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WEAK-FORM EFFICIENCY TESTING ON BITCOIN

Bachelor's thesis

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I hereby declare that I have compiled the thesis independently
and all works, important standpoints and data by other authors
have been properly referenced and the same paper
has not been previously presented for grading.

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TABLE OF CONTENTS

ABSTRACT

Cryptocurrency has gained a significant amount of attention due to its exponential growth throughout the years, specifically Bitcoin (BTC), which will be investigated based on its historical price movements. The primary aim of this thesis is to delve into Bitcoin and implement weak-form efficiency testing based on the Efficient Market Hypothesis (EMH) to identify how past price information has affected future price movements. The way this is investigated is by having three separate time intervals and sample periods and analysing them. The time intervals were the following: 1-minute intervals between 4^{th} of April 2024 to 9^{th} of April 2024, 1-hour intervals between 10^{th} of January 2024 to 9^{th} of April 2024 and 1-day intervals between 26^{th} of December 2013 to 8^{th} of April 2024 with all data extracted from TokenInsight. Each time interval will be separately investigated by utilizing two different tests to indicate whether the sample period has experienced reversals, randomness or momentum determining its efficiency. The utlized statistical measurements were the Hurst exponent (R/S analysis) and the Moving Average Convergence Divergence (MACD). The findings of this empirical study indicate that based on the Hurst exponent, each time interval showcased long-term memory and persisting momentum countering the weak-form testing. In addition to this, based on the MACD testing, inefficiencies were detected, however progressively decreasing heading to be more efficient.

Keywords: Bitcoin, weak-form, Efficient Market Hypothesis (EMH), Hurst exponent, Moving Average Convergence Divergence (MACD)

INTRODUCTION

Cryptocurrencies being one of our modern worlds most advanced technological innovations have experienced exponential growth since it's introduction in a relatively short time period. The attention digital currencies have been able to attract has become a popular phenomenon to the public and the financial sector. The most magnetizing cryptocurrency Bitcoin (BTC) has sparked an interest in researchers, economists, investors and more due to it's technological advancements and potential to alter the finance sector.

Bitcoin operates with blockchain technology paired with a decentralised network providing the users of it anonymity and non-reliable transactional authetication from third parties such as financial institutions like banks. Concerns have been issued regarding Bitcoins price fluctuations and unpredictibility making it a popular topic for efficiency based research. The purpose of this thesis is to delve into the financial aspects of Bitcoins past prices and examine if the price of Bitcoin can be predicted or not through momentum and reversals. The way this is executed, is by utilizing the weak-form of the Efficient Market Hypothesis (EMH), which was developed by Eugene F. Fama (1970). In accordance to Fama (1970), markets can only be identified as ''efficient'' when asset prices fully relfect public and private information. In essence, on the basis of Fama (1970), predictability cannot be done through historical information but works completely randomly.

This research uses three separate timelines the analyse if Bitcoin prices examine a weak-form of efficiency. One of the three chosen timelines deals with 1-minute price fluctuations of the Bitcoin prices from a sample period of seven days. The chosen timeframe investigates the most present data available during the examination being the 4th of April 2024 to 9th of April 2024. The second timeline deals with Bitcoin prices with an interval of 1-hour fluctuations for three months / 90 days. This timeframe includes prices during the 10th of January 2024 all the way to April 9th 2024. The third, being the final timeframe of this research, includes Bitcoin prices from the 26th of December 2013 all the way to 8th of April 2024. All of the data was extracted from a free access online platform known for cryptocurrency data tracking named TokenInsight due to the availability

Link: TokenInsight https://tokeninsight.com/en/coins/bitcoin/historical, used to extract Bitcoin historical price data of easily accessabile time intervals of digital assets. The author notes that the extent of available crypto data tracking platforms might alter the results due to marginal price differences.

This research utilises two different analytical measurement tools to indicate Bitcoin price efficiencies with the Hurst Exponent (R/S Analysis) and the Moving Average Convergence Divergence (MACD) method. Both of these methods will be implemented to each time interval separately for further analysis to compare the results within each other. The ultimate goal is to answer the research question and test out the hypothesis, which are the following:

The research question for attemting to investigate:

- Do Bitcoin prices examine a weak-form of efficiency based on the Efficient Market Hypothesis (EMH)?

Hypothesis based on the research question:

- H0 = Past informaion and historical prices do not provide predictive power for future price movements of Bitcoin.
- H1 = Past information and historical prices do provide predictive power for future price movements of Bitcoin.

A determined thesis structure will be followed to demonstrate the way of conduction. The first chapter will include the literature review, where the author delves into cryptocurrency and the fundamentals of it. This will be follow by Bitcoin and its fundamentals on how it operates. After this, an overview of the Efficient Market Hypothesis (EMH) and the specifications of different forms and importance of it. The first chapter will end with information about the previous studies regarding cryptocurrency market efficiency, Bitcoin price predictibility and other relevant topics followed by a short chapter on how the hypothesis were developed for this paper.

The second chapter will touch basis on the data and methodology. Specifically it will address what data has been used to conduct this thesis, what the data extraction point and process was and what was the method of this study. This will also include a table with the authors calculations of the descriptive statistics regarding the utilised dataset for investigation. The methodology part will delve deeper into the description of the utilised efficiency measurement tools being the Hurst exponent (R/S Analysis) and the Moving Average Divergence Convergence (MACD) method providing explanations of what they are and what they are used for.

Third chapter will analyse the results of the calculations in detail paired with a short discuission and section providing an overview on the limitations of the research. This section will include two separate statistical tables to indicate the results of both measurements for all time intervals. This will be followed by the limitations of the research, which will provide an overview of what previous studies have done, how this would differenciates itself from others, what could have been done for further improvements and overall complications and meantion worthy aspects that impacted the investigation.

Once these chapters have been covered, the thesis will move on to the conclusion section, where the author focuses on comparing the results and analysis to the initial research question and the stated hypothesis to draw a finalised conclusion if the research had reached its goal or not. It will also shortly summarise the entire research paper into a shorter version to properly idealise the core of it.

After this the paper shows its list of references with the used academic literature to conduct this thesis paired with the appendixes including the R-Studio coding sources, datasets and summarised statistics of calculations done in R.

1. LITERATURE REVIEW

In this chapter the author delves into giving an overview of what the definition of cryptocurrency is and the works behind it including what decentralized technology and blockhain is. In addition to this, an overview of Bitcoin (BTC) will also be included with details on how it works and what the potential of it is. This will be followed by an overview of the Efficient Market Hypothesis (EMH) regarding what it is, what the three forms of it are and the importance of it. After this, a sub-section with literature reviews and empirical background on Bitcoin, its efficiency and predictability will close up this chapter.

1.1. Cryptocurrency

Cryptocurrency is one of the worlds most advanced technological innovations that has been able to atract a significant ammount of peoples attention through a short period of time. A phenomenon that was introduced to the modern world has been able to impact the publics financial capabilities and become a worthy asset globally. The representation of cryptocurrency is also identified as digital currencies, digital assets, virtual currencies or virtual assets (Zohuri et al., 2022).

Cryptocurrencies have a market of their own from which the public can freely purchase or sell assets through various third party online platforms that provide precise informtaion on crypto data tracking. As of 12th of March 2024, there are 724 different exchanges that give access to the public according to CoinMarketCap. In addition to this, as of 12th of March 2024, there are 13,217 cryptocurrencies in cirulation in accordance to CoinMarketCap, however some may be worth nothing and some may be inactive.

Cryptocurrency separates itself from any other traditional form of currencies due to the fact that they are not physical and cannot be physically obtained but also because they are not controlled by financial institutions such as central banks or any government, making digital currencies non-reliable to transactional monitoring by them (Zohuri et al., 2022).

Cryptocurrency works mainly through through a decentralized network database utilizing blockchain technology, however some are centralized. Decentralized technology enables cryptocurrencies to scatter non-reliably through the blockchain database, which stores all

Link to: CoinMarketCap https://coinmarketcap.com, used to indicate approximate number of available cryptos transactional history indicating ownership of each digital asset. The combination of blockchain technology, decentralized technology and cryptography gives cryptocurrency the ability to not be overseen or controlled by any govenrment or financial institution (Zohuri et al., 2022). Cryptocurrencies utilize cryptography, which enables data confidentiality to make transactional actions firm and more secure for its users by protecting them from unauthorized data access and data manipulation (Rivest, 1990)

The blockchain technology is what lies beyond cryptocurrencies as it plays a crucial role in terms of maintaining cryptocurrency transaction records. A blockchain refers to a computerized database network where data based information is entered after transactional activities and stored formed as blocks, which upon fulfillment continuize to another block creating a ‘’blockchain’’ (Sarmah, 2018). The fundamentals of blockchain includes two specific parts being the transaction and the block. The transaction indicates a transactional activity initiated by a peer, while the block indicates the data collection part where the transaction is collected and stored. Blockchains can either be private or public, where public generally permits all users and private gives limited access for more security and protection from data manipulation. Blockchains can be divided into three networks being centralized, decentralized and distributed with all of them having different characteristics. A centralized blockchain indicates that in terms of decision-making, only one individual has authority to oversee the activity (Sarmah, 2018). A decentralized blockchain, also used for Bitcoin, indicates a more complex decision making process as the activity is more spread and does not require authorized authentication from third parties, making it a peer-to-peer transaction (Nakamoto & Bitcoin, 2008). A distributed system refers to a situation where all peers involved have information symmetry of the database giving them full transparency to the data synchronized between them (O’Dwyer, 2015)

1.2. BITCOIN (BTC)

Bitcoin is a cryptocurrency, which was developed in 2008 and publicly introduced in 2009 anonymously under the developer name of Satoshi Nakamoto (Segendorf, 2014). Since its introduction to the public, it has been able to attract a significant amount of attention and grow exponentially throughout the years. Bitcoin set a modern trend, which initiated a major intrest for the public to familiarize with cryptocurrencies and invest in them, followed by a wave of the creation of various new virtual currencies such as Ethereum (ETH), Tether (USDT), Solana (SOL) and Binance Coin (BNB) and many more. As a cryptocurrency industry leader, Bitcoin overrides all other digital currencies in terms of price and market capitalization.

