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"Efficiency in cryptocurrency market"

Master Thesis U.S.E.
Academic Year: 2021-2022

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Abstract:

The cryptocurrency market has drawn much attention in recent years. The efficient market hypothesis, one of the essential basics of finance researches, has been investigated in this market repeatedly. However, the existing studies have been mostly focused on Bitcoin and the results in this area have been mixed. Considering the rising debates about replication crisis in finance, we replicated two previous studies by Urquhart (2016) and Nadarajah and Chu (2016) in order to validate their findings. These studies were further updated with a current data set and extended with analyses on 8 other altcoins to check if the results stand for other time-spans and assets. We used the same method as the two pre-mentioned studies to test for weak forms of efficiency, and found that the results of the previous studies are generally replicable and, by adding an odd power to the daily returns of cryptocurrencies, are mainly efficient.

Keywords: Market Efficiency, Cryptocurrency, Replication Crisis.

JEL classification: G14, G15

Contents:

1. Introduction

This research aims to examine the efficiency of cryptocurrency markets. Efficient market theory has been one of the bases for much financial research and theories. This important characteristic of cryptocurrency markets is still unclear.

Financial markets are meant to make the allocation of resources fair. That means that in an ideal market, prices should be accurate in order to give the right signals to investors for resource allocation. For this to be the case, the prices at any time need to "fully reflect" all the available information. A market, which has this characteristic, is "efficient" (Fama, 1970). Efficient Market Hypothesis (EMH), firstly stated by Fama (1970, 1991), describes an efficient market as a market in which all the available information is reflected in the prices. Therefore, being efficient leads to a right distribution of investable resources. That is the reason why this has been a point of attention for regulators and researchers.

Fama (1970) offers three possible states of efficiency for a market: strong efficiency, semi-strong efficiency, and weak efficiency. As Langevoort (1992) explains, the weak form of this hypothesis means that prior price movements can not be used systematically to make predictions of future changes, while in semi-strong form, publicly available information can not be used thusly. The strong form is only present if no such informational access will systematically confer a trading advantage. In this study, we tested for weak form of efficiency.

The cryptocurrency market as a recently emerged market has been attractive, drawing the attention of more investors and growing rapidly. Bitcoin was the first well-known cryptocurrency, causing the crypto-boom to occur. The low value of Bitcoin in its early years is evident from the statement of an early Bitcoin user, who in 2010 stated: “I just want to report that I successfully traded 10,000 Bitcoins for pizza” (Sharma, Jain, Mahendru, Bansal, & Kuma, 2019 from Zohar, 2015). 12 years later, its value has exceeded 40.000 Euro. This surge affected other cryptocurrencies and the whole market developed rapidly as a result. However, while this market is global now, there has not been much research on it and regulators have not paid much attention to this emerging market. Consequently, it has remained largely unknown and unregulated.

We have seen in other financial markets that the efficient market hypothesis has played a role in regulations since there have been dramatic changes in the beliefs about markets' efficiency over time. At This opinion began to change in the late 1980s, when increasingly detailed data sets and the use of new technologies in research led to inconsistent predictions of prices. Subsequently, excess volatilities and pricing anomalies were increasingly observed(Langevoort, 1992).

In light of these revelations and considering both the importance of EMH and the growing popularity of cryptocurrencies, we present the following research question:

Are the markets of cryptocurrencies efficient and if yes, to what extent?

Researchers, investors, and potential future regulators can benefit from the answer to this question in several ways: Firstly, an efficient market will lead to a fair distribution of resources. Secondly, an efficient market takes the opportunity of gaining abnormal returns for the investors, meaning there is no chance to beat the market if it is efficient; it is only possible to gain more by taking more risk. Consequently, insights from this research could provide investors with the information necessary to gage the risk inherent in the crypto-market. Lastly, as mentioned before, EMH is an integral part of market-regulation. If cryptocurrencies keep growing as expected, we will likely see an increase in regulations on the market. Similar to other financial markets, having data about market efficiency can be useful for regulating this market and moving towards an efficient market.

