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Exploring the random walk in cryptocurrency market

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Abstract: This paper explores efficiency in cryptocurrency market. Using data of the 8 large cryptocurrencies (Bitcoin, XRP, Ethereum, Litecoin, Stellar, Monero, Dash and NEM) and MVIS Crypto Compare Digital Assets for large cap index, we apply a battery of 13 robust tests to check randomness and correlation in returns. The results show that all cryptocurrencies are inefficient except the Bitcoin which show weak efficiency in more than 50% of the tests. Since, cryptocurrency is relatively new market, we can estimate more efficiency over time as more investors are analyzing and trading.

Key words: Cryptocurrency, Efficiency, randomness

Jel classification: G12, G14, G40

1- Introduction

Cryptocurrency, the digital currency is a new investment source accepted in the global market. This market is propagated with the introduction of the first digital coin, the Bitcoin in 2009 priced as low as $5 per coin, and since then, well over 2000s cryptocurrency types are being traded 24/7 on the internet. For the first time, having attained stable and astral increase in prices till late 2017 to around $20000 per coin, Bitcoin crashed and cause prices of other alternative coins to fall. Cryptocurrency is characterized by its huge volatility, so the predictability of the price that is efficiency of the market could be of interests to portfolio manager and traders.

The efficient market hypothesis is a vital concept in the field of finance. A weak-form efficiency means that the prices cannot be forecasted because the current pricesthat already reflects the information of the past prices(Fama, 1970). The issue on market efficiency has been explored in stock market, futures market, foreign exchange market and other markets (Kristoufek and Vosvrda, 2014 and David et al., 2013).

In the literature of cryptocurrency Cheung et al. (2015) show the existence of bubbles in the bitcoin market over the period and find a number of short-lived bubbles but also three huge bubbles. Cheah and Fry (2015) argue that if Bitcoin were a true unit or account, or a form of store of value, it would not display such volatility expressed by bubbles and crashes.

Wei (2018) examines the liquidity of 456 different cryptocurrenciesand show that return predictability diminishes in cryptocurrencies with high market liquidity. Zhang et al. (2018) adds to the literature by investigating nine forms of cryptocurrencies, i.e., Bitcoin, Ripple, Ethereum, NEM, Stellar, Litecoin, Dash, Monero and Verge, with a battery of efficiency tests and the empirical results indicate that all these cryptocurrencies are inefficient markets. Urquhart (2016) studied the inefficiency of bitcoin through a battery of robust tests, evidence reveals that returns are significantly inefficient over full sample, but after splitting the sample into two subsample periods, he finds that some tests indicate that Bitcoin is efficient in the latter period.

Bouri et al. (2018) studied the predictability of return and volatility in cryptocurrency market and find that volume Granger causes return volatility for only three cryptocurrencies (Litecoin, NEM, and Dash) when the volatility is low. Al-Yahyaee et al. (2018) assess the efficiency of Bitcoin market compared to gold, stock and foreign exchange markets by applying a MF-DFA approach and found that the long-memory feature and multifractality of the Bitcoin market was stronger and Bitcoin was therefore more inefficient than the gold, stock and currency markets.

In this paper we will explore efficiency in cryptocurrency market. Using data of the 8 large cryptocurrencies (Bitcoin, XRP, Ethereum, Litecoin, Stellar, Monero, Dash and NEM) and MVIS Crypto Compare Digital Assets for large cap index. We apply a battery of 13 robust tests to check randomness and correlation in returns for period from January 1, 2015 to January 31, 2019. Our results show that only Bitcoin is more efficient than other currencies.

The remainder of this study is organized as follows. Section 2 describes data, methodology and conducts a preliminary analysis. Section 3 discuss the empirical results. Section 5 provide the concluding remarks.