In the table and figure below, the author demonstrates a graphical an numerical representation of the priorly mentioned currencies paired with theyre market capitalization and percentage of the total market cap. Data is extracted from TokenInsight.com (TokenInsight, 2024) based on available information on the 1st of April 2024 and calculated in Excel.

Table 1. Cryptocurrency Market Capitalization

Name	Market capitalization	Percentages
BTC	1 367 049 788 104,00 €	50,63 %
ETH	425 544 208 046,64 €	15,76 %
USDT	104 446 647 127,00 €	3,87 %
SOL	87 585 563 991,90 €	3,24 %
BNB	87 279 598 324,55 €	3,23 %
Total	2 071 905 805 594,09 €	76,74 %
Total Market Cap	2 700 000 000 000,00 €	100 %

Source: Author’s calculations based on data from Appendix 3.

As represented in Table 1, we can see that Bitcoin (BTC) leads the cryptocurrency industry significantly having the largest market capitalization at 50,63%. The second largest cryptocurrency is also vastly known and has been able to staple itself as a strong cryptocurrency industry second being Ethereum (ETH) 15,76%. Other cryptocurrencies in active circulation equal to 33,61% of the total market capitalization. The author notes that Table 1 ‘’Total’’ refers to the summarised value of the five digital currencies used to exemplify portions of the market capitalization (Total = Bitcoin BTC + Ethereum ETH + Tether USDT + Solana (SOL) + Binance BNB). The virtual currencies left out of this example cover the remaining portion of the market capitalization being 23,26%. The author believes that with the plateaued state of other active digital currencies within the market, the top ten most significant currencies will be stationary and only compete amongst each other, in terms of market capitalization value.

1.2.1. How does Bitcoin work?

Bitcoin operates through a decentralized blockchain network secured by cryptography. Without having a centralized system, Bitcoin does not require any intermediaries to authenticate transactional activities but operates on trust through a peer-to-peer process with full anonymity as its own electronic cash system (Nakamoto & Bitcoin, 2008). Peers associated with Bitcoin operate individually through various third-party crypto platforms such as CoinMarketCap, where no one has ownership of it but only control based on transactional information such as history of prices and more. Once a transaction between peers has taken place, a signature with an encrypted private key must be done to fully execute the buy or the sale of Bitcoin, which is followed an update to the blockchain and confirmation from the miners. Bitcoin transactions between two peers do not have a dependency for any governmental authority to confirm the activity resulting in minimal processing time and minimal fees (Nakamoto & Bitcoin, 2008)

1.3. Efficient Market Hypothesis (EMH)

As one of the essential corner stones of finance and theories used to study the overall behaviour of the markets, the efficient market hypothesis is one of many accompanied by others. A financial market can only be identified as efficient when all the information available are transparently reflected ‘’fully” (Fama, 1970). In essence, Fama (1970) atriculates in his hypothesis that having consistency in receiving higher than average returns is not possible because of the information reflection of all prices. However, this theoretical concept has been questioned because of the altering of market dynamics due to technological advancements that have influenced other mechanisms (Li, 2024)

In the next sub-chapter, the author takes a deeper dive into providing an overview of the different forms of the efficient market hypothesis.

1.3.1. Different EMH forms

The efficient market hypothesis includes a division of three separate forms that provide assistance on analysing the financial markets. The information provided from each form of efficiency differ and may always alter depending on the type, which can be defined as unpublished private information, published public information and historical information (Kang et al., 2022). Market efficiency can be identified as weak, semi-strong or strong depending on results.

Markets that result in a weak-form of efficiency cannot use data from the past as leverage to analyse its predictibility for its future (Malkiel, 2003). According to Malkiel (2003), stock prices cannot be predicted and ethusiast who invest in them cannot receive any irregular returns, which is due to stock market prices being unpredictibly volatile and random.

Semi-strong market efficiency indicates that the stock prices of the past and present information that are publicly available provide assistance for future altering and adapting of stock prices because of market anticipation (Fama, 1970). Thus, this form of efficiency does not support the predictability of price fluctuations based on thorough analysis of available information (Fama, 1970)

The strong form of market efficiency presumes that the present stock prices fully reflects all of the three forms both public and private information (Degutis & Novickytė, 2014). The market cannot be beaten by enthusiastic investors with access to inside information (Fama, 1970).

1.3.2. Importance of EMH

The efficient market hypothesis is a commonly used theory for financial economist to investigate forms of efficiencies in corporate finance, investment strategies, risk management and more (Sewell, 2012). Extensive research has been done for several different digital assets and many more financial aspects, which will be exemplified by the author in the next sub-chapter. Price determination in financial markets with assets depends on the peers who invest in stocks and pay for them according to the unpredictible price at the time. As prices of stocks and cryptos are highly volatile, this makes systematic price prediction highly unlikely and impossible to do.

1.4. PREVIOUS STUDIES FROM BITCOIN

In this section the author will provide and overview on previous studies that have investigated Bitcoin, cryptocurrency, efficient market hypothesis and and predictibility.

Cryptocurrency market efficiency has gained attention throughout the year since the introduction of virtual assets. Mostly the attention skews towards Bitcoin due to it being the industry leader. Endless studies have been conducted to properly delve into the world of cryptocurrencies to further understand how they work and whether they are efficient or not. Several academic literatures have focused on crypto efficiency in the early stages, which resulted primarily in inefficienses. As time has passed, cryptos have developed exponentially, Bitcoin in this thesis, which provide a more recent insight on price efficiencies.

One of the first studies focusing on the cryptocurrency market efficiency, focus being Bitcoin BTC, was investigated by various tests to search for characteristic evidence to support the conclusion of the cryptocurrencies being efficient or inefficient (Urquhart, 2016). Based on the results supported by thorough analysis, Bitcoin BTC did conclude to be more inefficient rather than efficient, however Urquhart (2016) was convinced that time supported by the growth of Bitcoin BTC would result in the improvement of its efficiency. This study was conducted with the closing prices of Bitcoin from three separate time periods and were extracted from an online platform, which combines the prices of Bitcoin from multiple sites due to its popularity to estimate a weighted average price.

Investigating the efficiency with a primary focus on daily returns in the Bitcoin BTC market was also conducted with a sample pair concluding that only the first sample turned out to have clear efficiency (Nadarajah & Chu, 2017). This study focused on Bitcoins prices from the beginning of August 2010 all the way to 31st of July 2016 with three separate periods divided as the following: total period from 1st of August 2010 to 31st July 2016, 1st of August to 31st July 2013 and 1st of August 2013 to 31st of July 2016. Similarly, Urquhart (2016) investigated Bitcoin with the same data. This study also used the same tests for market efficiency examination with the same hypothesis as well. Based on the results of this study and the analysis of eight different tests it was concluded that Bitcoins returns indicated weak efficiency (Nadarajah & Chu, 2017).

The crypto market efficiency was also approached with a focus on the price volatility of the Bitcoin BTC market by performing a test to examine the unitary test, however this resulted in the indication of the market being strongly inefficient (Aggarwal, 2019). The goal of this study was to investigate if Bitcoins prices follow a random walk model or not leading to using the following time period as the frame: 19th July 2010 to 20th March 2018. The prices of Bitcoin extracted from an online platform were followed by calculations of the natural logarithm for analysis and measurement purposes (Aggarwal, 2019).

A study by (Wei, 2018) was also completed by examining how Bitcoin BTC liquidity and it's efficiency and relationship between the two impact the market. The findings of the study conlcluded that efficiency improves as liquidity rises. In addition to this, the findings indicate that as time grows, efficiency grows and inefficiency decreases (Wei, 2018). This study investigated a total of 456 cryptocurrencies focusing on the prediction of the returns of crypto, liquidity and volatility changes and fluctuations. This study followed the same calculations as Urquhart (2016) to test out market efficiencies through measurements and analysis.

Cryptocurrency markets have also attracted lots of focus due to the prices, how volatile and fluctuate they are primarily concluding the inefficiency of digital assets initially in the beginning stages.

