

Statistical Analysis of the (In)efficiency of Bitcoin

A comparison of the weak form efficient market hypothesis in
the US and Venezuela

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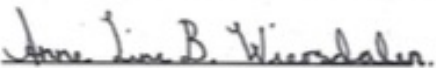
Preface

This master thesis is written as a final part of our master program in Business Administration at the University of Agder. We have chosen financial economics as a specialization and we wanted to write a thesis where we got the opportunity to use, and further develop, the knowledge we have gained during our studies. Our main focus was to find an interesting and relevant topic, that at the same time challenged us academically. The topic “statistical analysis of Bitcoin” was proposed by our supervisor, and we found it intriguing due to its news relevance over the recent years. By reading provided material on the subject, in addition to more of the available literature, we found papers involving the efficient market hypothesis appealing.


The learning curve through the process of writing this thesis has been steep, and the last months have consisted of long days filled with frustration and hard work. However, we have attained a lot of new knowledge and managed to complete a thesis we are proud of.

Our supervisor Jochen Jungeilges deserves a special acknowledgement for his contribution throughout this process. His help with understanding and performing different statistical tests, in addition to providing us with useful input and follow-up along the way, has been indispensable. We would also like to thank our families for their support and encouragement.

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Abstract

Bitcoin is a phenomenon that has received a lot of attention during the last years. Although the literature on the subject has expanded, there is still need for more research. This paper replicates the work of Urquhart (2016) and examines whether there is evidence of weak form efficiency in the Bitcoin market. He found that the Bitcoin market in the US showed signs of moving towards weak form efficiency. We contribute to the existing literature by adding recent data and comparing two different markets; the US and Venezuela. To obtain robustness of the results, the analysis is conducted by performing six different statistical tests, to detect whether Bitcoin returns can be viewed as realizations of independently identically distributed random variables. Despite that the findings are somewhat contradictory for the US, our conclusion is that the market is considered as inefficient. However, we found evidence of weak form efficiency in our last subsample period. This is the period that includes more recent data, hence our findings support Urquhart's statement. For Venezuela, the findings are more coherent, and we conclude that there are no signs of weak form efficiency in the market.

Keywords: Bitcoin, cryptocurrency, efficient market hypothesis, i.i.d., long memory randomness, statistical analysis

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1. Introduction

Fiat money has been used as the main medium of exchange ever since it replaced the barter system. As new technology has developed over the last decades, there have been some attempts of creating a digital currency. However, none have been successful until the introduction of the cryptocurrency Bitcoin in 2008. Bitcoin has the beneficial property of not needing a third party when carrying out a transaction. Instead it is based on blockchain technology, which relies on a peer to peer system, where the transactions are verified through a network of nodes. The functions of Bitcoin differ with the interests of the users. It was originally introduced with the objective of being a digital currency, but replacing fiat money turned out to be a comprehensive process. When first introduced, Bitcoin became popular as an investment object and the price increased abruptly, reaching an all time high late 2017. Ever since it was established the price has been highly volatile. Over the recent years there have been signs of Bitcoin being used as a currency, especially in underdeveloped countries with lack of faith in their financial system.

Some research has been done to test whether it is possible to predict future Bitcoin prices. If the price is predictable there will be arbitrage opportunities for investors. On the other hand, if the prices are random, the market is efficient and developing trading strategies will be useless. Market efficiency is present if prices fully reflect all available information in the market. To generate evidence for weak form efficiency in the Bitcoin market, one can test whether the Bitcoin returns can be viewed as realizations of independently identically distributed (i.i.d.) random variables. The first published researcher to examine this phenomenon was Andrew Urquhart (2016).

This thesis is motivated by the findings of Urquhart (2016), who found that the Bitcoin market in the US shows signs of moving towards weak form of market efficiency. We are replicating his work, applying more recent data. In addition, we are curious to find out whether market efficiency varies with the different functions of Bitcoin. From reading articles about the use of Bitcoin we found that Venezuela is a country where a large fraction of the Bitcoin users, utilize it as a currency. The situation in the country causes a future need for such an alternative to counteract the problems with the financial system. Based on this, we

test for weak form market efficiency by applying statistical tests to data, including exchange rates from both American Dollars (USD) and Venezuelan Bolivars (VEF).

This thesis consists of three main parts; background, methodology and analysis. Furthermore, it is divided into 10 chapters. Chapter 2 includes background information about the history of money and describes the basic concept of Bitcoin, including its development over time. In chapter 3 we will look closer into the usage of Bitcoin and its key concepts. In this chapter, we will provide an explanation of the underlying technology, the blockchain, and we show how transactions are conducted. In addition, we will have a closer look at the development and the different functionalities of Bitcoin in the US and Venezuela. Chapter 4 provides information about the efficient market hypothesis and how it is divided into three different levels based on access to information; weak form, semi-strong form and strong form of efficient market hypothesis. In chapter 5, we review the current relevant literature concerning Bitcoin, efficiency and related topics. Chapter 6 presents our selection of data sources and which exchange platforms the data is obtained from. It also includes description of the different sample periods. Additionally, we will explain why we use log returns, rather than normal returns, when performing the different statistical tests. Furthermore, this chapter displays the descriptive statistics of the two different datasets. A presentation of the applied methodology is given in chapter 7. In this section, we introduce six tests for independently identically distributed (i.i.d.) random returns; Ljung and Box test, Runs test, Bartels test, Automatic Variance Ratio test (AVR), Brock, Dechert & Scheinkman test (BDS), and R/S Hurst analysis. In chapter 8, we obtain the empirical results by conducting the different tests in Stata, R and EViews. The results from these tests, in addition to short comings of our approach and potential for improvements of this thesis, will be discussed in chapter 9. Lastly, a summary of our findings and the conclusion, together with proposals for further research, is presented in chapter 10.