During the past years, some researchers have investigated this subject, but the results of those studies have been mixed. At the same time, debates about the replication crisis in finance studies have been steadily increasing. The replication crisis speaks of the belief that the findings of a study can not be reproduced if the study is repeated. Due to this problem rising in the field of finance and the mixed results available in previous studies on cryptocurrency efficiency, the replicability of prior research is questionable.

Moreover, with the growing rate of this market, we could imagine changes are happening relatively fast. This can cause the results of all the previous studies to be irreplicable when conducted using updated data sets.

Finally, previous research on this issue has mostly focused on Bitcoin efficiency, mainly due to the coin’s high market capital and importance. Bitcoin was the cryptocurrency that started the first put the crypto market into the public eye, although currently it is not the only one with a significant market capital. Due to the rise of altcoins, their efficiency should be similarly investigated. In this research, we tried to consider a wider scope and pick eight other cryptocurrencies to investigate.

This study contributes to the existing literature in two ways. Firstly, by testing for the replicability of previous research on the efficiency of crypto markets. To do so, we tried to replicate two of the existing studies to see if we can reach the same findings. Secondly, by testing for transferability. With updating the data sets, we checked if in the fast changing environment of cryptocurrency market the old results still hold. In addition to that, we tested if the results hold for other assets by conducting similar analyses for 8 altcoins.

In the next sections, we will define the theoretical framework, go over the existing literature, then explain the statistical methods and data. Finally, we will interpret our results and report our conclusion.

2. Literature Review and Theoretical Framework

The efficient market hypothesis has been a major issue in the financial literature, for the past 40 years (Borges, 2010). Many studies have been conducted around market efficiency of established markets, because of its importance for various groups of users. With the globalization of financial markets these studies have become increasingly frequent (Borges, 2010).

With the globalization of cryptocurrency market, the interest in its efficiency is similarly rising. This globalization started with Bitcoin: Bitcoin first emerged in 2009 and since then, while experiencing severe fluctuation along the way, it has grown substantially, and made cryptocurrency popular. This popularity can be explained by some of the coin's characteristics, namely being usable for online transactions and giving the opportunity of trading and transferring without intermediaries. Furthermore, because of the privacy it gives to the traders, it has seen increasing use in criminal activities (Sharma et al., 2019). Following the rise of Bitcoin, the market for cryptocurrencies continuously developed and new coins began to emerge.

In spite of this growth, Bitcoin still can be considered as the most important cryptocurrency, since it has the highest market capital[1], and its value affects other coins in the market (Meynkhard, 2020). As of April 2022, this market offers 9780 coins based on coinmarketcap.com. Today the investment volume in cryptocurrencies has got higher, while still being considered as a high-risk investment. With this high popularity and relatively high volume of investments the crypto market increasingly came under academic scrutiny: During the first years of its appearance academics and researchers used to ignore the crypto market, believing it to be a short-lived trend in spite of evidence to the contrary (Sharma et al. , 2019). Recently however, this view began to change: The literature in this area is improving and academics have started paying more attention to crypto markets.

As mentioned, one of the important characteristics of a market is market efficiency. It is one of the most fundamental topics in economics and finance(Lee, &Lee , 2006, p.585) and an essential topic to build a part of literature on. The Efficient Market Hypothesis (Fama,1970 &1991) is defined in by Lee and Lee in their book "Encyclopedia of Finance". They state that "a market is efficient if

[1] coinmarketcap.com

security prices at any time fully reflect all available information to the level in which the profits made based on the information do not exceed the cost of acting on such information. The cost includes the price of acquiring the information and transaction fees." In a more scientific and formal definition a market is considered efficient with respect to some information set, Ω_t, if with revealing that information set to all participants, prices stay the same. (Timmermann, & Granger, 2004) Based on the definition of Market Efficiency, it is impossible to beat the market and earn abnormal returns in an efficient market. Thus, in such a market investors would be able to earn more only by taking more risk, because all the fundamentals has already affected the prices.