Analysis done by (Köchling et al., 2019) regarding the efficient market hypothesis EFM (Degutis & Novickytė, 2014) and its form of weakness was projected into Bitcoins BTC pricings and futures to further investigate the predictability of them. The study resulted in pricings and futures being restrictedly predictable to a certain extent (Köchling et al., 2019). This study had two samples investigating the following time periods: 10th December 2017 to 10th April 2018 and August 10th 2017 to December 2017 with a main focus on testing out market efficiency by examining autocorrelation and randomness of the price returns (Köchling et al., 2019). This study also investigated long term memory of the sample periods by using the Hurst exponent, which was also used as one of the measurement tools of this paper.

The expansion to examine other digital currencies such as Ethereum ETH, Litecoin LTC, Solana SOL, Ripple XRP and many more has been able to provide a deeper comprehension on how efficient the cryptocurrency market is (Caporale & Plastun, 2019; Bouri et al., 2021; Benzekri & Özütler, 2021; Kang et al., 2022; Kristoufek & Vosvrda, 2019). These studies have taken a deeper dive into the crypto currency market and shifted their focus on other digital assets in the industry providing more information and relevant data on other currencies. With Bitcoin being the industry leader and most popular virtual currency, extensive research on other currencies is crucial to provide perspective towards other cryptos.

An examination of four popular cryptocurrencies being Bitcoin BTC, Litecoin LTC, Dash DASH and Ripple XRP was conducted to investigate how the daily returns of them keep their persistency. This was done by utilizing the R/S analysis (Hurst, 1951) and Hurst exponent to identify trends and patterns within the prices (Kroha & Skoula, 2018). This study resulted in all investigated coins being inefficient, however they tended to be decreasingly inefficient (Caporale & Plastun, 2019). The main focus was to investigate how the day of the week impacts the movements of the chosen cryptos by utilizing advanced approaches such as the trading strategy to assess results (Caporale & Plastun, 2019).

A study by Kristoufek & Vosvrda (2019) was done to detect cryptocurrency efficiency through a specific timing period based on the following digital assets; Bitcoin BTC, Dash DASH, Litecoin LTC, Monero XMR, Ripple XRP and Stellar XLM. Extensive analysis based comparison between these currencies resulted in them being inefficient (Kristoufek & Vosvrda, 2019).

1.5. HYPOTHESIS DEVELOPMENT

The hypothesis to this thesis was developed by doing extensive research on the topic and going through several academic literatures regarding Bitcoin price efficiency and prefictibility to better understand what prior studies have found and what they have indicated througout the examination within the given time periods. After going through different research papers, the majority of them desired to investigate whether Bitcoin prices were efficient or not by diving deeper into the historical price data and testing out if they have experienced declining reversals, random walks or uplifting momentum (Urquhart, 2016; Caporale & Plastun, 2019; Nadarajah & Church, 2017; Aggarwal, 2019; Wei, 2018; Köchling et al., 2019). This lead to the author to use the Efficient Market Hypothesis (EMH) to investigate whether Bitcoin prices indicated a weak-form of efficiency durin any of the three time frames. The hypothesis was developed after creating a research question, which was the following:

- Do Bitcoin prices examine a weak-form of efficiency based on the Efficient Market Hypothesis (EMH)?

Once this was correctly formulated and simplified, the thesis was conducted on the basis of the research question. The main goal of this research paper is to investigate if Bitcoin prices have examined a weak-form of efficiency. The hypothesis are formulated accordingly to help analyse the results and to draw conclusions.

Hypothesis based on the research question:

- H0 = Past informaion and historical prices do not provide predictive power for future price movements of Bitcoin.
- H1 = Past information and historical prices do provide predictive power for future price movements of Bitcoin.

2. DATA AND METHODOLOGY

In this chapter the author will provide an overall description of the data that was used to conduct this thesis and where the data orginated from followed by a descriptive statistics table demonstrating the samples time period and interval periods results.

2.1. Data

The dataset utilised for this thesis has been obtained from Tokeninsight (TokenInsight, 2024), which is a independent third party, open-source online community focusing on analytical data to provide precise information regarding the blockchain sector of the crypto industry. The data consist of three different sample periods of Bitcoins prices and three different weighted time measurement periods. The first sample was a seven day time period with a price interval of 1-minute fluctuations beginning from 4th of April 2024 to the 9th of April 2024. The second sample was a ninety day time period with a price interval of hourly fluctuations beginning from the 10th of January 2024 to the 9th of April 2024. The third sample was the all time price data of Bitcoin with daily price fluctuations from 26th of December 2013 to the 8th of April 2024.

The first sample period beginning from 4th of April 2024 to the 9th of April 202 including a total of 11520 observations points of the prices of Bitcoin. The second sample period beginning from the 10th of January 2024 to the 9th of April 2024 consisted of 2160 observations and lastly, the third sample period was the all time price data of Bitcoin with daily price fluctuations from 26th of December 2013 to the 8th of April 2024, which consisted of 3755 observation points. In total, the full dataset was 17,435 observations after processing and cleaning.

The datasets have been cleaned and re-organized due to empty cells in Excel and an extra column for Bitcoin volatility for more precise and accurate calculations. The datasets were imported into R-Studio for further measurements and calculations to investigate market efficiency. In addition to this, the author must point out that there are multiple various platforms for crypto currency price tracking and other information, which may give a slightly different price for Bitcoin according to the time period of samples and the time of data extraction. Prior studies have used platforms that require registration and payments for access and some have used other reliable sources, which have not required registration nor payments.

2.1.1. Descriptive statistics

The data analysis table with descriptive statistics regarding Bitcoins prices on each time interval and sample period are visualised in Table 2.

Table 2. Descriptive statistics on Bitcoin BTC price

Interval Period	Sample Period	N	Mean	Median	Standard Deviation	Min	Max	Skewness	Kurtosis
Per minute	4th April 2024 - 9th April 2024	11520	68179,49	67979,67	1876,83	64691,84	72581,56	0,37	-0,73
Per hour	10th Janruary 2024 - 9th April 2024	2160	55723,91	52030,03	11445,43	38694,08	73498,05	0,04	-1,65
Per day	26th December 2013 - 8th April 2024	3755	14667,73	7683,64	17238,63	172,15	73068,26	1,27	0,64

Source: Author's calculations based on data from Appendix 3.

The descriptive statistics for Bitcoins price is shown for each investigated time interval periods. For each sample period, the amount of observations differ due to different intervals and time periods. The highest mean was for the minute price interval, which was 68179,49, followed by hourly interval 55723,91 and daily interval being 14667,73. The median for all three intervals were lower than the mean with the biggest difference being 6984,09 on the daily prices. The highest standard deviation 17238,63 was for the daily prices of all time, while the smallest 1876,83 was the minute intervals for seven days. The difference is so major due to the fluctuative price volatility of Bitcoin between 2013 and 2024. The minimum and maximum values also indicate major price movements in specific time periods. For instance the lowest minimum on Table 2 was 172,15 while the highest was 73068,26 in the longest interval period. The skewness of all three were positive indicating that the data values were right tailed or right skewed. A skewness of 0,37 indicates positively that values are higher than the mean. Skewness of 0,04 is significantly close to zero meaning that the data is almost neutrally symmetrical with no skewness to left or right, negative or positive. Lastly the skewness of 1,27 shows a very significantly right tailed skew. The distribution of the datapoints measured by kurtosis were dominantly negative. A kurtosis value of -0,73 indicates that the distribution was ''platykurtic'', similarly to the value -1,65 meaning that the likelyness of finding outliers such as extreme values within the dataset is less likely than the value 0.64, thus the value is relatively close to being negative.

Other studies have done extensive research on older data with different time intervals and sample periods, which have resulted in significantly different statistics. A relevant example from Urquhart

(2016) who utilized older data from between years 2010 to 2017 in two different studies with a interval period of 5-minutes to investigate the closing prices of Bitcoin.

2.2. Methodology

This study uses a quantitative approach to calculate whether Bitcoin prices have been efficient within the three given time intervals and sample periods. The amount of observations used to conduct this study was 17,435 price points of Bitcoin in specific times. This study uses two different test to further examine the efficiency and predictability of Bitcoins prices. As Fama (1970) has stated that the market is only efficient when the information is available and fully reflectable with all three public and present information. The author points out that in this study, we are testing out the ‘’weak efficiency’’ from the efficient market hypothesis and implementing it to the Bitcoin prices and its predictability. The data used in this thesis is purely historical and only includes Bitcoins past prices meaning that we are testing out the form of ‘’weak-efficiency’’.