2. Background

2.1 Functions of Money

There is considerable disagreement among economists about the correct definition of money. According to Britannica Encyclopedia, money is “a commodity accepted by general consent as a medium of economic exchange” (Meltzer & Friedman, 2019). Regardless of the definition and its form, money is traditionally associated with three main functions within the economy; a medium of exchange, a store of value and a unit of account (Taylor, 2010).

The first function, a medium of exchange, is a requirement to facilitate any transaction. If this is not in place, trades must take place by exchange of one item for another. Hence, the transactions would have to be conducted by barter, which would require that both parties have something that the other party needs or wants. The second function, a store of value, means that money must retain its worth over time. The value should be the same even if it is put aside and used at a later stage. The last function, unit of account, is a measure of economic value, which is needed to understand the worth of different items in relation to each other. Only when goods and services are measured in the same unit it becomes possible to compare the value that they individually bring to the table (University of Oslo, 2015).

2.2 Brief History of Money

The general opinion is that in early times, before the existence of physical or fiat money, humans survived by exchanging goods. This form of trading is called barter. Two persons, each having goods or services wanted by the other, made an agreement to exchange their goods with each other (Rothstein, 2016, s. 68). The main challenge of barter is that it is difficult to satisfy the needs of all parties involved. Somebody needs to want whatever you have an excess of. For example, if a farmer one year had a surplus of potatoes and wanted a pair of trousers in return, not only did he need to locate a tailor, but he needed to find one in need of root vegetables as well. To complicate things further, for the exchange to be fair, the value of the trade items should be about the same, which is challenging without a common measure of economic value (Jevons, 1896).

To avoid such difficulties getting successively bigger, one had to standardize on common bartering commodities, such as gold, silver and other precious metals. Other popular trade items, like cigarettes, were also commonly used. The period in which such trade took place is therefore referred to as an extension of the barter period. Goods and services were now exchanged for objects with an intrinsic value. Individuals accepted payments in a form that they did not have an immediate need for. This was made possible because the merchandises maintained their original value over time and could therefore be saved for later use. Over the course of time such commodities, with “built-in” value, gained general acceptance by the public. They facilitated further trade since they were not consumed or used by the purchaser in production of other goods. A medium of exchange had developed, but which item that represented value would typically differ from situation to situation, and from society to society (Champ & Freeman, 2006, s. 38). Even though the introduction of common commodities helped reduce the problems with barter trade, they also had some inherent challenges. Firstly, the common commodities were hardly divisible, which made it difficult to conduct smaller purchases. Secondly, they only existed in limited amounts, which would reduce the volume of trades possible (Jevons, 1896).

Therefore, as an alternative to the commodity system, fiat money was introduced. Fiat money is the money we know today. They differ from common commodity system by not being secured by any underlying assets, and its value is determined by the issuing institution or government. Fiat money represents worth through its role as a medium of exchange, and is used by authorities to focus an economy around one transaction medium (European Central Bank, 2015). The acceptance and trust of society are the basic enablers of the use of Fiat money. That is what generates its real value. The amount of money in circulation is controllable, and governmental agencies, at least in theory, control the supply, which is not reliant of non-renewable resources.

2.3 Introducing Bitcoin

In 2008, a new era within money was created when the cryptocurrency Bitcoin was introduced by a person under the pseudonym Satoshi Nakamoto. Bitcoin differs from fiat money in the way that it has no intrinsic value. It also has the advantageous property that transactions do not require a third party, like a bank or a government institution, to validate and settle transactions. Instead Bitcoin relies on a peer-to-peer network in which transactions are secured by an internal incentive system consisting of a cryptographic technology, called the blockchain.

During the period 2009 to 2017 Bitcoin became a hugely successful, and by late 2017 the price of one Bitcoin was almost \$20 000 (CoinMarketCap, 2019). The driver behind this historical growth is unclear. Some argue that the lack of confidence in the banking system after the financial crisis paved the way for the historical growth in the value of Bitcoin, since the initial ambition for the Bitcoin project was to prevent corruption by decentralizing payment systems. Others claim that Bitcoin has bubble-like tendencies and compare it to the Dutch tulip bulb market bubble in 1636 (Christensen & Schröder, 2017).

Satoshi Nakamoto mysteriously disappeared from the internet shortly after the introduction of the groundbreaking new currency, but Bitcoin was here to stay. The Bitcoin software was launched in January 2009, and soon thereafter, the first Bitcoin transaction was made. It consisted of 50 Bitcoin and was performed between the creator Nakamoto and the well-known cryptographer Hal Finney. The implementation of Bitcoin as a payment system however, was slow. In the beginning, it was mainly used for small transactions and in niche markets; the first case took place on 22nd of May 2010 where 10 000 Bitcoins was traded for a pizza-delivery.

On 17th of July, the same year, the first real cryptocurrency exchange was created by Jed McCaleb. It was named Mt.Gox and right after the opening one Bitcoin was worth eight cents (Rothstein, 2016, s. 11). Over time, this exchange platform evolved to become the biggest trader of Bitcoin until it was forced to shut down in February 2014, due to several schemes (Rothstein, 2016, s. 158). However, the real growth in Bitcoin prices started with the establishment of the dark-web-site Silk Road, in January 2011. Silk Road was an online marketplace that allowed their users to trade illegal products, such as drugs, anonymously by

using the Bitcoin technology. Silk Road operated with Bitcoin as the only accepted currency, and provided an unmatched privacy for the traders (Norry, 2018). The publicity around Silk Road had pushed the Bitcoin prices to an, at the time, all-time high of \$266.