When it comes to measuring the market efficiency, we refer to Fama's (1970) three states of efficiency: strong, semi strong, and weak. In the weak form of efficiency, only previous prices are considered as the information set. It means future returns should not be predictable by previous returns. For semi-strong form of efficiency, the information set is publicly available information. Finally, strong form of efficiency is based on all the available information (Fama, 1970). In this thesis, we are investigating the weak form of efficiency, focusing on predictability of future prices based on past returns.

Various studies have been done to investigate this fundamental and essential concept around various financial markets. However, when it comes to the cryptocurrency market, studies have been mostly focused on Bitcoin.

We can state that Urquhart (2016) was the first to investigate the efficiency of cryptocurrency markets. Some subsequent studies (e.g. Nadarajah and Chu, 2017; Tiwari, Jana, Das, and Roubaud, 2018; Bariviera, 2017) tried to improve the methodology used by Urquhart (2016) and added some further tests. Urquhart (2016) in his study found out Bitcoin was not efficient during a period from 2010 to 2016. Nonetheless, by dividing the period into two subperiods and investigating those periods separately, he found signs of moving towards efficiency.

Then, Nadarajah and Chu (2016) did a follow up study of the study by Urquhart. They improved the Urquhart's original methodology by adding a few tests, and most importantly, adding a power to the time series of Bitcoin returns. The conclusion they got is different from Urquhart's, suggesting Bitcoin to be efficient during the same time period.

In 2017, Bariviera focused on the long-term memory of time series, using two alternative ways of investigated long-term memory in Bitcoin return and its volatility. His research was based on data from 2011-2017 and states that Bitcoin has not been efficient before 2014. However, he found some evidence for Bitcoin efficiency after 2014. The volatility of the market showed persistent behavior during the whole period and exhibits long memory.

Regarding the long-term memory, Tiwari, Jana, Das, and Roubaud (2018) added some more tests to what Barivira (2017) did and found evidence of Bitcoin efficiency along the timeline except for the periods of April–August 2013 and August–November 2016.

Wei (2019) investigated efficiency in a more wide frame of cryptocurrency market. He picked 456 altcoins, and checked for efficiency considering the liquidity in 2017. He put the coins in 5 groups based on their liquidity using Amihud’s illiquidity ratio (Amihud, 2002). He again used the same method as Urquhart (2016) and got that in the groups with higher liquity efficiency is stronger.

In 2020 Tran and Leirvik picked 5 cryptocurrencies with the highest market capital and investigated the efficiency during a period between 2013 and 2019. Instead of Urquhart’s (2016) methodology they utilized a method for measuring Market Efficiency they themselves had derived one year earlier (2019). They found cryptocurrencies had been inefficient during those years, further implying that efficiency had been on a steady incline.

In summary, prior research shows that the efficiency of cryptocurrency markets has been steadily increasing across the observed time. However, it is unknown how the efficiency of the market has developed amid the rising it is unknown how the efficiency of the market has developed amid the rising volume of trades in recent years. So other than considering the replication crisis, we will also contribute to the literature by updating data on the efficiency of cryptocurrency markets. Moreover, we will try to check for a wider window and consider more altcoins.

3. Methodology

As mentioned previously, in a weakly efficient market future prices should not be foreseeable based on previous prices, meaning prices should follow a random walk. There are various tests we can do in order to determine this, such as testing for unit root or for autocorrelation etc. In this study, we used the methods used in two existing studies[2] to replicate the researches in Cryptocurrency Efficiency area. These studies are focused on Bitcoin efficiency in the same time span, so that the results would be comparable. The first one, which has been done by Urquhart (2016) is the base for many other researches in this area (Nadarajah & Chu, 2017; Bariviera, 2017). Then the other one by Nadarajah and Chu (2017) is a follow up and extension to this one.