The Hurst exponent used in this thesis is one of the many ways to investigate market efficiency by running tests to determine price trends, reversals and momentum. Originally the Hurst exponent made by Harold Edwin Hurst was developed in the purpose of hydrodynamics to optimally detemine the size of a dam in the Nile hiver (Hurst, 1951). The hurst exponent works as a tool for statistical measuring purposes to identify long-term memory in a specific time period. In accordance to (Di Matteo et al., 2005) the hurst exponent tool can be implemented to determine both correlated and non-correlated information from long-run memory. Di Matteo et al., (2005) also argues that short-term memory may cause difficulties regarding the hurst exponent due to the sensitivity to outlying variables. Several academic papers have applied this method to asses and differentiate structured development (Di Matteo et al., 2005)

The Hurst exponent provides a numeric value between 0 and 1, enabling the categorization of the time series being persistent negatively meaning reversal, random persistent positively meaning momemtum (Kroha & Skoula, 2018). According to Kroha & Skoula (2018), the category can be divided into three:

- H ≤ 0.5 indicating reversal action, ultimately meaning that values decrease and have a negative correlation
- H = 0.5 indicates randomness meaning that there is no predictability in momentum or reversal within the time series
- H 0.5 ≥ 1 indicating long-term momentum and potential predictibility with a positive correlation

The hurst exponent also known as the rescaled range method (R/S analysis) helps determine how unpredictible, random or predictible values are within a specific time series. The equation utilized to test financial aspects for research (Qian & Rasheed, 2004) can be defined as the following:

$$\mathbb{E}\left[\frac{R(n)}{\mathrm{S(n)}}\right] = Cn^{H} \tag{1}$$

where

$\mathbb{E}$ = the expected value

n = the data points within the preferred time series

$R(n)$ = the range of (n) standard deviations from the mean

$S(n)$ = the sum of the (n) standard deviations

C = the constant

H = the Hurst exponent

Another method used in this thesis to assist the detection of price trends of Bitcoin prices was the Moving Average Convergence Divergence (MACD). In financial analysis, this method is used to measure and better understand how the market prices move making this an extremely effective measurement tool for investigating indicaotors of momentum within the data. The Moving Average Convergence Divergence (MACD) method was created by Gerald Appel in 1970 to provide assistance to traders revealing changes in terms of direction of price trends enabling traders to make evidence based choices on to either exit a trade or enter it (Appel, 2005). This measures the market conditions within a specific period of time based on price fluctuations. The way MACD operates, is by calculating moving price averages between two variables known as EMA's. Exponential Moving Averages (EMAs) are most commonly divided into two time cycles being a 12-day and a 26 day period, which are indicated as short-term EMA and long-term EMA according to Appel (2005). In addition to this, MACD consist of of two other main components, which are known as signal line and MACD histogram. The signal line is a shorter EMA time cycle of 9-days and the MACD histogram is generally a visual plot to support the visualisation of price movements and directional trends (Appel, 2005)

This tool indicates trends by demonstrating the correlated or non correlated relationship between the two default EMAs (Hafid et al., 2023). The equation used to calculate Moving Average Convergence Divergence (MACD):

$$MACD = EMA_{N1} - EMA_{N2} \tag{2}$$

where

$MACD$ = the Moving Average Convergence Divergence indicator

EMA_{N1} = the short-term 12-day Exponential Moving Average of prices

EMA_{N2} = the long-term 26-day Exponential Moving Average of prices

To better understand the MACD method, cumulative returns and distributions of returns has also been calculated and visualised to showcase how Bitcoin prices have changed during the investigated time intervals to see the overall performance of it. In addition to this, buy and sell positions were used to strategically examine how the short and long positions looked like during the time periods. The cumulative returns represent the percentage change of Bitcoin prices during the given time indicating where losses of profits were experienced. A t-test was also performed to measure the statistical significance of each interval.

3. RESULTS AND LIMITATIONS

This chapter will include the authors analysis and overview regarding the results of each exercised test conducted to determine if Bitcoin prices have experienced undpredictibility, randomness or momentum during the examined time frame followed by a discussion section of the limitations experienced during the analyzation of the findings.

3.1. Results

Table 3. Results of the Hurst exponent test to determine each sample period.

Interval period	Time period	R/S Hurst
Per minute	4th April 2024- 9th April 2024	0,905
Per hour	10th January 2024- 9th April 2024	0,901
Per day	26th December 2024- 8th April 2024	0,891

Source: Author's calculations based on the dataset in Appendix 3.

The Hurst exponent (R/S Hurst) for minute intervals resulted in 0,905, for hourly intervals 0,901 and lastly for daily intervals for all time 0,891 with a significance level of 0,05. All of the results are above 0,89 and under 1, which signify momentum of price fluctuations. Based on the results of all interval periods, the dataset does provide a clear indication of persistence and long-term memory. We must take into consideration that each dataset deals with a different time period of examination but all shared Bitcoins growing trend. As Hurst exponent divides into three categories being $H \leq 0.5$, $H = 0.5$ and $H\ 0.5 \geq 1$, our results fall into the third category ($H\ 0.5 \geq 1$), which implies that during the examination periods each interval demonstrated a positive correlation with momentum based on long-term memory of prior prices. However these results counter with the theoretical view of prices having true randomness leading the author to reject the null hypothesis.

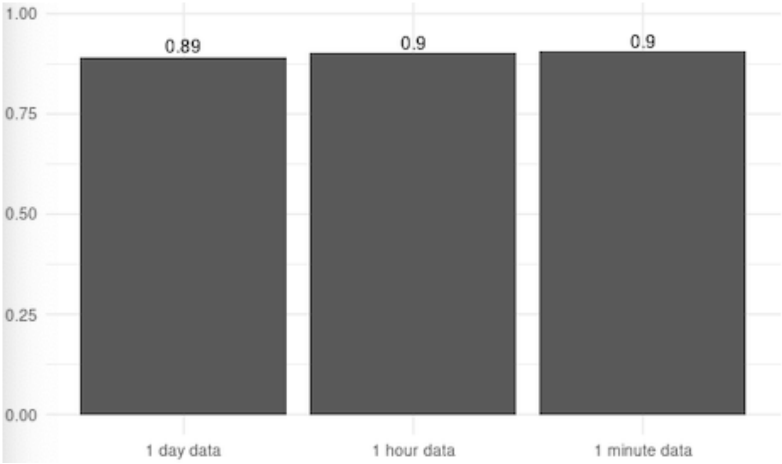
The results of the R/S Hurst in Table 3 is important as it can be compared to other similar studies that have investigated Bitcoin prices during a different time. For instance, a study conducted by Urquhart (2016) investigated Bitcoin price efficiency with several tests with Hurst exponent being one of them, where the examined time frame between the years 2013 and 2016. It is crucial to note that the growth of Bitcoins prices have been exponential when comparing prior studies to the authors research with updated data. The values resulted from Urquhart (2016) research were $H \leq 0.5$, which indicated that Bitcoin prices decreased and showed negative price correlation. With no auto-correlation, Urquhart (2016) research demonstrated signs of reversals.

A study conducted by (Caporale & Plastun, 2019) examined four popular cryptocurrencies at the time being Bitcoin BTC, Litecoin LTC, Dash DASH and Ripple XRP aiming to investigate daily price returns and their persistency. The R/S Hurst was implemented in this study, which similarly to Urquhart (2016) study, indicated signs of inefficiency as the value of R/S was lower than 0.5. However, Caporale & Plastun (2019) research indicated decreasing inefficiency.

Initially the first studies regarding Bitcoin and its efficiency primarily resulted in being inefficient. In addition to this, various other empirical researches on Bitcoin prices have resulted to be inefficient. However, Urquhart (2016) argues that the evolution of Bitcoin through time would positively correlate with its improvement on efficiency.

In the next page the author will demonstrate visualisations in figures regarding the Hurst Exponent calculations paired with short analysis, where one figure will show the exponent results and the remaining figures will showcase a more in-depth version of the last 10 sub periods and changes within the time intervals.

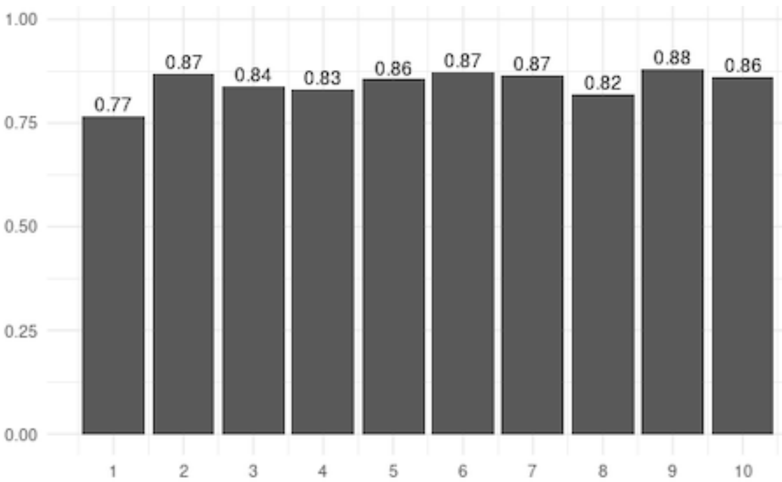
Figure 1. Hurst Exponents by Time intervals



Source: Author’s calculations based on data from Appendix 3.

The Figure 1 represents the Hurst exponents by time intervals in the following order: 1-day data Hurst 0.89, 1-hour data Hurst 0.9, 1-minute data Hurst 0,9. All exponents resulted in being relatively high indicating long-term price memory countering the weak-efficiency testing.