Silk Road was shut down by the FBI in October 2013, and its founder was sentenced to life time in prison. Since then, several attempts of using cryptocurrencies on the dark web have been revealed, and therefore some nations boycott cryptocurrencies and domestic cryptocurrency exchange platforms. China is one of the countries that have implemented restrictions on trading in cryptocurrencies. Since much of the trading in Bitcoin was performed in Chinese Yen, the ban of Bitcoin by the end of 2017 caused prices to drop significantly (Williams-Grut, 2018). After the drop in 2017, Bitcoin has struggled to bounce back to previous highs. Despite of this, one can see that the traded volume of Bitcoin is increasing in some countries, particularly in parts of South America. Bitcoin appears to be a good alternative payment system for countries with a non-trustable banking system or a volatile and inflated currency. One of these countries is Venezuela, and the situation will be described more thoroughly later in this paper.

3. The Use of Bitcoin

3.1 The Blockchain

A key component behind the creation of Bitcoin is the blockchain technology. The blockchain starts with a genesis block. The properties of this block define the following blocks in the chain. The process of creating a new block is called mining. Throughout the mining process, proof of work is implemented. Proof of work is a process where the likelihood of solving a complex mathematical algorithmic problem, depends on the amount of computational power used. However, verifying the answer is simple (Lisk Academy). The overall infrastructure of the blockchain consists of electrical nodes. When a new transaction occurs, it is broadcasted to all nodes. These transactions are unconfirmed and drift around in a pool waiting to be picked up. Miners select transactions from the pool and add them to a block. For the transactions in a block to be verified, the nodes need to solve the complex mathematical algorithmic problem, resulting in a code with a string of unique characters called a hash. The string can be of any size and produces a fixed size output of 256 bits. Another requirement to be met is that the hash has to start with a certain number of zeros, and the difficulty of computing a correct hash depends on the amount of zeros. When a miner has solved the mathematical problem and arrived at a hash, a new block is added to the chain. Thereafter, the block has to be validated by all the nodes in the system. This is done by broadcasting the block to all nodes. The validation is confirmed when all the transactions are verified by the network of nodes (Nakamoto, 2008).

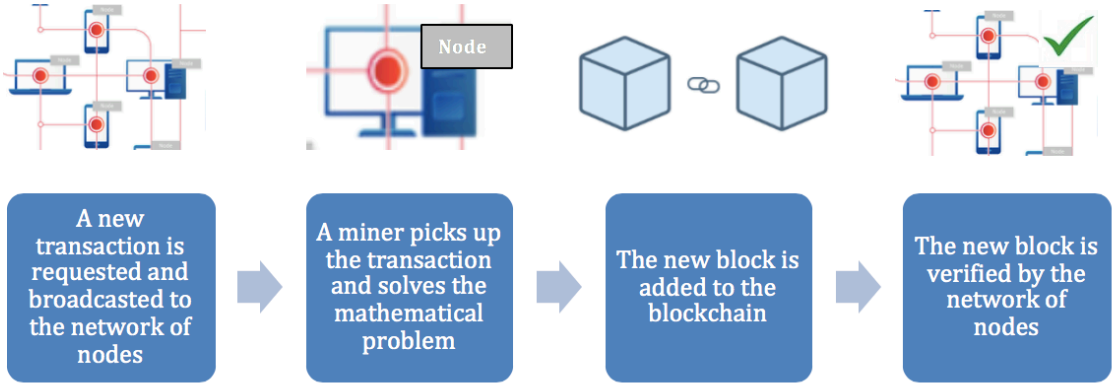


Figure 3.1: The blockchain process step-by-step

A verified block has the size of 1MB and contains a block header which consists of specification of the version, the hash of the previous block, the merkle root, the timestamp, “bits” and the nonce. The specification of version keeps track of upgrades in the software. The merkle root descends from the transactions in the block and is the only transaction data included in the header. The timestamp defines the time of the transaction and proves the legitimacy of the data. The bits is the difficulty target of the block, defined by amount of zeros. The nonce is the random number that the miner targets to find by trial and error. Final acceptance of the block is expressed when nodes starts working on creating the next block using the hash of the accepted block as the previous hash.

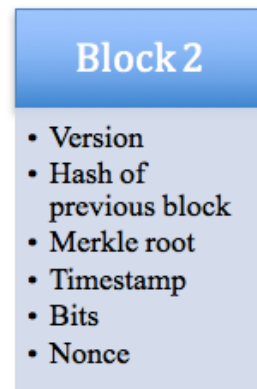


Figure 3.2: The block content

The miner who owns the node that first manages to create a new block successfully, is rewarded with Bitcoin. This reward is the miner’s incentive to invest computational power and function as verification tools in the system. The initial reward for creating a new block was 50 Bitcoin and is halved for every 210 000th block. This means that the finite number of blocks add up to 21 million. If today’s trend continues, the rate drops approximately every fourth year. The last drop was in 2016, which makes the reward today 12.5 Bitcoins.

It is important to mention that if changes are made in the record of one block in the chain, the hash of the block will change. The result will be that the new hash does not correspond with the connected blocks’ hashes. For the change to be accepted it will require a change in the hashes of all the blocks in the blockchain, including the new blocks that will be added to the end of the chain. This will demand more computational power than all of the networks combined and is assumed to be nearly impossible (Narayanan, Bonneau, Felten, Miller, & Goldfeder, 2016).

3.2 Transactions

As referred to in section 3.1, the block chain removes the need for a third part in the completion of transactions by providing a decentralized process. The underlying mechanisms of this process relies on cryptography in which a transaction can be narrowed down to a three-step procedure. The baseline is that every person in possession of Bitcoin is given a private key referred to as a “wallet”. The wallet holds all necessary information, including details about the previous transactions, and is visible for the owner only. Additionally, every Bitcoin-owner have a public key, also referred to as a publicly known address. The public key can be generated by using the private key, but the reversed process is extremely difficult.

