Research into Cryptocurrencies and Long Term Memory

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Abstract:- Retrieving a set of 14 cryptocurrencies for a sample spanning 2015–2018. In this paper, we investigate Efficiency Market Hypothesis (EMH) by applying ARFIMA model for 14 cryptocurrencies which average price didn't meet over $1 during a period 3 years, from Sep 2015 to Sep 2018. The Long term memory which is detected in time series of price, is in contradiction with Efficiency Market Hypothesis.

Keywords:- *Efficiency Market Hypothesis, Market Efficiency, Cryptocurrency, ARFIMA.*

I. INTRODUCTION

The advent of Bitcoin on 2009 by Nakamoto, have changed the business world and created new type of digital asset which is called Cryptocurrency. Soon the market expanded by different types of cryptocurrencies with variety intriguing application. Coin Offerings (ICOs) is increasing as more people and organizations embrace the use of cryptocurrencies. Liquidity attracted more people to participate and invest in fast-paced cryptocurrency market. Due to risk possibility, the ability of market prediction can protect investors of losing the fund.

The Efficient Market Hypothesis (EMH) is one of the fundamental theories for analyzing financial assets (Fama, 1970). The efficiency of Bitcoin market, as the first cryptocurrency, has been studied in many literatures. Urquhart (2016) discovered the weak form of Bitcoin data by applying five different tests, the result rejected the null hypothesis of a random behavior in time series of Bitcoin returns. Kristoufek (2018) studied the market efficiency of Bitcoin and found market mostly inefficient between 2010 and 2017. Al-Yahyaee et al (2018) applied Multifractal Detrended Flunctuation (MDF) approach to study Bitcoin efficiency in compare to gold, stock and foreign exchange markets, long strong memory is detected in Bitcoin market among others. Bariviera (2017) studied long memory behavior in Bitcoin for 2011 to 2017, he discovered long memory in volatility of Bitcoin. Recently, Grobys (2019), found digital currency market moves to be more efficiency than earlier.

The rest of the paper is structured as follows. Section 2, revisits Data and Methods, section 3 reviews Conclusion.

II. DATA AND METHODS

All required data are downloaded from coinmarketcap.com. We employed those cryptocurrencies for which, closing price average, had not meet over $1 and data were available in the portfolio from 1st September 2015 to 1st September 2018. Daily closing prices in USD are retrieved for Bitshare, Emercoin, Digicoin, Dogecoin, Maidsafecoin, XEM, Nexty, Reddcoin, Stellar, Tether, Verge, Ripple, Bytecoin and Siacoin.

Statistical characteristics of the research variables are presented in Table 1.The raw data of this series were treated in E-views 10, in which the values of statistical information were generated.

	Average	Max	Min	Standard Deviation	Skewness	Kurtosis	Jarque–Bera Test	Probability
BTS	0.090928	0.891892	0.002921	0.136957	2.370774	10.19567	3394.297	0
DGB	0.012677	0.126931	4.70E-05	0.019042	2.16236	9.388347	2720.294	0
DOGE	0.001639	0.017088	0.000114	0.002254	2.389153	10.77963	3810.009	0
EMC	1.094562	9.45	0.014908	1.408757	2.055452	8.074739	1949.575	0
MAID	0.239803	1.17	0.011637	0.216349	1.255227	4.905573	454.0476	0
XEM	0.150069	1.84	8.60E-05	0.255295	3.154028	15.46214	8917.537	0
NTY	0.087407	1.82	0.005239	0.171091	5.367487	42.01271	74835.11	0
RDD	0.001978	0.029256	8.00E-06	0.003629	2.896545	14.17168	7238.662	0
XLM	0.084641	0.896227	0.001444	0.146745	1.943599	6.443437	1232.642	0
USDT	0.999838	1.08	0.913595	0.010649	-2.923717	30.19612	35370.09	0
XVG	0.014778	0.255441	8.00E-06	0.032557	3.283306	15.79635	9455.54	0
XRP	0.246959	3.38	0.00409	0.422513	3.172368	17.04204	10852.73	0
BCN	0.001545	0.030134	2.40E-05	0.002555	3.408153	24.15255	22574.99	0
SIA	0.006481	0.094008	1.30E-05	0.010921	3.26426	18.39012	12774.44	0

Table 1:- Statistical Characteristics of the Research Variables

The autoregressive fractional integral moving average (ARFIMA) model is a well-known parametric tool for testing long memory characteristics of the conditional mean (Mensi et al., 2018).