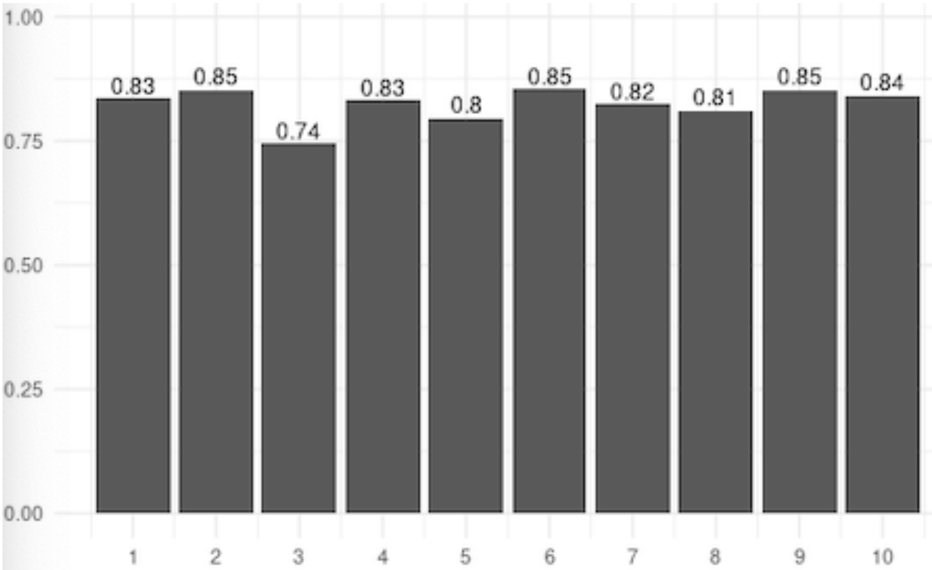
Figure 2. Hurst Exponents, 1-minute data, last 10 sub periods



Source: Author’s calculations based on data from Appendix 3.

The Figure 2 represents how the exponent has changed during the last 10 sub periods within the time interval.

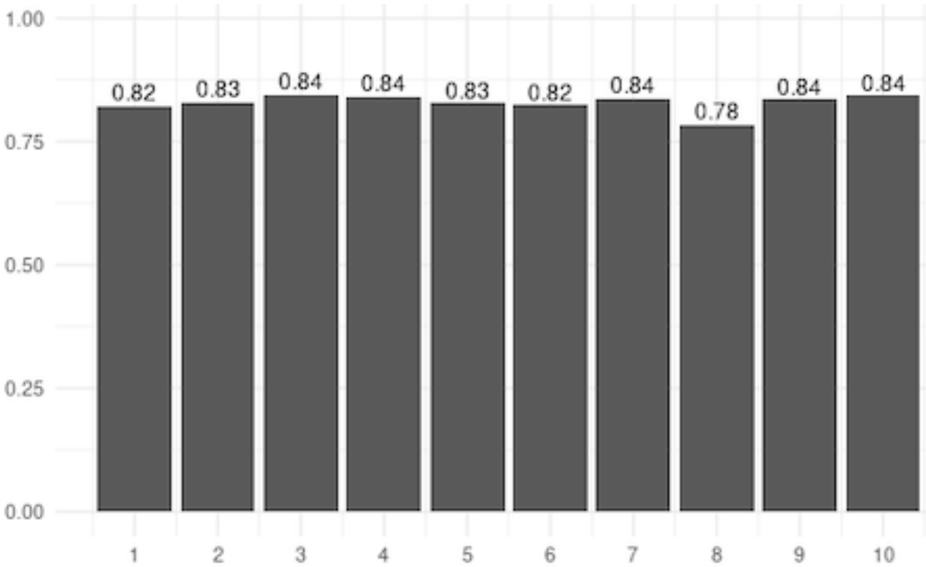
Figure 3. Hurst Exponents, 1-hour data, last 10 sub periods



Source: Author’s calculations based on data from Appendix 3.

Figure 3. represents how the exponent has changed during the last 10 sub periods within the time interval.

Figure 4. Hurst Exponents, 1-day data, last 10 sub periods



Source: Author’s calculations based on data from Appendix 3.

Figure 4 represents how the exponent has changed during the last 10 subperiods within the time interval.

Table 4. Results of Moving Average Convergence Divergence (MACD).

Interval Period	MACD		Signal	
Per minute	Min. :	0.000743	Min. :	0.00076
	1st Qu. :	0.002528	1st Qu. :	0.00255
	Median:	0.003822	Median:	0.00384
	Mean :	0.006824	Mean :	0.00676
	3rd Qu.:	0.007154	3rd Qu.:	0.00721
	Max. :	0.186224	Max. :	0.15836
	NA's :	25	NA's :	33
Per hour	Min. :	0.02913	Min. :	0.03041
	1st Qu. :	0.07067	1st Qu.:	0.07145
	Median:	0.10586	Median:	0.10614
	Mean :	0.20361	Mean :	0.20276
	3rd Qu.:	0.23278	3rd Qu.:	0.23591
	Max. :	1.94118	Max. :	1.82015
	NA's :	25	NA's :	33
Per day	Min. :	-14.6287	Min. :	-12.7005
	1st Qu. :	-2.0313	1st Qu. :	-1.9702
	Median:	0.4304	Median:	0.4310
	Mean :	0.6452	Mean :	0.6434
	3rd Qu.:	3.1884	3rd Qu.:	3.2886
	Max. :	19.9509	Max. :	18

Source: Author’s calculations based on the dataset in Appendix 3.

The results of the Moving Average Convergence Divergence (MACD) were implented to all time intervals separately for comparison reasonings. To analyze the results, we must take into consideration the range between the minimum and the maximum of both MACD and the Signal. In addition to this, attention must be paid to compare the median and the mean.

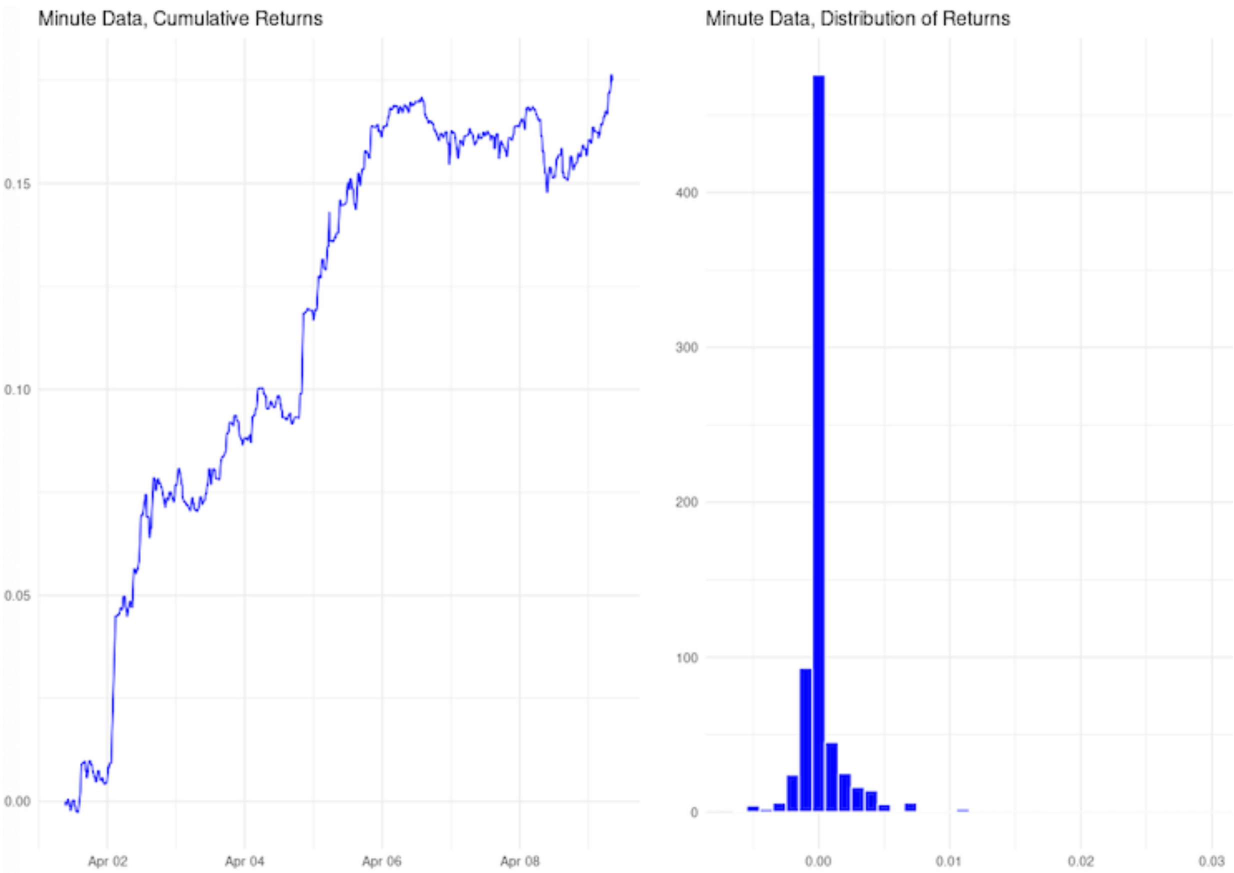
The results indicate that within the 1-minute interval of Bitcoin prices, the values defining the range resulted in a minimum of 0.000743 and a maximum of 0.186224 for the MACD, while the Signal range was 0.00076 to 0.15836 respectively. Demonstration of high volatility of Bitcoin prices can be seen when comparing the minimum to the maximum, where the value of range indicated the level of volatility. For both MACD and Signal, the range was relatively high indicating highly volatile price fluctuations during the 1-minute time intervals. The median values for MACD was 0.003822 with a mean result of 0.186224. Median values for Signal was 0.00384 with a mean of 0.00676. The median values for both resulted in close proximity to one and other, ultimately indicating a central tendency to be slightly skewed to to right side. In addition to this, a greater mean compared to the median indicates that Bitcoin prices experience more momentum and positive fluctuations in comparison to revesal action. A higher mean compared to the median could be due to the dataset having a mixture of both smaller and larger values that could increase the averages. Typically as the means resulted in being greater values than the medians, it can indicate that movements of market dynamics paired with strong momentum could cause inclining movements of the price.