First, we tried to replicate each research using the exact same method and data in order to see if we can reach the same results. Then, we updated the data set, and checked for the cryptocurrency market efficiency using the same methods and updated data.

Other than updating the data to date of doing the research (06-06-2022), we also widened our focus to more cryptocurrencies. We picked the nine cryptocurrencies with highest market capitalizations. The reason to take the first 9 is that the market capital of the 10th one was almost half of the 9th one, i.e. the market capital of XRP as the 9th one was about almost 40 million dollars, while it was a bit higher than 20 billion dollars for Avalanche (AVAX) which is the 10th rank of market capital. So we investigated the efficiency in the ones with notably high market capital. A list of these altcoins can be found in the table below:

Table 3-1:
List of coins added to study

Name	Symbol	Name	Symbol
Ethereum	ETH	Solana	SOL
Tether	USDT	Terra	LUNA
BNB	BNB	Cardano	ADA
USD Coin	USDC	XRP	XRP

[2] "The inefficiency of Bitcoin" by Urquhart (2016), "On the inefficiency of Bitcoin" by Nadarajah & Chu (2017)

As mentioned above, we use different tests. These tests have been used on time-series of altcoins' daily returns. We used the closing price of the desired altcoin to calculate its daily return using the following formula:

$$R_t = \ln\left[\frac{P_t}{P_{t-1}}\right] * 100 \qquad (3.1)$$

We mainly used R for the statistical testing of our data, although to control our results we checked them in some cases with Python and/or Stata.

All the tests used in these studies for this purpose are as follows:

First tests would be tests for autocorrelation, the Ljung-Box test (Ljung and Box, 1978) and robustified portmanteau test (Escanciano and Lobato, 2009). The hypotheses for these tests are as follows:

H_0: No autocorrelation exists

H_1: The returns are autocorrelated

Then we use two tests to check for randomness of the returns: Runs test (Wald and Wolfowitz, 1940) and Bartels test (Bartels, 1982). When a time series is random, it does not follow a pattern, thus it will be unpredictable. And it is exactly the characteristic of an efficient market.

H_0: The sequence of returns is random

$H_{1:}$ The sequence of returns is not random

Next step would be to test for random walk. To solve the problem of determining parameters in the variance ratio test (Lo and MacKinlay, 1988), we use the automatic variance test (AVR) (Choi, 1999), in this test the choice of those parameters happens automatically. (Urquhart, 2016)

H_0: The series follows random walk

H_1: The series does not follow random walk

We also run the Wild-Bootstrapped AVR test (Kim, 2009), which has the same hypotheses.

Another way to check for random walk is using spectral shape tests. Firstly, using Anderson-Darling test we can check if the sequence follows a specific distribution, then using Cramer-von Mises we can check for goodness of fit, and finally the generalize spectral shape test checks if martingale effect exists (Durlauf, 1991).

Hypotheses for Anderson-Daling and Cramer-von Mises are as follows:

H_0: Data comes from a specific distribution

H_1: Data does not come from a specific distribution

Next, the BDS test (Broock et al., 1996) is used. This test checks for time based dependence in a series, i.e. serial dependence.

H_0: Data is independently and identically distributed

H_1: Serial dependence exists

After all, to measure the long-term memory of the returns, the Hurst exponent has been used. We used the R/S estimations of Hurst exponent.

R/S stands for Range/Standard Deviation. To estimate Hurst exponent using R/S first data should be devided to sub groups. Then deviation from the mean will be calculated for each subgroup. The range of these deviations rescaled by standard deviation will be used to calculate the R/S Hurst exponent.

$$(R/S)_\tau \equiv 1/s_\tau[\max_{1\leq t\leq \tau} \sum_{t=1}^{\tau}(r_t - \bar{r}_\tau)] \qquad (3.2)$$

If the Hurst exponent equals to 0.5, means that, the series follows a random walk. So after calculating the Hurst exponent a test was used about the difference of this exponent to the ideal value (0.5), to see if the difference is significant or not.