2- Data and Methodology

Our data consists of daily closing prices of 8 largest cryptocurrencies by market capitalization (Bitcoin, XRP, Ethereum, Litecoin, Stellar, Monero, Dash and NEM) from January 1, 2015 to January 31, 2019, which corresponds to a total of 1492 trading day. All data is extracted from coinmarketcap.com. We select MVIS CryptoCompare Digital Assets 100 Index for large cap as a market portfolio (downloaded from Bloomberg) which is a market cap-weighted index that tracks the performance of the 100 largest digital assets. The index serves as benchmark and universe for the other MVIS CryptoCompare Digital Assets Indices. After that, we calculated the returns ($R_{i,t}$) as follow:

$$\boldsymbol{R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}}} \quad (1)$$

Where *P* denotes the price of a coin *i* at time *t*. Table (1) summarizes descriptive statistics for all the data.

Table 1: Descriptive Statistics (1/1/2015 – 31/1/2019)

Name	Ticker	Weight (MVIS)	Mean	Std. Dev.	Kurtosis	Skewness
Bitcoin	BTC	59.3%	0.002774	0.039808	8.040406	0.144367

XRP	XRP	12.3%	0.005954	0.089813	136.6741	7.915707
Ethereum	ETH	10.7%	0.005701	0.073321	16.08072	0.274503
Litecoin	LTC	1.9%	0.003296	0.060167	23.89642	2.464706
Stellar	XLM	1.5%	0.006461	0.093468	38.83483	4.056954
Monero	XMR	0.7%	0.005766	0.074345	18.99273	2.080621
Dash	DASH	0.6%	0.004228	0.062378	12.77966	1.572171
NEM	XEM	0.4%	0.008650	0.101451	71.13234	5.106105
MVIS large	-	**100%**	0.002992	0.041471	7.138886	-0.124277

From table (1), we can observe the positive performance for the market (mean equal 0.00249) and all currencies. The standard deviation is small for all data which indicates low spread in returns. The market index is also approximately symmetric almost data are skewed to the right. Also, we have very high value of kurtosis which mean that the distribution is leptokurtic. The peaks are very high which means that data are heavy-tailed and profusion of outliers.