The results of the hourly intervals of Bitcoin were the following: MACD minimum 0.02913 and maximum 1.94118, Signal minimum 0.03041 and maximum 1.82015. The range in both is extremely high compared to the 1-minute intervals, which indicate an even higher volatility influenced by longer period of investigation. In comparison to the 1-minute interval, the higher volatility of prices could be caused by significant price changes. Similarly, the skewness does indicate a right-sided position in terms of the central tendency due to the median values being the following: MACD median 0.10586 and mean 0.20361, Signal median 0.10614 and mean 0.20276.

The results of the daily intervals of Bitcoin were the following: MACD minimum -14.6287 and maximum 19.9509, Signal minimum -12.7005 and maximum 18. The range in both are extremely high compared to other intervals investigated, which results in even more larger price volatility due to the duration of the period. Significant changes in the price are driven by how volatily Bitcoin has been all time. Given the MACD median and mean values 0.4304 and 0.6452 and Signal values 0.4310 and 0.6434 respectively being relatively close to each other, no significant skewness indicating a overall inclining price momentum through the entire time. Note that the largest dataset was the daily changes through all time of Bitcoins price history, which includes a large range of different values because of how volatile the market has been and how the price has changed drastically.

The author will next demonstrate visualisations of the MACD returns data and the Signal data for all time intervals paired with analysis. In addition to this, a demonstration of the price points and both buy and sell signals with the implemented trading stategy will be shown with a simplified version of only 10% of the data.

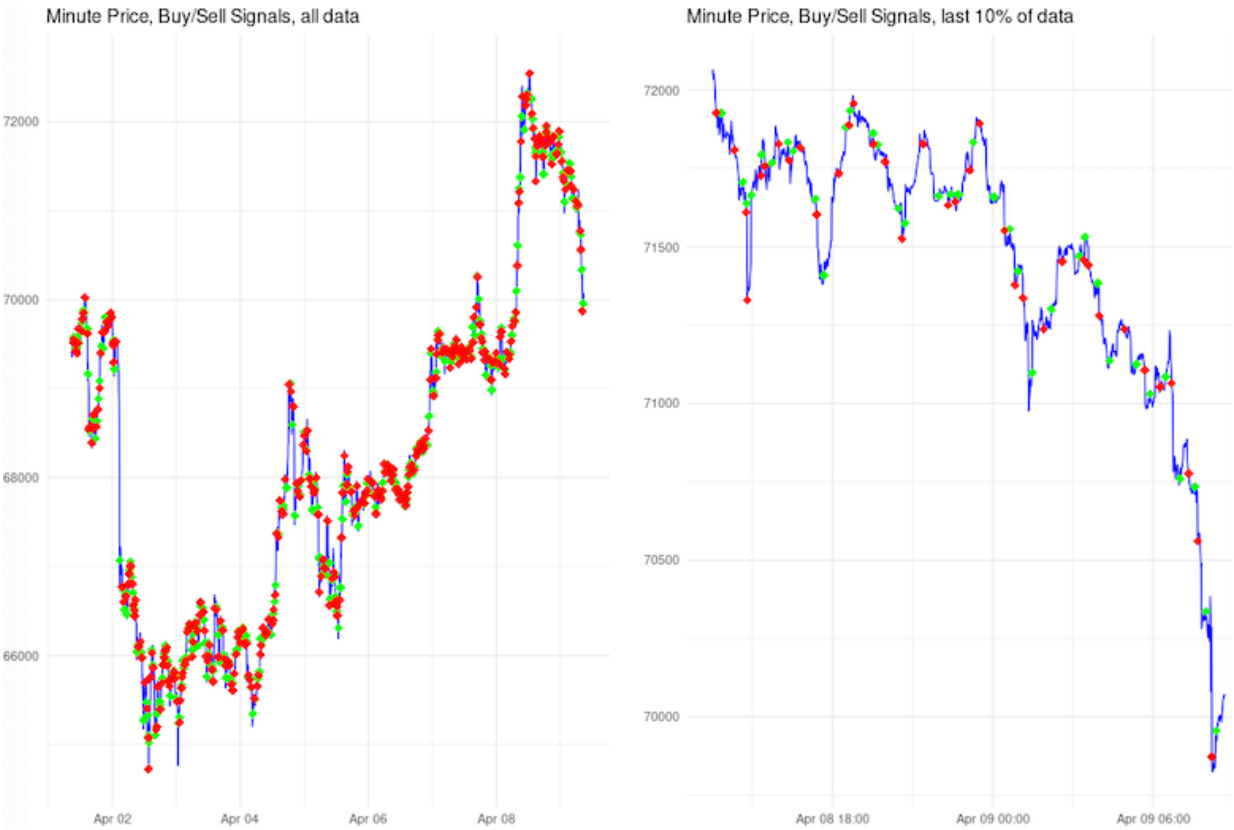
Figure 5. Minute data, cumulative returns (left) Minute data, distribution of returns (right)



Source: Author's calculations based on the dataset in Appendix 3.

Figure 5 showcases the 1-minute data of Bitcoin prices and the calculated cumulative returns on the left side paired with the distributions of the returns on the right. The t-test resulted in a p-value of 0.004626 countering the alternative hypothesis indicating statistical significance. The mean of cumulative returns resulted in 0.000248679. The results indicate that past information of Bitcoin prices do not provide predictive power for the future, meaning that we reject H1 and accept H0.

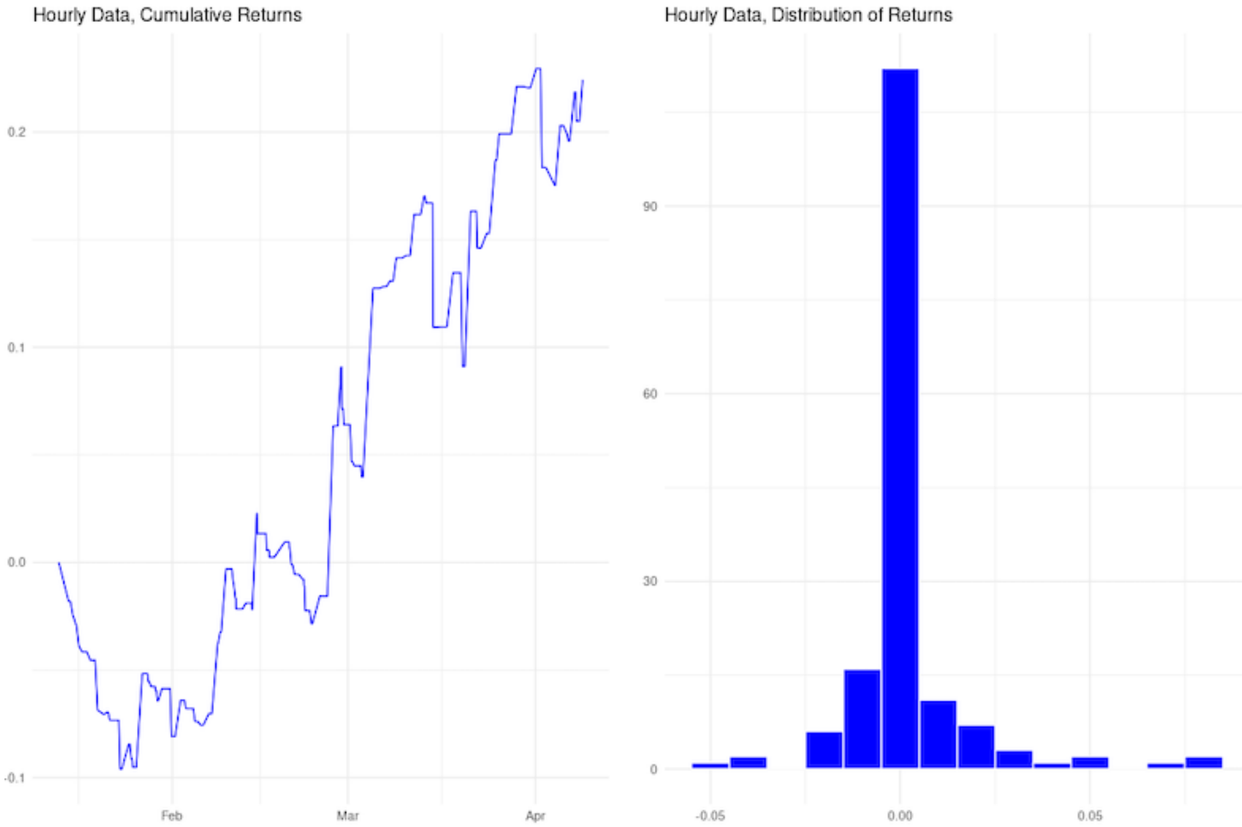
Figure 6. Minute price, buy & sell signals (left) / last 10% of data (right)



Source: Author's calculations based on the dataset in Appendix 3.