4. Data and Results

4.1 Data

For all parts of the research, we used investing.com to extract the data. The time frame in each part was different. For the replication part of our research, we used the same data as those researches, i.e. Bitcoin daily return from 2010 to 2016. Then for updating the Bitcoin efficiency, we used data from 06-06-2017 to 06-06-2022. Finally, for other eight altcoins we used daily returns from the earliest day available to 06-06-2022, which would be different for each coin. The exact dates can be found in table 4-1.

Table 4-1:

Starting date of time-frame for each altcoin

Name	Start date	Name	Start date	Name	Start date	Name	Start date
Ethereum	2016-03-11	Solana	2020-07-14	BNB	2017-11-10	Cardano	2018-01-01
Tether	2017-04-15	Terra	2021-02-26	USD Coin	2018-12-07	XRP	2015-01-23

The descriptive statistics for the replication papers' data can be found in table 4-2 and 4-3.

Table 4-2:

Summary of descriptive statistics compared to the reference study- first replication paper

first study : returns							
study	**N**	**Mean**	**SD**	**Max**	**Min**	**Kurt**	**Skew**
original	2183	0,42	5,42	37,22	-44,56	13,03	-0,39
our study	2191	-0,40	8,17	84,88	-147,42	67,28	-2,66

Table 4-3:

Summary of descriptive statistics compared to the reference study- second replication paper

second study : returns to the power of 17							
study	**N**	**Mean**	**SD**	**Max**	**Min**	**Kurt**	**Skew**
original	2191	−2,406 × 10^−7	1,225 × 10^−5	4,735 × 10^−5	−5,706 × 10^−4	2147,745	-46,084
our study	2191	−3,347 × 10^33	1,567 × 10^35	6,165 × 10^32	−7,334 × 10^36	2190,999	-46,808

As it can be seen, descriptive analysis shows a notable difference between our data and the reference articles. Because the data needed is relatively old (from 2010) we did not have many sources available to access it. Although we tried a dataset from bitstamp[3] too, in order to check if that is closer to our original study and we need to change our data source. This dataset's time slot was starting form 1 year later than our proper time frame, August 2011. But, the numbers were still significantly different from the reference studies. This can be a sign that the old data available around cryptocurrencies, which was mainly Bitcoin at that time, is not trustable.

Summary of descriptive statistics for the updating part of our research can be found below in table 4-4.

Table 4-4:

Summary statistics of the updated series

Symbol		count	mean	std	min	median	max
BTC	Return	1826	0,13	4,25	-49,73	0,15	22,76
	return^17	1826	-3,80 x 10^+25	1,63x10^+27	-7,00 x 10^+28	1,36x10^-14	1,18x10^+23
ETH	Return	2279	0,22	5,64	-58,96	0,13	25,86
	return^17	2279	-5,5x10^+26	2,64x10^+28	-1,2x10^+30	8,21x 10^-16	1,03x10^+24
USDT	Return	1878	0	0,47	-5,75	0,00	4,53
	return^17	1878	-4,25x10^+9	1,88x10^11	-8,14x10^12	0,00	1,42x10^11
BNB	Return	1670	0,3	6,24	-58,12	0,15	53,06
	return^17	1670	-4,35 x 10^+26	2,47x10^+28	-9,84 x 10^+29	1,51x10^-14	2,09x10^+29
USDC	Return	1278	0	0,97	-22,81	0,00	12,46
	return^17	1278	-9,57 x 10^+19	3,42x10^+21	-1,22 x 10^+23	0,00	4,22x10^+18
SOL	Return	664	0,53	8,53	-54,83	0,25	49,99
	return^17	664	-4,36 x 10^+26	1,45x10^+28	-3,6x10^+29	1,33x10^-10	7,61x10^+28
LUNA	Return	465	-0,04	61,86	-604,82	0,08	1071,73
	return^17	465	6,98x10^+48	1,51x10^+50	-1,94 x 10^+47	2,87x10^-19	3,25x10^+51
ADA	Return	1618	-0,01	6,24	-53,72	-0,02	34,88
	return ^ 17	1618	-1,60 x 10^+26	6,42x10^+27	-2,58 x 10^+29	-9,86x10^-29	1,67x10^+26
XRP	return	2692	0,12	9,11	-99,65	-0,02	102,8
	return ^ 17	2692	3,50x10^+30	3,64x10^+32	-9,43 x 10^+33	-8,24x10^-31	1,60x10^+34