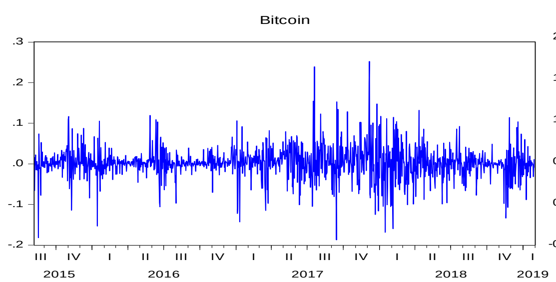

Figure 1: Bitcoin

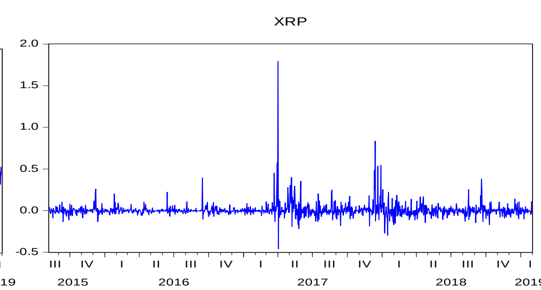

Figure 2: XRP

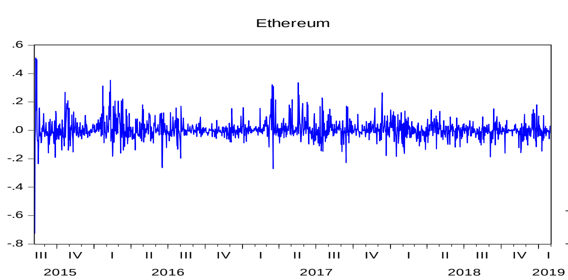

Figure 3: Ethereum

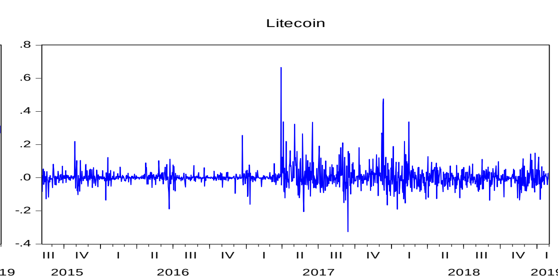

Figure 4: Litecoin

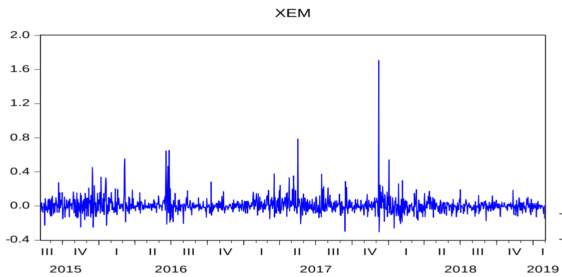

Figure 5: Nem

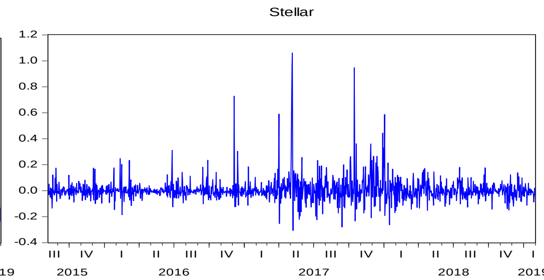

Figure 6: Stellar

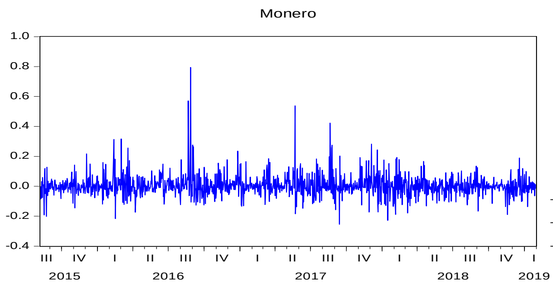

Figure 7: Monero

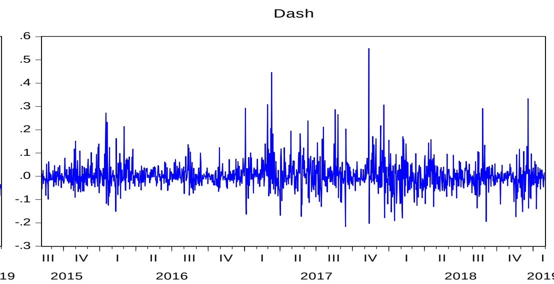

Figure 8: Dash

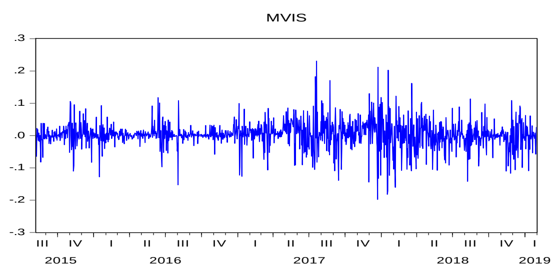

Figure 9: Market (MVIS)

Figures from (1) to (9), represent the returns of all cryptocurrencies and MVIS market and show that returns are relatively stable except the period from end 2016 to mid-2017.

The efficient market hypothesis (EMH) states that markets are efficient and that prices already reflect all known information concerning a security and that prices rapidly adjust to any new information. Information includes not only what is currently known about a currency, but also any future expectations. It seeks to explain the random walk hypothesis by positing that only new information will move prices significantly, and since new information is presently unknown and occurs at random, future movements in prices are also unknown and, thus, move randomly. To test this, we apply a battery oftests for randomness in order to track down all movements in cryptocurrencies. The employed tests are summarized in table (2).