Two estimation methods maximum likelihood (ML) and generalized least squares (GLS) were compared to generate the data. The Optimum lags for self-correlation and moving average processes has been determined by Schwartz criterion. Due to the lag, when the model presents a lower Schwartz criterion, the interruption remains in the model. To find the appropriate degree of the model, p<10 and q<10 for different lags are estimated for ARMA (p,q). Among all different estimated equations, suitable model would be the one takes the lowest Schwartz criterion. Results for Arfima (5, d, 5) is presented on Table 2.

	ML				GLS			
	d	t	Prob	interpretation	d	t	prob	interpretation
BTS	0.32954	6.05077	0.00000	Long memory	0.38123	2.92258	0.0035	Long memory
DGB	0.38274	4.02987	0.00010	Long memory	0.49993	4.35380	0.00000	Long memory
DOGE	0.43058	4.83931	0.00000	Long memory	0.49999	42.27405	0.00000	Long memory
EMC	0.39569	2.04818	0.04080	Long memory	0.49977	3.18939	0.00150	Long memory
MAID	0.21083	2.60576	0.00930	Long memory	0.23109	1.69100	0.09110	Long memory
XEM	0.18583	2.85500	0.00440	Long memory	0.27609	1.44891	0.14770	Long memory
NTY	0.03556	0.73452	0.46280	Long memory	0.49999	44.72974	0.00000	Long memory
RDD	0.44374	3.99624	0.00010	Long memory	0.04182	0.47977	0.63150	Long memory
XLM	-0.12490	-1.39391	0.16360	Short memory	-0.12377	-0.92822	0.35350	Short memory
USDT	-0.41841	-1.40449	0.16050	Short memory	-0.27477	-2.24034	0.02530	Short memory
XVG	0.26067	1.11856	0.26360	Long memory	0.43638	2.36708	0.01810	Long memory
XRP	-0.44970	-1.16595	0.24390	Short memory	0.49987	2.95141	0.00320	Long memory
BCN	-0.02695	-0.31536	0.75260	Short memory	-0.02861	-0.37417	0.70840	Short memory
SIA	0.04128	1.34818	0.17790	Long memory	0.04176	0.66260	0.50770	Long memory

Table 2:- ARFIMA (5, d, 5)

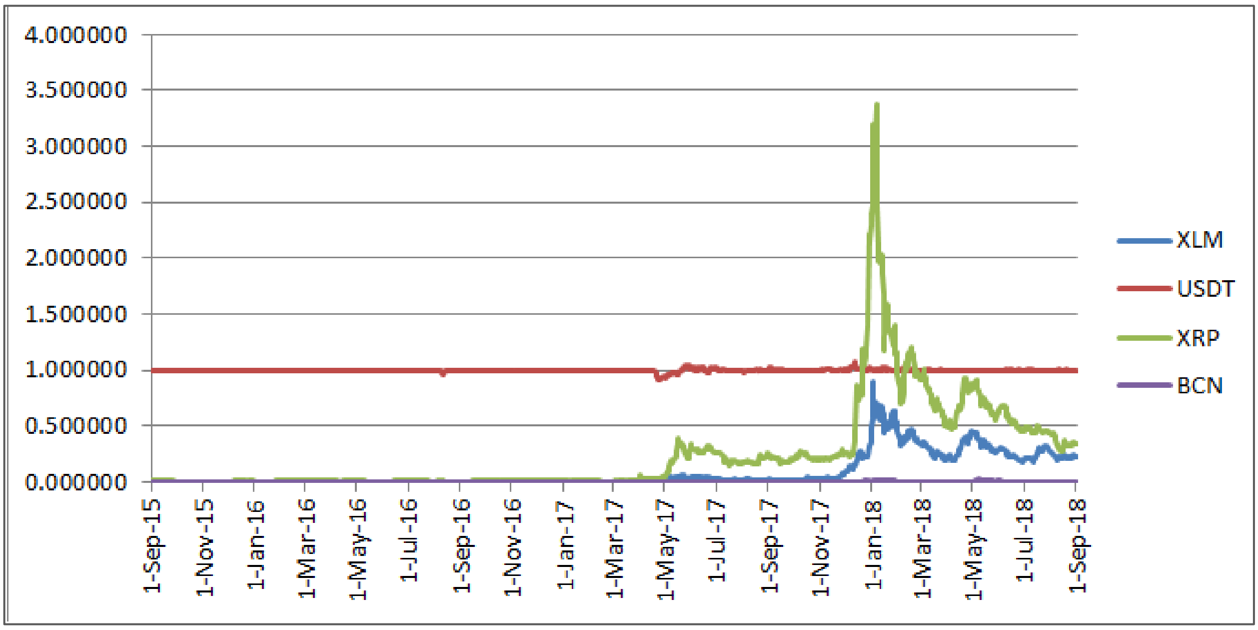

Fig 1:- Price development of XLM, USDT, XRP, BCN. This figure presents prices of 4 Cryptocurrencies showed the short term memory using ARFIMA model.