Figure 6 represents the implemented trading strategy to visualise long and short positions to analyse losses and profits during the 1-minute intervals dataset. The right side of the figure provides a more clarified version demonstrating the last 10% of the signals, while prices were declining.

Figure 7. Hourly data, cumulative returns (left) Hourly data, distribution of returns (right)



Source: Author's calculations based on the dataset in Appendix 3.

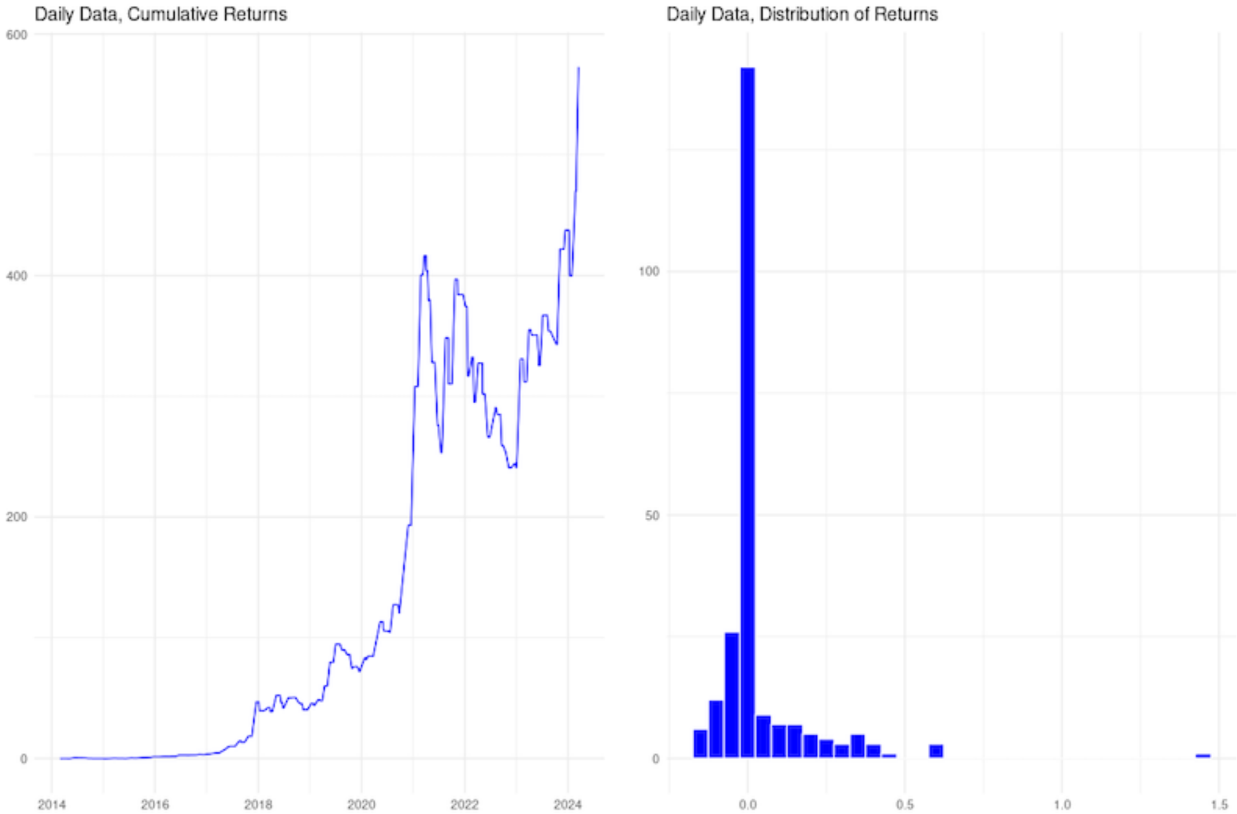
Figure 7 demonstrates the hourly data of Bitcoin prices and the calculated cumulative returns on the left side with the distributions of the returns on the right side. The t-test resulted in a p-value oif 0.263 countering the alternative hypothesis indicating statistical insignificans due to means not being equal to zero. The mean return resulted in 0.00134936. Based on the results, past information of Bitcoin prices in the hourly time interval and given time period do not provide predictive power for future price movements.

Figure 8. hourly price, buy & sell signals (left) / last 10% of data (right)

Source: Author's calculations based on the dataset in Appendix 3.

Figure 8 represents the implemented trading strategy to visualise long and short positions to analyse losses and profits during the 1-hour intervals dataset. The right side of the figure provides a more clarified version demonstrating the last 10% of the signals.

Figure 9. Daily data, cumulative returns (left) daily data, distribution of returns (right)



Source: Author’s calculations based on the dataset in Appendix 3.

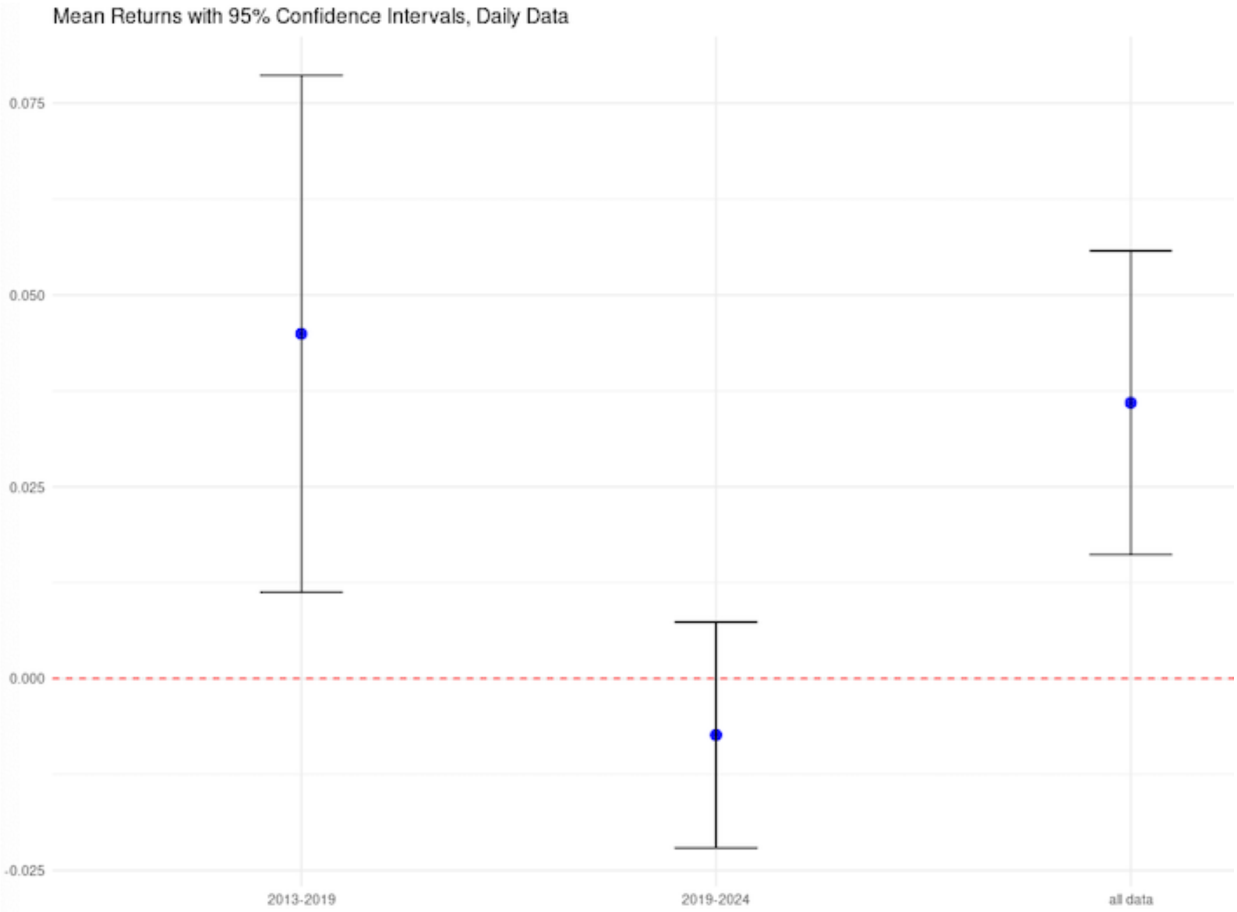
Figure 9 showcases the all time Bitcoin data and the calculated cumulative returns on the left side and distributions of returns on the right. The t-test resulted in a p-value of 0.000421 indicating failure to reject the alternative hypothesis. The returns indicated statistical significance with a mean of 0.03595888.