Table 2: Efficiency tests and hypothesis

Test	Author	Null Hypothesis
BDS test	Brock et al. 1996	Series of i.i.d. random variables
Portmanteau Test for white noise	Box and Pierce, 1970	White noise process
Bartels Test	Bartels, 1982	Randomness is tested against a trend

Cox Stuart Test	Cox and Stuart, 1955	The probability of a positive slope is the same as the probability of a negative slope, that is, there is no correlation (trend absence)
Ljung–Box Test	Ljung and Box, 1978	The data values are random and independent up to a certain number of lags
Mann–Kendall Rank Test	Mann 1945, Kendall 1975, Gilbert 1987	There is no monotonic trend in the series
Rank Score VR Test	Wright, 2000	Random walk
Rank Variance Ratio Test	Wright, 2000	Random walk
Runs Test	Wald and Wolfwitz, 1940	Each element in the sequence is independently drawn from the same distribution.
Sign Variance Ratio Test	Wright, 2000	Random walk
Turning Point Test	Moore and Wallis, 1943	Randomness against either a positive or negative serial correlation
Variance Ratio Test	Lo and MacKinlay, 1988	Martingale
Wild-bootstrapped AVR test	Kim, 2009	Random walk

At the end, we use the rescaled Hurst exponent for long memory of cryptocurrency returns. Bariviera et al. state that Hurst exponents stabilize around a value of 0.5 ± 0.05, indicating a more informational efficient market. Therefore, we assume the market is inefficient if H/R > 0.55 or H/R < 0.45.

3- Results

Table (3) recap the results of the employed tests with the *p*-values (except for Hurst exponent). The BDS test is significant at 1% level for all cryptocurrencies which means that returns are not iid. According to Portmanteau test, only Bitcoin follow a white noise process.The hypothesis of randomness is rejected for all cryptocurrencies using the tests: Rank score, Rank variance, sign variance and variance ratio. While, we failed to reject the null hypothesis of randomness against trend (upward and downward) for almost cryptocurrencies using the tests: Mann-Kendall rank, run test, turning point, Bartels. According to the results we can deduce that the Bitcoin is the only cryptocurrency that seems to efficient according to seven tests.

Table 3: Efficiency tests' results

Test	BTC	XRP	ETH	LTC	XLM	XMR	DASH	XEM	MVIS
BDS test	0.03 (0.00)***	0.042 (0.00)***	0.029 (0.00)***	0.029 (0.00)***	0.037 (0.00)***	0.016 (0.00)***	0.02 (0.00)***	0.028 (0.00)***	0.032 (0.00)***
Portmanteau Test for white noise	48.913 (0.15)	114.309 (0.00)***	64.962 (0.00)***	61.732 (0.01)***	84.709 (0.00)***	90.415 (0.00)***	67.885 (0.00)***	71.113 (0.00)***	69.815 (0.00)***
Bartels Test	0.6207 (0.53)	0.6517 (0.51)	-0.267 (0.78)	2.4594 (0.01)***	2.9564 (0.00)***	2.975 (0.00)***	1.9426 (0.052)*	2.3493 (0.02)**	0.1869 (0.85)