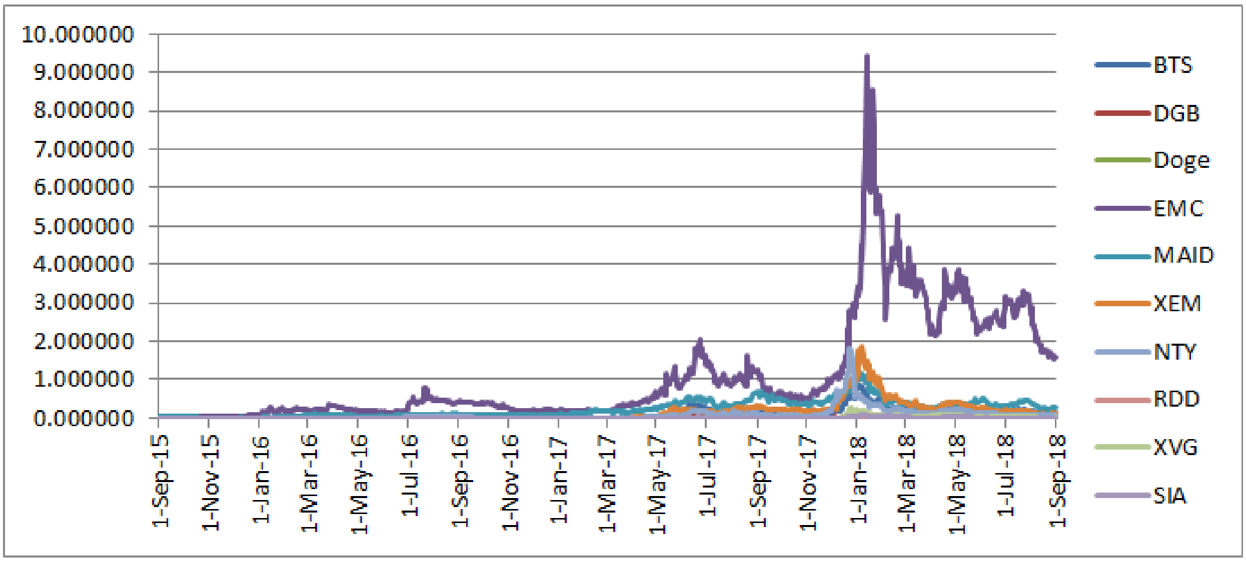

Fig 2:- Price development of BTS, USDT, DGB, DOGE, EMC, MAID, XEM, NTY, RDD, XVG and SIACoin. This figure presents prices of 10 Cryptocurrencies showed the long term memory.

III. CONCLUSION

In this paper, we applied time-series analytical mechanisms to daily data of 14 cryptocurrencies to detect long memory by using ARFIMA model from 1 Sep 2015 to 1 Sep 2018, data is collected from coinmarketcap.com. All cryptocurrencies under the estimation showed similar interpretation in both ML and GLS models, except XRP. There is Inconsistency between XRP interpretation in ML and GLS models. Under ideal conditions the choice between ML and GLS methods is thus arbitrary. Consistent with earlier findings the results show that ML compared to GLS under conditions of misspecification provides more realistic indexes of overall fit and less biased parameter values for paths that overlap with the true model (Olsson, 2000). Therefore long memory is not proved in XRP, more studies with different models should be taken to consider the best model for similar cases to XRP. According to outcomes detected long term memory on cryptos shown in Fig2. Proved that market of those virtual currencies is not efficient.

For XLM, USDT and BCN, short term memory is discovered, so they provide traders with efficient market beside these cryptos also we considered XRP market as efficient market. According to table 2, long memory is strongly detected for the rest 10 cryptos. Traders can gain significant profit by market prediction through technical and fundamental analysis.

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