[3] bitstamp.net

4.2. Results

4.2.1. Replication

To replicate the first study by Urquhart(2016) we used Ljung-Box test, Runs test, Bartels test, automatic variance ratio test, BDS test and finally R/S Hurst exponent. The result for these tests from the original study and our investigation are reported in table 4-5.

Table 4-5:
Results of the first study's replication

Test	Ljung-Box	Runs	Bartels	AVR	BDS	R/S Hurst
Original	0,00	0,00	0,00	0,01	0,00	0,353
Results	0,99	0,00	0,02	0,00	0,00	0,494

Results of the original study in all tests were against market efficiency. Our results for 4 out of 6 tests (Runs, Bartels, AVR and BDS) shows the same. P-values for these tests are lower than the significance level (0.05), so the null hypothesis is rejected. In both Runs test and bartels test it means the sequence is not random. In AVR we reject that the time series follows a random walk. And with the BDS test result we can say serial dependence exists. All these tests, similar to the reference study, show inefficiency of Bitcoin.

On the other hand, our results of Ljung-Box test and Hurst exponent are different from the original study. Based on our result of Ljung-Box we could not find evidence against the hypothesis of no autocorrelation.

For interpreting the Hurst exponent, we calculated a P-value to check if the difference of our Hurst exponent and the ideal value for it (0,5) is significant. While in the original study the Hurst exponent is lower than 0,5, in our case the P-value equals to 0,999 which means the difference is not significant, and our series follows a random walk.

In replicating the second study by Saralees Nadarajah and Jeffrey Chu we run the tests on the series of returns to the power of 17. This power should be an odd number, because in this way numbers will keep their sign[4], thus we will not lose any information. Although, using smaller numbers is possible, we used 17 following the reference study. The tests used in this study are: Ljung-Box, Runs, Bartels, Wild-Bootstrapped AVR, Spectral shape, BDS, Portmanteau, and Generalized spectral shape. The results of this study in comparison with our results can be seen in the tables below.

Table 4-6-1:
Results of the second study's replication

Test	Ljung-Box	Runs	Bartels	Wild AVR	Anderson–Darling
Original	0,99	0,019	0,009	0,475	1,000
Results	0,98	0.000	0,028	0,3	0.999

Table 4-6-2:
Results of the second study's replication

Test	Cramer–von Mises	BDS	Portmanteau	Generalized spectral
Original	1,000	0.930	0,513	0,287
Results	0,999	0,980	1,000	0,25

Looking at the tables 4-6-1 and 4-6-2 we can see our results of tests are different from the main study; however, this differences does not lead to a different interpretation.

Based on our results of randomness tests, Runs test and Bartels test, we can say there is enough evidence to reject the null hypothesis of the series being random. So the series is not random and the findings are against the weak form of efficiency.

On the other hand, all the other tests' results are in accordance with the weak form of efficiency in Bitcoin. Running the Ljung-Box test, we found no evidence against no autocorrelation. With Wild-Bootstrapped AVR test we got the results with no evidence against random walk in our series. Spectral tests (Anderson–Darling and Cramer–von Mises) also showed no evidence against our series being a random walk. Portmanteau test showed no evidence against no serial correlation.

[4] i.e. negative numbers will stay negative, positive ones will stay positive, and zero will be zero.