Step one in the transaction process between two parties is initiated by the receiver sharing his publicly known address with the sender. After this, the sender completes the transaction by combining the private key with the transaction details and sends it into the Bitcoin network.

Transaction details contains the amount of Bitcoins being sent and the public keys of the receiver and the sender. The blockchain verifies the transaction by confirming that the Bitcoin indeed originates from the sender's private key and that it has not been used in previous transactions. If the transaction is approved by the network, the wallet will be updated with the new data (Rothstein, 2016, s. 27).

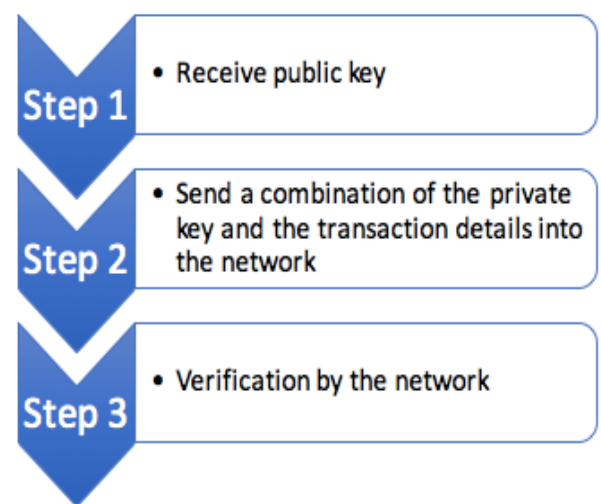


Figure 3.3: Steps for the transaction process

3.3 Bitcoin in The United States

The first currency Bitcoin was traded for was the US Dollar. Since then, a big part of the volume traded in Bitcoin has been in USD. The functions of Bitcoin vary with the users’ preferences. Some use it as a currency to buy different goods or services, which is attractive because of the low transaction costs provided by the peer-to-peer network. Others want access to purchase special, and in some cases, illegal goods (Baur, Hong, & Lee, 2017). The main application area is however to hold Bitcoin as an asset for investment purposes. According to

several researchers Bitcoin is a good diversifier because its return properties differ from traditional asset classes, including currencies. Baur, Hong and Lee (2017) concluded that Bitcoin works well as a diversifier both in normal times and in times of economic recessions. This is supported by Molnar et al. (2015) who states that inclusion of Bitcoin into a diversified portfolio is highly profitable (Bouri, Molnár, Azzi, Roubaud, & Hagfors, 2016). Due to the volatile nature of Bitcoin and its increase in value, many have benefited from this type of investment. As mentioned in section 2.3, the first Bitcoin was traded in the beginning of 2009. The first peak in prices found place in December 2013. Figure 3.2 shows that the price fluctuated somewhat in the range of \$200 to \$1000, up until 2017. This was followed by a significant rise, reaching an all-time high of nearly \$20 000 during December 2017. The following years the price has decreased, but it has remained above the level it was prior to the rise in 2017.

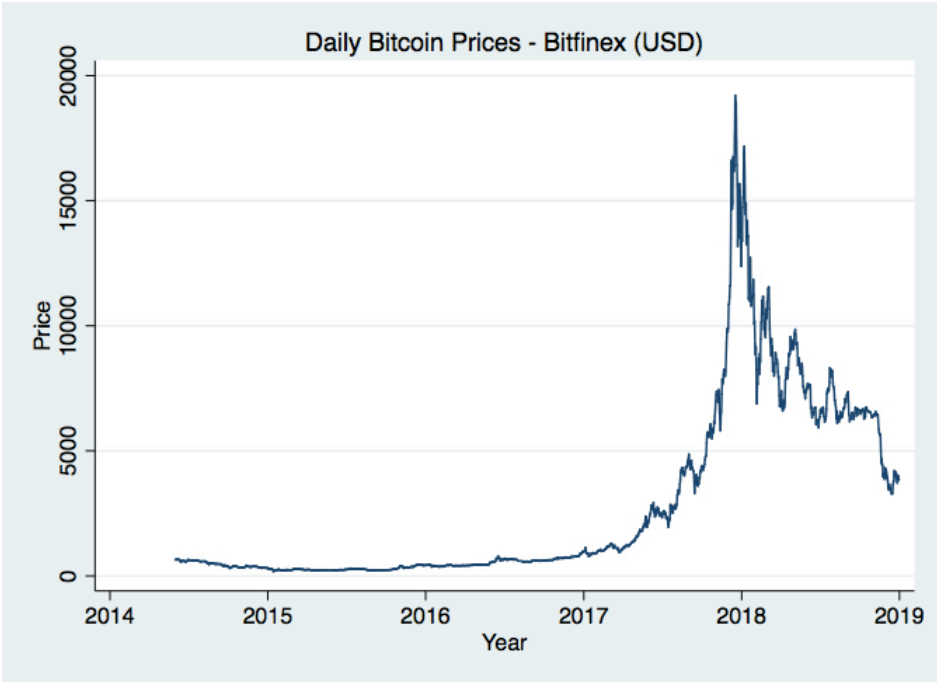


Figure 3.4: Bitcoin prices (last) obtained from Bitfinex

3.4 Bitcoin in Venezuela

The Venezuelan Bolivar (VEF) has over the recent years been characterized by hyperinflation. This is a consequence of the recession in the oil industry during 2014, combined with poor government monetary decisions (Sagmoen, 2016). The country's export earnings consisted of approximately 95% revenue from crude oil, making it particularly vulnerable to fluctuations in the oil price. Furthermore, prior to the oil crisis, Venezuelan politics was characterized by socialist policies. Hugo Chavez was voted for President in 1999, and governed the country until 2013. During his candidacy costly social programs were implemented to fight poverty and high unemployment rates. The initiatives were successful, but resulted in high debt. Another contributing factor resulting in the economic drawback was the foreign currency control instigated by the President in 2003 (BBC, 2019).

