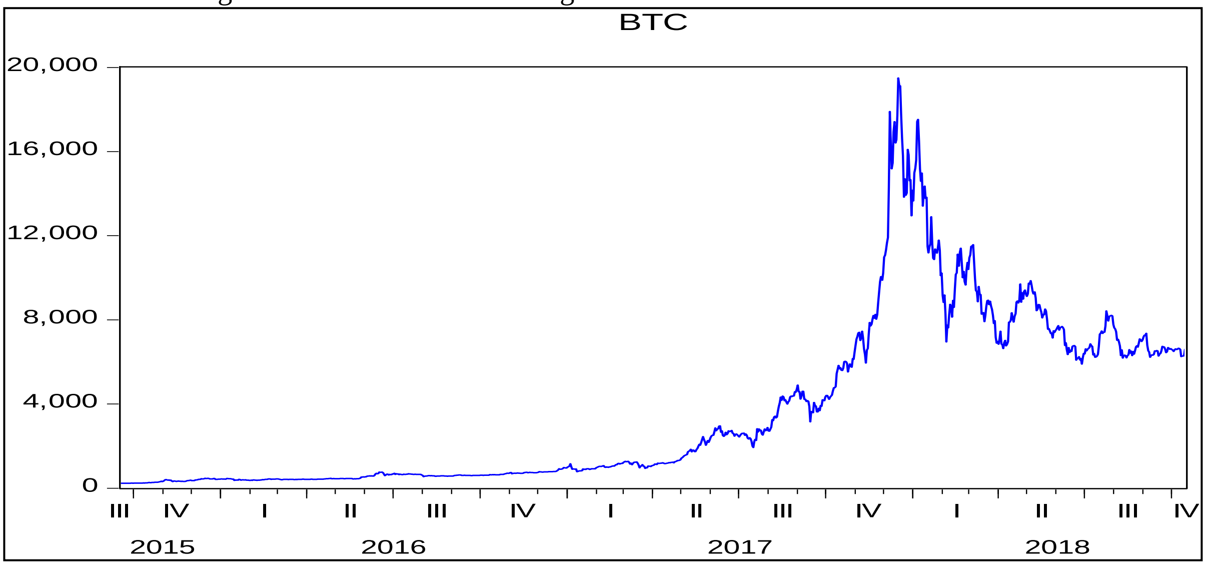

Figure 2: Bitcoin daily price

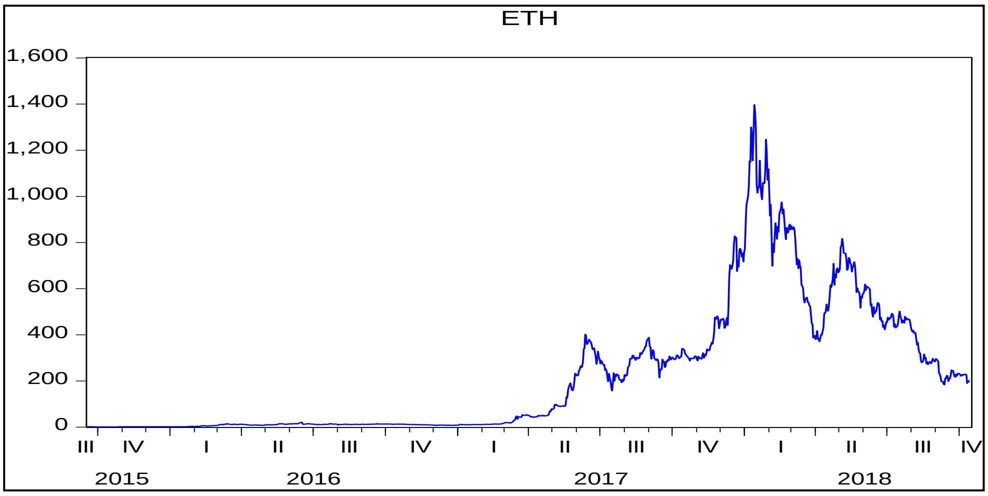

Figure 3: Ethereum daily prices

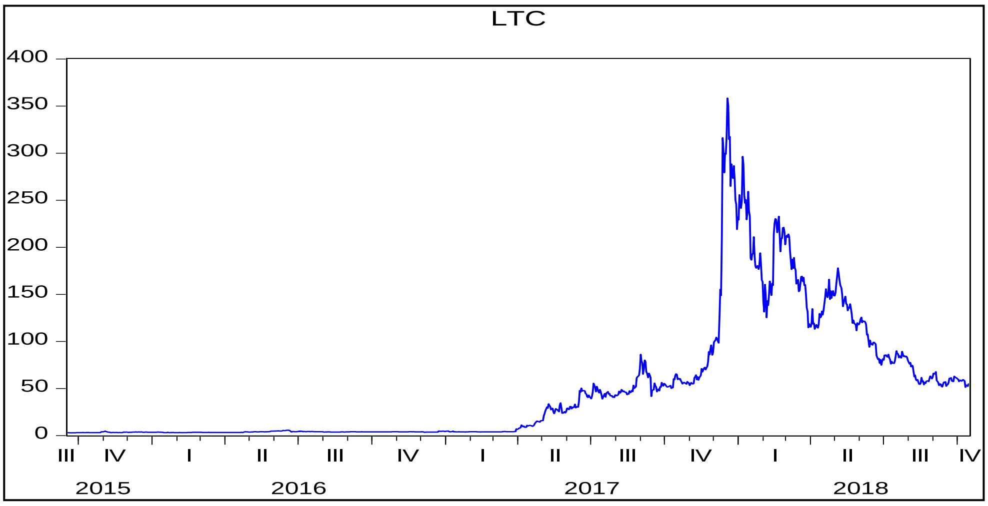

Figure 4: Litecoin daily prices

In this paper, H (1) and standard error for each year of the selected dataset of Bitcoin, Ethereum and Litecoin was calculated to check the Wald statistics. Wald statistics test is used to check the existence of the long memory effect in the return series with this null hypothesis that long memory does not exist. Estimated Hurst exponents for Bitcoin, Ethereum and Litecoin return series per year are shown in the Fig 5, 6 & 7 respectively. It is obvious that the Hurst exponent for sample crypto currencies is either almost 0.5 or above 0.5each year for Bitcoin, Ethereum and Litecoin. For Ethereum, the hurst exponent values for all sample years are greater than 0.5 which means that there is persistence in the Ethereum market. While in Bitcoin market, the value of Hurst exponent is almost 0.5 in 2017 and 2018 which shows that returns follow random walk, thus depicting weak form of EMH which means that the investors cannot earn abnormal profit on the basis of past information. Similarly, in Litecoin market, in 2018, the value of Hurst exponent is 0.5 which shows random walk behavior of Litecoin market during this year. The average Hurst exponent was estimated which is 0.63 for Ethereum, 0.559 for Bitcoin and 0.546 for Litecoin that shows strong persistence level in the selected cryptocurrencies market. Table:3 shows the average Hurst exponent for return series of Bitcoin, Ethereum and Litecoin and their bootstrapped standard error. It also shows Wald statistics for the null hypothesis H=0.5 (absence for long memory effect), p-value for Wald test is given at the end, which is less than 0.05, meaning null hypothesis at 5% significance level can be rejected.