Figure 10. daily price, buy & sell signals (left) / last 10% of data (right)

Source: Author's calculations based on the dataset in Appendix 3.

Figure 10 represents the implemented trading strategy to visualise long and short positions to analyse losses and profits during the all time daily intervals dataset. The right side of the figure provides a more clarified version demonstrating the last 10% of the signals.

Figure 11. Mean returns with 95% confidence intervals, Daily data



Source: Author’s calculations based on the dataset in Appendix 3.

Figure 11 is a visual representation calculating returns and statistical significance for two sub periods being 2013-2019 and 2019-2024 and also all data. We can identify the mean for both periods with the first sub period having a return mean reaching over zero, second sub period sligthly under zero and all data resulting in over zero. The confidence intervals are visualised with the dark lines giving a high and low limit around the mean dot indicating where the mean return would most likely fall with a 95% confidence level. The first sub period greater than the second one, which indicates higher volatility and variability of the returns. In terms of all data, returns mean is greater than zero with an indication of smaller returns compared to the first sub period meaning that in general the returns resulted in being slightly lower and stable. The first sub period shows statistical significance similarly to all data as they do not cross the red line meaning that returns are generally positive. The second sub period crosses the red line, meaning that returns were more negative than positive being statistically insignificant.

3.2. Limitations

This thesis primarily shadows the studies conducted by Caporale & Plastun (2019), Zhang et al., (2018) and Urquhart (2016), with updated information of the present state of Bitcoin BTC and its price. The usage of minute, hourly and daily time intervals differs from the previous studies as they only use data between 1 to 5 minute time intervals. This makes it more challenging to accurately contrast the authors research with previous studies due to different time intervals and different data extraction platforms, where prices might differ slightly. Priorly mentioned studies have used either Bitcoinaverage.com or CoinMarketCap.com, while this study used TokenInsight.com. Some cryptocurrency data tracking platforms may be costly and require payments for access, which led to the choice of TokenInsight.com. In addition to this, prior studies have utilized different measurement tools to examine the efficiency of Bitcoin, which again makes the analytical precision more complex. Future studies should replicate prior studies by the usage of the same data extraction platforms and utilized time intervals for more accuracy.

The size of the cryptocurrency market has grown drastically providing endless opportunities for researchers to investigate efficiency with various methods. The extent of the thesis could have been improved by leveraging the usage of other digital assets. The analyzation of other popular virtual currencies such as the industry second known Ethereum (ETH), Solana (SOL), BNB (BNB) or others could have provided a more broader perspective on cryptocurrency efficiency. In this thesis, the author chose to focus on the industry leader Bitcoin (BTC). Future studies could implement other cryptocurrencies and investigate them by other characteristics for more perspective.

This thesis provides a trading point of view based on the MACD method and additional calculations and figures to assist proper visualisation of the results giving more perspective on how Bitcoin has performed during the investigated sample periods and time intervals. In addition to this, comparing three different time intervals can be relatively misleading as seven days, 90 days and all time historic prices to include drastically different price information, which can be misleading. The main focus being on the daily all time dataset provide the broadest overlook of Bitcoin price performances prioritizing long-term over short-term.

CONCLUSION

This thesis focused on Bitcoin BTC and its price efficiency based on the Efficient Market Hypothesis (EMH) by testing examining the weak-form of EMH. Data extraction was from a free cryptocurrency data tracking online platform known as TokenInsight.com. Data used for calculations were minute intervals, hourly intervals and daily intervals of Bitcoin price from different time periods:

- Minute intervals - 4th April 2024 – 9th April 2024
- Hourly intervals – 10th January 2024 – 9th April 2024
- Daily intervals – 26th December 2013 – 8th April 2024

The main prior papers shadowed to conduct this thesis were by Caporale & Plastun (2019), Zhang et al., (2018) and Urquhart (2016), with updated information of the present state of Bitcoin BTC and its price. Note that the author has not used the same data extraction platform, same sample period, all same tests to investigate efficiency or same logarithmic closing price returns with the identical time frequency as the prior studies.

As stated in the introduction, this thesis attempts to answer the following research question:

- Do Bitcoin prices examine a weak-form of efficiency based on the Efficient Market Hypothesis (EMH)?

Hypothesis based on the research question:

- H0 = Past informaion and historical prices do not provide predictive power for future price movements of Bitcoin.
- H1 = Past information and historical prices do provide predictive power for future price movements of Bitcoin.

A weak-form efficient market is identified if the price is determined to be both reversal and momentum based randomly without predictibility. This thesis uses Hurst exponent (R/S Hurst) as one of the measurement tools to examine if the current state of Bitcoin prices are deemed efficient.

In addition to this, the author uses Moving Average Convergence Divergence (MACD) as another measurement tool to provide deeper analysis on Bitcoins price efficiency.

Based on the results from the tests we identified that all three time intervals resulted in relatively close Hurst exponents, which all were high indicating that Bitcoin prices did experience long-term memory and momentum, however this counters the weak-efficiency testing and accepts the alternative hypothesis. Ultimately the results of Hurst exponent inform us that during the investigated time periods and time intervals, Bitcoin prices were not following a random-walk model and not examining a weak-form of efficiency and experienced momentum and more inclining price fluctuations than declining.

The results regarding the Moving Average Convergence Divergence method provided a significant amount of results of all time periods. Based on the results Bitcoin prices demonstrated inefficiencies mostly due to high volatility and fluctuations in all intervals, however improved with time and moved towards being slightly more efficient. The cumulative returns and distributions of them were also visualised paired with a strategic trading method to showcase the MACD and Signals of buys and sells, profits and losses to better see the performance of Bitcoin prices. Investigation of statistical significance showcased that Bitcoins price efficiency during 2013-2019 period was more volatile, had efficient characteristics and profitability rather than 2019-2024, where prices were inefficient in general. Throughout 2013-2024, the prices generally provided positive returns and indicated randomness, which leads the author to reject the alternative hypothesis and accept the null hypothesis stating that past information of Bitcoin prices do not provide predictive power for future prices. As Urquhart (2016) argued in a prior study, Bitcoin prices have the potential to grow and improve its efficiency trought time, which also was the case in this study with the long investigation periods but based on the results the conclusion is that the research does answer the research question and rejects the alternative hypothesis.

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APPENDICES

Appendix 1. Replication codes

The following link provides the authors R-Studio codes via cloud:
https://posit.cloud/content/yours?sort=name_asc

Appendix 2. Summary results

Summary results for Hurst exponent

hurst_hourly <- hurstexp(bitcoin_data_minute$Price)

Simple R/S Hurst estimation:	0.9047825
Corrected R over S Hurst exponent:	1.007725
Empirical Hurst exponent:	0.9948542
Corrected empirical Hurst exponent:	0.9856816
Theoretical Hurst exponent:	0.5245281

hurst_hourly <- hurstexp(bitcoin_data_hourly$Price)

Simple R/S Hurst estimation:	0.9010558
Corrected R over S Hurst exponent:	1.028394
Empirical Hurst exponent:	1.008108
Corrected empirical Hurst exponent:	0.9914761
Theoretical Hurst exponent:	0.533868

hurst_daily <- hurstexp(bitcoin_data_daily$Price)

Simple R/S Hurst estimation:	0.8909588
Corrected R over S Hurst exponent:	1.008606
Empirical Hurst exponent:	0.9671197
Corrected empirical Hurst exponent:	0.9544256
Theoretical Hurst exponent:	0.5298751

Hurst exponents

"Hurst Exponent (Minute Data):	0.90478249286339"
"Hurst Exponent (Hourly Data):	0.901055783995451"
"Hurst Exponent (Daily Data):	0.890958813291805"

Summary results for Moving Average Convergence Divergence (MACD)

minute

macd		signal	
Min. :	0.000743	Min. :	0.00076
1st Qu. :	0.002528	1st Qu.:	0.00255
Median :	0.003822	Median:	0.00384
Mean :	0.006824	Mean :	0.00676
3rd Qu. :	0.007154	3rd Qu.:	0.00721
Max. :	0.186224	Max. :	0.15836
NA's :	25	NA's :	33

hourly

macd		signal	
Min. :	0.02913	Min. :	0.03041
1st Qu. :	0.07067	1st Qu. :	0.07145
Median:	0.10586	Median:	0.10614
Mean :	0.20361	Mean :	0.20276
3rd Qu.:	0.23278	3rd Qu.:	0.23591
Max. :	1.94118	Max. :	1.82015
NA's :	25	NA's :	33

daily

macd		signal	
Min. :	-14.6287	Min. :	-12.7005
1st Qu. :	-2.0313	1st Qu.:	-1.9702
Median:	0.4304	Median:	0.4310
Mean :	0.6452	Mean :	0.6434
3rd Qu.:	3.1884	3rd Qu.:	3.2886
Max. :	19.9509	Max. :	18.1253
NA's :	25	NA's :	33

Appendix 3. Dataset

The dataset can be downloaded from TokenInsight from the link below. Note that it requires cleaning and preparation before used in R Studio for calculations:
https://tokeninsight.com/en/coins/bitcoin/historical

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