Due to the hyperinflation of VEF a big part of the population suffers from poverty. Venezuela's supply of goods mainly relies on imports, which escalates the negative development in the financial situation. This results in short supply of groceries and other necessities, such as medicine, in the country. Bitcoin has recently been a rescuer from financial problems for many people. It represents a safer investment than more traditional alternatives. In a New York Times article, a citizen states that holding money in Bolivars would be "financial suicide". The Venezuelan daily inflation rate is about 3,5%, meaning that the yearly rate is almost 1.7 Million percent. When shopping for groceries many Venezuelan citizens therefore goes to Localbitcoins.com. At this website, they use Bitcoin to buy the amount of Bolivar needed for the specific shopping. This way the Bolivars will not lose significant value while holding them (Hernández, 2019). Even though the use of Bitcoin avoids loss of value, in the local currency, to a certain extent, it does not solve the problem with domestic supply issues. Many Bitcoin holders therefore import groceries from the US. This can be done by using Bitcoin to buy gift cards in the US, for instance on the web-based store Amazon (Lahrichi, 2016).

In addition to the use of Bitcoin as a currency, mining has become a source of income for a part of the population. As mentioned, mining requires a significant amount of electrical power, and due to this Venezuela is attractive, from a cost perspective, compared to other countries. Electricity is heavily subsidized by the government, which results in it being almost free. Mining Bitcoin is not considered illegal, but the miners live in fear of getting caught by

the government. Although no one has been arrested for mining, the government tend to arrest the miners using other crimes as a legal shield. The feeling is that the government use this as a smokescreen to keep the mining activity at bay. The violations leading to arrests are in the scale of electricity theft and internet fraud. In a response to this, the miners attempt to stay anonymous by for instance spreading their computers to several different locations (Zuniga, 2017).

Looking at the traded volume at LocalBitcoins for VEF, Bitcoin experienced a rise in popularity late in 2016, followed by a decrease in the end of 2017. Figure 3.3 shows a significant increase starting in mid 2018. Since then the volume has still been highly volatile, but remains high compared to previous years.

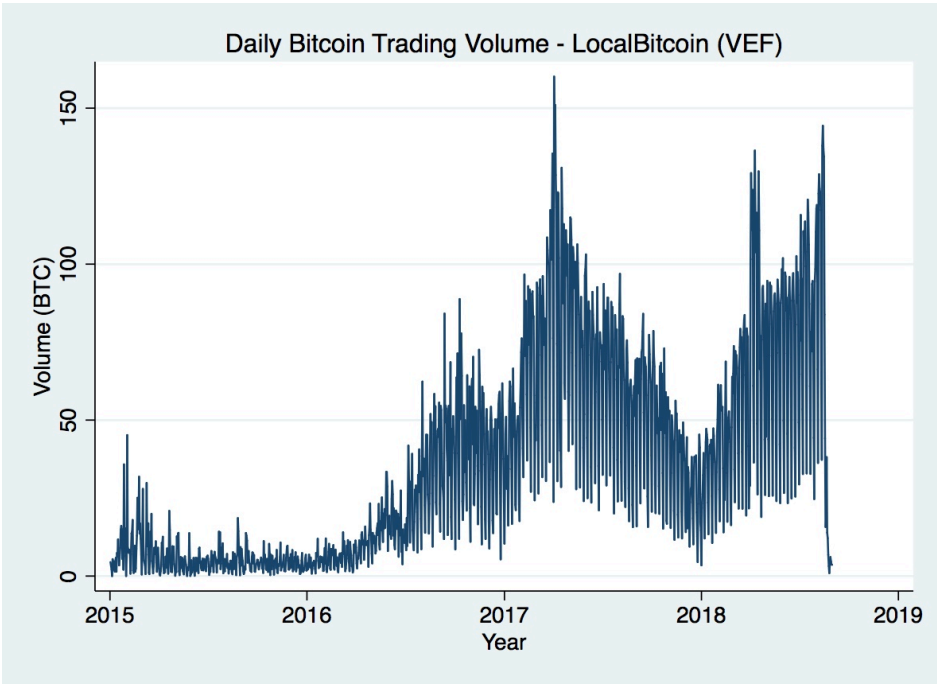


Figure 3.5: Daily LocalBitcoins volume traded in Venezuelan Bolivar

4. The Efficient Market Hypothesis (EMH)

A market is defined as efficient if it “fully reflects” all available information (Fama, 1970). This means that the fundamental and technical analysis are useless in terms of predicting future values and prices. Since new information moves quickly and is available to all market participants, the prices responds immediately and it should be impossible to obtain gains on investments (Malkiel B. G., 2003). Empirical results show that the market does not always fully reflect all available information. It is common to divide the efficient market hypothesis, later referred to as EMH, into three subsections, which contain different levels of information impounded in the price. In the weak form of EMH, the prices depend solely on information about the historical prices. The use of technical analysis to take advantage of potential profit from investments can therefore not be used. In the semi-strong form the prices additionally reflect all publicly available information such as annual earnings, dividend yields and stock splits. Strong form of the EMH includes all the information available on the market. Even monopolistic knowledge, including inside information from company owners, are reflected in the prices (Fama, 1970).