Finally, based on Generalized spectral test there is no evidence against the martingale difference hypothesis.

As stated earlier all these tests other than the two tests for randomness showed no evidence against the null-hypothesis, which means our tests mainly approved the weak form of efficiency in bitcoin.

4.2.2. Updating

After redoing previous researches, we tried to add to the literature with updating the results.
As explained previously, this update includes investigating Bitcoin efficiency with updated data, and investigating the efficiency of 8 other altcoins. The results of this part can be found in tables 4-7-1 and 4-7-2.

For discussing the results we will interpret them for different groups of coins with similar results. Nevertheless, we will first mention a notable point, which is in common among almost all the coins. Considering the results of the spectral shape tests, we can see the p-values for spectral shape tests have small values for the return series, while the results are greater for the series of returns to the power of 17. This means returns to the power of 17 are a better fit to a normal distribution, and follow a random walk. So the results of other tests are more trustable for that sequence.

- Bitcoin (BTC) & Ethereum (ETH):

  Interpreting the returns' series, all the tests are against efficiency other than AVR test, Hurst exponent, Portmanteau test, and Cramer-von Mises test.

  Based on the powered returns, we can conclude bitcoin is efficient. All the results are in accordance with efficiency; only the randomness tests, Bartels and Runs test, giving us evidence opposite to the other ones.
- Tether (USDT) & USD coin (USDC):

  For these coins, spectral shape tests for the returns to the power of 17 implies evidence for normal distribution and random walk, whereas they show evidence against random walk for the returns series. The general conclusion of other tests is the same as BTC and ETH. Based on returns USDT and USDC are not efficient and based on powered returns, they are efficient. The only difference is that for USDT and USDC returns series, Portmanteau test and Cramer-von Mises also offer evidence against efficiency.

- BNB (BNB):

  This coin has the same results as BTC and ETH, except two tests on returns' series. Here the Portmanteau test indicates inefficiency, while Ljung-Box test gives results in accordance with efficiency. However Ljung-Box evidence is not strong.

  So the overall conclusion does not change. Based on returns to the power of 17 BNB is efficient.

- Solana(SOL):

  For this coin, we can say all evidence is in accordance with efficiency. All the tests on the returns' series; which is not following normal distribution based on Anderson-Darling; other than BDS and Portmanteau test show evidence in accordance with market efficiency. Even the Cramer-von Mises is in accordance with efficiency. However, result of Ljung-Box is not strong too. Also considering the powered returns, all the tests are in accordance with efficiency. Thus, based on both series we can conclude that this altcoin is weakly efficient.

Table 4-7-1:

Results- updated datasets for all 9 altcoins

Currency		Ljung-Box	Runs	Bartels	AVR	BDS
BTC	return	0,01	0,00	0,01	0,94	0,00
	powered return	0,98	0,00	0,01	1,00	0,98
ETH	return	0,02	0,00	0,00	0,96	0,00
	powered return	0,98	0,00	0,00	1,00	0,98
USDT	return	0,00	0,00	0,00	0,37	0,00
	powered return	0,44	0,00	0,00	0,98	0,98
BNB	return	0,42	0,00	0,00	0,98	0,00
	powered return	1,00	0,00	0,00	1,00	0,94
USDC	return	0,00	0,00	0,00	0,18	0,00
	powered return	0,98	0,00	0,00	1,00	0,98
SOL	return	0,07	0,73	0,49	0,90	0,00
	powered return	0,98	0,73	0,49	1,00	0,92
LUNA	return	0,00	0,26	0,67	1,36	0,00
	powered return	0,96	0,26	0,67	1,00	0,95
ADA	return	0,01	0,00	0,00	0,93	0,00
	powered return	0,98	0,00	0,00	1,00	0,98
XRP	return	0,00	0,00	0,00	0,64	0,00
	powered return	0,00	0,00	0,00	0,85	0,00

Table 4-7-2:

Results- updated datasets for all 9 altcoins

Currency		R/S Hurst	portmanteau	Anderson–Darling	Cramer–von Mises
BTC	return	0,54(0,99)[5]	0,07	0,00	0,82
	powered return	0,50(1)	1,00	1,00	1,00
ETH	return	0,56(0,99)	0,13	0,00	0,88
	powered return	0,50(1)	1,00	1,00	1,00
USDT	return	0,47(0,95)	0,00	0,00	0,00
	powered return	0,50(1)	1,00	1,00	1,00
BNB	return	0,54(1)	0,00	0,00	0,94
	powered return	0,50(1)	1,00	1,00	1,00
USDC	return	0,44(0,95)	0,00	0,00	0,00
	powered return	0,50(1)	1,00	1,00	1,00
SOL	return	0,59(0,99)	0,03	0,00	0,96
	powered return	0,50(1)	1,00	1,00	1,00
LUNA	return	0,51(1)	0,00	0,00	0,98
	powered return	0,50(1)	1,00	1,00	1,00
ADA	return	0,59(0,99)	0,05	0,00	0,88
	powered return	0,50(1)	1,00	1,00	1,00
XRP	return	0,53(1)	0,00	0,00	0,01
	powered return	0,49(1)	0,99	0,00	1,00

- Solana(SOL):

  For this coin, we can say all evidence is in accordance with efficiency.

  All the tests on the returns' series; which is not following normal distribution; other than BDS and Portmanteau test show evidence in accordance with market efficiency. However, result of Ljung-Box is not strong either. Also considering the powered returns, all the tests are in accordance with efficiency. Thus, based on both series we can conclude that this altcoin is weakly efficient.

- Terra(LUNA):

  We can state that this coin is efficient too. It has the same result as SOL with one difference.

[5] The number in parentheses shows the p-value related to the Hurst exponent, to know if the difference between the Hurst exponent and 0,5 is significant or not.

The only difference of this one with Solana is that Ljung-Box shows evidence against efficiency in the returns' series. Therefore, the results of the tests on powered returns imply efficiency of Luna.

- Cardano (ADA):

  This coin has the same results as BTC and ETH, other than Portmanteau test for returns' series, which is on the edge of being against efficiency for Cardano. Therefore, the conclusions are the same: based on testing the returns series, ADA is inefficient. However, with the exception of Runs and Bartels test, interpretation of the tests on the powered returns will lead us to the conclusion of efficiency of this coin.

- XRP(XRP):

  This altcoin has different result from all other coins. Firstly, based on spectral shape tests results, none of the series follows a random walk. Only Cramer-von Mises for the powered return implies evidence for it being random walk. Moreover, only AVR and Hurst exponent for both series and Portmanteau test for the powered return series implies evidence for its weak efficiency. Hence, overall we have no evidence for XRP being weakly efficient.

5. Conclusion

The purpose of this thesis was to investigate the market efficiency in cryptocurrencies, and check for replicability of prior studies. Based on our findings the results of prior researches are mainly replicable. In addition to that, we found out that the cryptocurrencies are mostly weakly efficient.

In the first part of our research, we did get the general results as the reference papers. However, the descriptive statistics showed major difference in our data from those studies. The reason for that might be unreliability of old data available on Bitcoin, which is understandable because those years where early on Bitcoin appearance.

Then on updating part of our research, we found out the odd power for returns make them closer to a normal distribution. Therefore, investigating those series can be more useful, because other test results would be more trustable.

Considering the series of return to an odd power (17), for all the coins other than XRP, SOL, and LUNA, randomness tests are against efficiency, and all other tests in accordance with efficiency.

- SOL and LUNA: Even the randomness tests are in accordance with weak form of efficiency.
- XRP: Ljung-Box and BDS test give evidence against efficiency for this coin. Moreover, spectral shape tests also show this series does not follow a normal distribution.

Hence, we can state that eight out of nine cryptocurrencies are weakly efficient.

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