Cox Stuart Test	299 (0.13)	315 (0.81)	299 (0.13)	301 (0.17)	314 (0.75)	306 (0.34)	300 (0.15)	294 (0.057)*	314 (0.75)
Ljung–Box Test	42.981 (0.19)	111.89 (0.00)***	63.292 (0.00)***	60.333 (0.00)***	83.442 (0.00)***	73.417 (0.00)***	56.900 (0.02)***	68.081 (0.00)***	67.761 (0.00)***
Mann–Kendall Rank Test	-1.085 (0.28)	-0.5973 (0.55)	-0.874 (0.38)	-1.238 (0.22)	-0.206 (0.84)	-0.749 (0.45)	-1.4058 (0.16)	-1.916 (0.055)*	-0.482 (0.63)
Rank Score VR Test	17.854 (0.00)***	17.152 (0.00)***	17.698 (0.00)***	17.955 (0.00)***	17.606 (0.00)***	18.439 (0.00)***	18.655 (0.00)***	17.673 (0.00)***	18.415 (0.00)***
Rank Variance Ratio Test	16.796 (0.00)***	15.892 (0.00)***	17.045 (0.00)***	17.552 (0.00)***	17.665 (0.00)***	17.881 (0.00)***	17.760 (0.00)***	17.179 (0.00)***	17.416 (0.00)***
Runs Test	1.241 (0.21)	1.548 (0.12)	0.808 (0.42)	2.421 (0.02)**	1.109 (0.27)	2.01 (0.04)**	1.255 (0.20)	0.249 (0.80)	0.298 (0.77)
Sign Variance Ratio Test	12.472 (0.00)***	11.183 (0.00)***	12.136 (0.00)***	13.145 (0.00)***	13.425 (0.00)***	13.539 (0.00)***	12.472 (0.00)***	13.145 (0.00)***	13.929 (0.00)***
Turning Point Test	0.6649 (0.51)	-0.8644 (0.39)	0.2659 (0.79)	1.5546 (0.12)	1.7954 (0.07)*	1.9948 (0.046)**	0.6649 (0.51)	1.4629 (0.14)	2.3938 (0.016)**
Variance Ratio Test	10.35 (0.00)***	2.757 (0.02)**	9.973 (0.00)***	6.944 (0.00)***	6.36 (0.00)***	8.618 (0.00)***	8.739 (0.00)***	3.549 (0.00)***	8.759 (0.00)***
Wild-bootstrapped AVR	0.1632 (0.76)	-0.376 (0.78)	2.910 (0.00)***	0.659 (0.45)	4.480 (0.00)***	-0.108 (0.77)	-1.373 (0.14)	-1.666 (0.19)	-0.948 (0.368)
Hurst exponent (R/S Hurst)	0.593	0.614	0.602	0.612	0.609	0.593	0.611	0.598	0.600

(***) indicates significance at level 1%, (**) indicates significance at level 5% and (*) indicates significance at level 10%

According to Hurst exponent, all values are more than 0.55 suggesting strong evidence for rejection of random walk. Therefore, this test indicates significant inefficiency in all cryptocurrencies. Which is coherent with the findings of Urquhart (2016).

Table (4) summarize the results of efficiency tests and show the bitcoin shows inefficiency in only 6 tests out of 13 which represents 46%. So, we can conclude that Bitcoin is efficient which is coherent with the works of Nadarajah and Chu (2017), Bariviera (2017). This is also in line with the conclusion of Urquhart (2016) that cryptocurrencies of higher liquidity show better efficiency than lower liquidity.

Table 4: Summary of efficiency results

	BTC	**XRP**	**ETH**	**LTC**	**XLM**	**XMR**	**DASH**	**XEM**	**MVIS**
Number of inefficiencies at	6	8	9	10	9	11	8	9	9

5%									
Percentage of inefficiency at 5%	46%	62%	70%	77%	70%	85%	62%	70%	70%

4- Conclusion

Cryptocurrency market has received a particular attention since its creation. Thus understanding, the stylized facts of digital moneyis crucial for investors, portfolio managers and academicians alike.

This paper contributes to the literature by exploring the weak form of efficiency cryptocurrencies market. We used a battery of 13 robust tests to detect a random walk using a sample of 8 cryptocurrencies from the MVIS large cap digital index from 1/1/2015 to 31/1/2019. The results show evidence of non-randomness for all cryptocurrencies except for Bitcoin. For this later, more than 50% of test confirm the weak form of efficiency.

The absence of random walk is evidence of inefficiency in cryptocurrency market which can be explored in further works to find evidence of some behaviors that can beprevailing in this market.

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