This paper focuses on testing the weak form of efficient market hypothesis. As mentioned, this form is based on the theory that today's prices only reflect information about historical prices, and that future prices are not predictable. Based on this, the price patterns do not follow any foreseeable patterns, hence the returns are unpredictable. The weak EMH can be tested with the null hypothesis of returns following a random walk. The logic of the random walk hypothesis is that returns follow a random and unpredictable path. For a process to qualify as random the observations need to be serially independent, and their probability distributions are required to be constant through time (Malkiel B. G., 1989, ss. 127-128). In addition, the autocorrelation of the returns, in the presence of weak form EMH, is zero.

If H_0 is true and the density function is constant through time, the following relationship holds between the probability distribution subject to the information set and the marginal probability distribution:

$$f(r_{t+1}|\phi_t) = f(r_{t+1}) \quad \text{Formula 4.1}$$

r_t is the return at time t and ϕ_t denotes the information set at time t (Philips, 1988, s. 244).

5. Literature Review

Bitcoin is a fairly new phenomenon and although it has become more popular as a research field the recent years, there are still areas that need more attention. The efficient market hypothesis in the Bitcoin market has been examined by a few researchers. The results are contradictory, which indicate need for more research. Some of the contributions to the literature on this area will be presented below.

Urquhart (2016) was the first to study the inefficiency of the market for Bitcoins. He applied six different statistical tests for randomness to test the existence of weak form EMH in Bitcoin returns. The statistical tests were Ljung and Box test, Runs test, Bartels test, AVR test, BDS test and R/S Hurst analysis. A time frame from 1st of August 2010 to 31st of July 2016, with subsamples from 1st of August 2010 to 31st of July 2013 and 1st of August 2013 to 31st of July 2016 were studied. The selection of a long time period facilitates the inclusion of important events, and the subsamples make it possible to discover whether the level of efficiency vary over time. Urquhart concluded that the Bitcoin market is not weakly efficient over the full time period. However, he found some evidence of weak form efficiency in the last subsample, which led to the conclusion that the Bitcoin market might be moving towards efficiency (Urquhart, 2016).

Nadarajah and Chu (2016) studied the same time period as Urquhart, under the same hypothesis of weak form market efficiency. They used a power transformation of the log returns by applying an odd integer power, emphasizing that this does not lead to any loss of information. In addition to the statistical tests performed by Urquhart, the spectral shape test, the robustified portmanteau test and the generalized spectral test were included. They conclude that using this method shows weak form efficiency over the full period in addition to the two subsample periods (Nadarajah & Chu, 2016).

Brauneis and Mestel (2018) extended the literature by including other cryptocurrencies in the research of EMH, and studied the relationship between cryptocurrency predictability and market liquidity. The period studied was 31st of August 2015 to 30th of November 2017, hence an extension of the last sub period from Urquhart (2016). Beside using the tests, as done in Urquhart (2016), a non-parametric test for market efficiency, suggesting a measure of

efficiency (MOE) with a range from zero to one, is added. Their conclusion is that Bitcoin passes more statistical tests for randomness in returns, than other cryptocurrencies. Additionally, they found that cryptocurrencies become less inefficient as liquidity increases (Brauneis & Mestel, 2018).

Kristoufek (2018) contributed further to the literature on EMH by looking at the Bitcoin markets in the United States and in China, and the development of these over time. A time period from 18th of July 2010 to 31st of July 2017 for the US, and 1st of February 2014 to 31st of July 2017 for China. An efficiency index is applied to detect long-range dependence, fractal dimension, and approximate entropy in the Bitcoin market. Excluding multiple periods with bubble-like behavior, the conclusion was that both Bitcoin markets were inefficient during the time periods (Kristoufek, 2018).

Bariviera (2017) examined the long memory of bitcoin returns from 18th of August 2011 to 15th of February 2017. To provide robustness of the test, the Hurst exponent was studied through application of both the R/S Hurst analysis and the DFA method. Bariviera found evidence of persistency in daily returns from 2011 to 2014. After 2014, the market shows signs of being weak form efficient (Bariviera, 2017).

The research presented above has provided us with valuable insight on how the Bitcoin returns can be analyzed in terms of EMH. The execution of this paper was especially motivated by the contradictory results of the previous literature and the opportunity to provide new research within this field. With this paper, we aim to contribute to the existing research by including a recent sample period (2014-2018) to analyze whether Urquhart's speculation of how the market moves towards efficiency is true. As done in Kristoufek (2018), two different Bitcoin markets will be analyzed. We seek to examine whether market efficiency vary across countries in which Bitcoin has different functionalities.

Author (year)	Sample period	Statistical method	Central findings
Urquhart (2016)	2010-2016	i.i.d. tests (Ljung and Box, Runs, Bartels, AVR, BDS, R/S Hurst analysis)	Inefficient, signs of moving towards weak form efficiency
Nadarajah and Chu (2016)	2010-2016	i.i.d. tests with odd integer power transformation (Ljung and Box, Runs, Bartels, AVR, BDS, R/S Hurst analysis, Spectral Shape, Robustified Portmenteau, Generalized Spectral)	Weak form efficiency
Brauneis and Mestel (2018)	2015-2017	i.i.d. tests (Ljung and Box, Runs, Bartels, AVR, BDS, R/S Hurst analysis, MOE)	Less inefficient market as liquidity increases
Kristoufek (2018)	2010-2017 (US) 2014-2017 (CN)	Efficiency index	Inefficient
Bariviera (2017)	2011-2017	R/S Hurst, DFA	Inefficient, signs of moving towards weak form market efficiency

Table 5.1: Summary of literature review

Based on the previous literature, together with information on the use of Bitcoin in the US and Venezuela, described in section 3.3 and 3.4, we have gained some expectations regarding the EMH, in the two countries. We expect the efficiency of the Bitcoin markets for the US and Venezuela to differ. Urquhart stated that investment assets in their infancy are less efficient. This is supported by various literature, that in general suggests that investment assets become more efficient as number of market participants and interest among investors increase (CFA Institute, 2019). In the US, Bitcoin has become more established, the previous years. Therefore we expect the US Bitcoin market to show more signs of weak form efficiency for our latest observations. The Bitcoin market in Venezuela is less established and the economic situation in the country is unstable. Due to this, we do not expect the Venezuelan Bitcoin market to be weak form efficient.