Table 2: Descriptive Statistics

Variables	N	Mean	Std	Min	Max	Kurt	Skew
BTC	1125	0.298399	3.986715	-20.753	22.5119	7.617605	-0.15655
ETC	1125	0.487297	6.675007	-31.5469	30.27704	6.417733	0.261886
LTC	1125	0.259749	5.813287	-39.5151	51.03482	16.08528	1.341101

Table 3: Hurst exponent for Bitcoin, Ethereum, Litecoin

Market	H	Std. error	Wald	p-value
Bitcoin	0.546803	0.083676	42.39072	0.00001
Ethereum	0.630036	0.0483	162.903	0.00001
Litecoin	0.559126	0.051668	115.794	0.00001

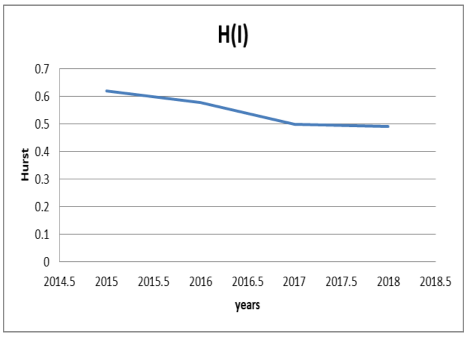

Figure 6: H (I) for Bitcoin Market

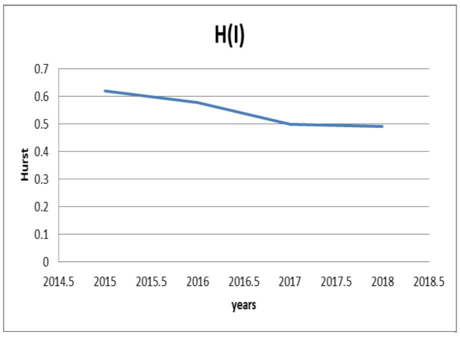

Figure 5: H (I) for Ertherum Market

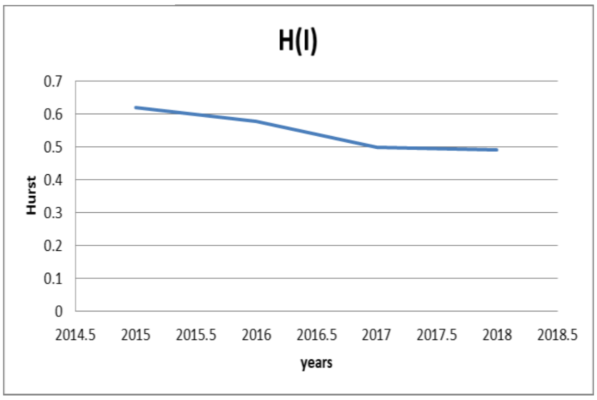

Figure 8: H (I) for Litecoin Market

Final Remarks

In this paper, Generalized Hurst exponent is developed to check the long-term memory effect in the Bitcoin, Etherum and Litecoin market. Among our three sampled crypto currencies, Ethereum shows more persistent behavior as compared to Bitcoin and Litecoin market. Wald statistics is used to rank the existence of long-range effect. The findings show that the crypto currency market exhibits strong persistence level hence the market is inefficient. Our results are consistent with the study held by Jiang and Ruan (2018). As the Bitcoin market is an emerging market, so the findings are not surprising. The results depict lack of pricing mechanism and irrational behavior of investors. Our findings have implications for policymakers and investors. Investors should not enter arbitrarily in such a risky market to invest on the basis of speculative purposes, so they need to vitalize their management while supervising emerging markets like Bitcoin, Ethereum and Litecoin. These findings will help investors and policy makers to make sensible decisions.

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