6. Data

6.1 Data sources

Under the process of gathering data sources the focus was on finding the most popular and reliable platform for Bitcoin exchange, in each country of interest. The selection is based on trading volume in the relevant country and popularity of the different platforms. There exists a lot of various platforms for exchange of Bitcoin, some newer than others, which means that the popularity and its trading volume may vary depending on the time period studied. To include the most important stages in the evolution of Bitcoin, a time period from 2014 to 2018 is chosen. Additionally, to get an understanding of the evolution of the efficiency of bitcoin we have divided the data into two sub periods for each currency. Since we are replicating Urquhart (2016) it would be most appropriate to use the same data source. Urquhart gathered data from bitcoinaverage.com, but limited access to this source has posed difficulties, which is why we had to look for other data sources.

In this paper, Bitfinex is used as the exchange platform for US dollars. Bitfinex was founded in 2012 to compensate for the expanding interest in cryptocurrency trading (Bitfinex). It is one of the largest exchange platforms after the shutdown of Mt.Gox in 2014, and it has the biggest trading volume in USD for the last five years (Bitcoinity, 2019). Historical data from Bitfinex is collected from quandl.com, which was acquired by the Nasdaq stock index late 2018. The website provides datasets, including Bitcoin exchange rates. Urquhart studied the returns of Bitcoin from 2010 to 2016. His conclusion was that the market was inefficient over the time period, but he suggested that it moves toward efficiency. To examine whether this holds we have included more recent data, and a time period from 1st of June 2014 to 31st of December 2018, is chosen. The sub periods are in the time intervals 1st of June 2014 to 31st of December 2016 and 1st of January 2017 to 31st of December 2018. Number of observations for the sample periods are 1636, 922 and 714, respectively. In the chosen time frame, there are some days observed in the historical prices for BTC/USD, where Bitfinex does not provide any information. Most of the omitted observations are single days in between. In addition to these single days, a period of eight days between 2nd of August 2017 and 9th of August 2017 is excluded from the historical prices provided by Bitfinex. This is due to a security breach that forced Bitfinex to shut down all activity on the platform (Bitfinex - The

Official Blog, 2016). Even though Bitfinex does not provide a price on some dates, this is not tantamount with Bitcoin not having any value, thus other exchange platforms may have prices available. There may be various reasons why the data collected from Quandl is incomplete. According to Quandl, “the original sources of the data sometimes copyright the data, remove data from their site or make changes to their website, that make it difficult for them to obtain certain data” (Raquel Sapnu, Personal communication, 2019). We have chosen to leave out the missing days, since we assume that it will not have any significant impact on our results.

For the Venezuelan Bolivar (VEF), data from the exchange platform LocalBitcoins is used. The platform was founded in 2012. Its purpose is to offer a platform to people from different countries to convert their local currencies to Bitcoin (LocalBitcoins). Data is collected from bitcoincharts.com, which is a website providing historical prices on Bitcoin exchange rates. The choice of data source is based on the amount of available data and that it is frequently used in other academic articles, such as Pieters and Vivanco (2017). A time period from 1st of January 2015 to 31st of August 2018 is studied, with the sub periods 1st of January 2015 to 31st of December 2016 and 1st of January 2017 to 31st of August 2018. The sample periods consist of 1337, 729 and 608 observations, respectively.

One extreme value of return is observed in the second subsample period. This is due to the implementation of a new currency in Venezuela. President Nicholas Maduro issued the new currency VES, 20th of August 2018, as an attempt to control the hyperinflation situation in the country. On this day, one new Bolivar (VES) was worth 100 000 of the old Bolivar (VEF) (Sterling, 2018). Introduction of VES lead to a shift in price levels for the last 12 observations in the dataset. Since we are working with relative changes in growth rates and not prices, inadequate results can be avoided by creating a missing value. However, some of the tests cannot be performed when missing values are present. To avoid this problem without affecting the results, we average the returns from the day prior to and the day after VES was implemented and use this value as the return on 20th of August.

6.2 Log Returns

To study the change in prices, daily logarithmic returns are used.

$$R_t = \log\left(\frac{P_t}{P_{t-1}}\right) * 100 \quad (\text{Formula 6.1})$$

R_t is the return of Bitcoin and P_t is the price at time t .

The benefits of using log returns are that they can be interpreted as continuously compounded returns. This ability makes them time-additive, which is beneficial when defining the properties of a time-series. In addition, if each periodic return is normally distributed, which is a common assumption for short periods, the sum of the returns can be assumed to be normally distributed (Brooks, 2008).

6.3 Descriptive Statistics

Figure 6.1 and 6.2 show the time series plots of Bitcoin returns for the US and Venezuela, respectively.

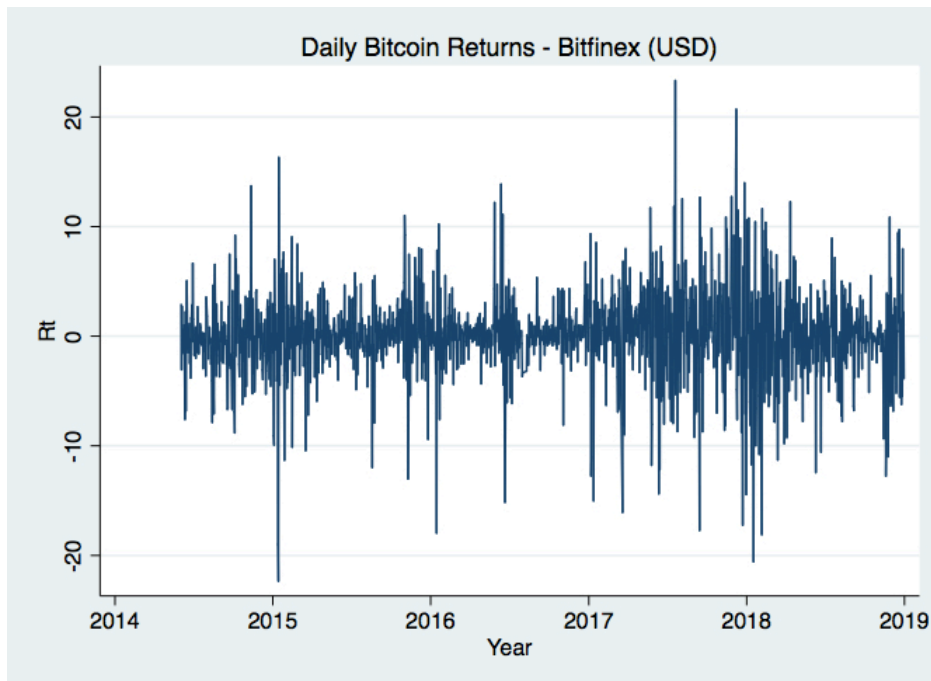


Figure 6.1: Bitcoin returns obtained from Bitfinex

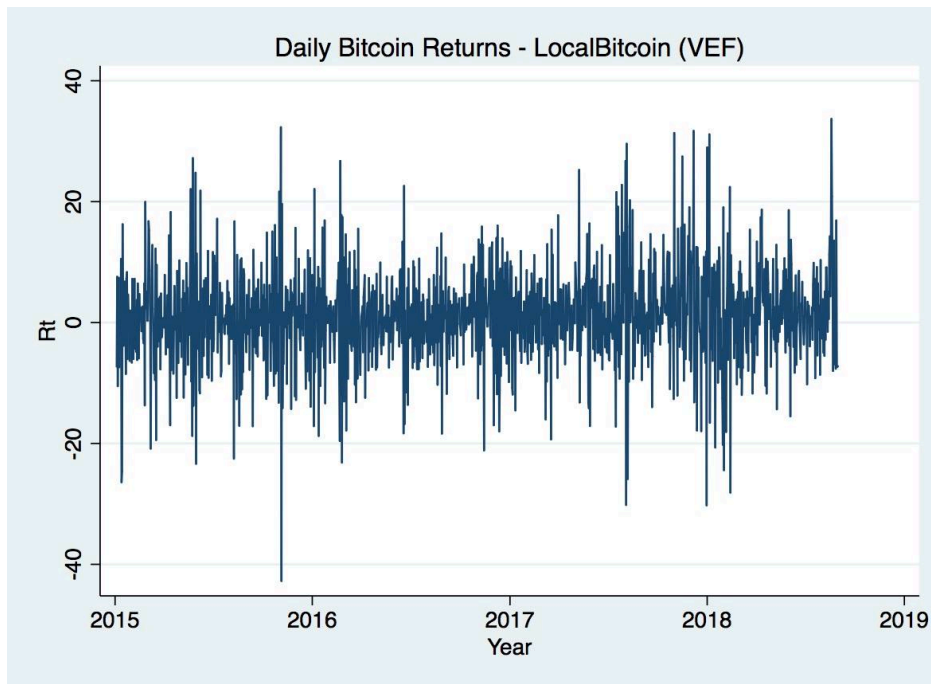


Figure 6.2: Bitcoin returns obtained from LocalBitcoin

Statistics	USA	Venezuela
Observations	1,635	1,336
Minimum	-22.3278	-42.7436
Maximum	23.3132	33.6860
Median	0.1472	1.0140
Mean	0.1088	1.0675
Standard Deviation	3.9677	8.1050
Variance	15.7425	65.6917
Skewness	-0.3465	-0.0250
Kurtosis	7.8452	5.2402

Table 6.1 Descriptive statistics for the full period in the US and Venezuela

Table 6.1 displays the descriptive statistics of the daily log returns in the US and Venezuela. Looking at the output for the US, with 1635 observations, the largest daily decrease in Bitcoin returns is -22.33% on 14th of January 2015, and the largest value of daily increase of 23.31% is observed on the 20th July 2017. The mean return is 0.11% and the estimated standard deviation of returns equals 3.968. A skewness of -0.346 indicates a distribution that is slightly skewed to the left, reflecting that vaguely more observations of log returns are above the mean. However, since the skewness lies between -0.5 and 0.5 the data is considered to be reasonably symmetrical. The kurtosis is 7.845, which means that the distribution is

leptokurtic, hence the peak is high and sharp compared to a normal distribution (Jain, 2018). This indicates existence of special observations in the dataset. However, since the Bitcoin prices are highly volatile, there are multiple observations fluctuating around the minimum and maximum of log returns and removing special observations will therefore have negative influence on the validity of the results.

For Venezuela, a minimum value of daily returns of -42.74% on 5th of August 2015 and a maximum return of 33.69% on 19th of August 2018, is observed. A mean of 1.07% and the standard deviation of 8.105, is estimated. The skewness and kurtosis is -0.025 and 5.240 respectively. A skewness close to zero tells us that there are approximately equal amounts of observations above and below the mean, hence the distribution is close to symmetrical. Leptokurtic distribution can be observed, with a kurtosis of 5.240. This is expected due to the high volatility of Bitcoin prices.

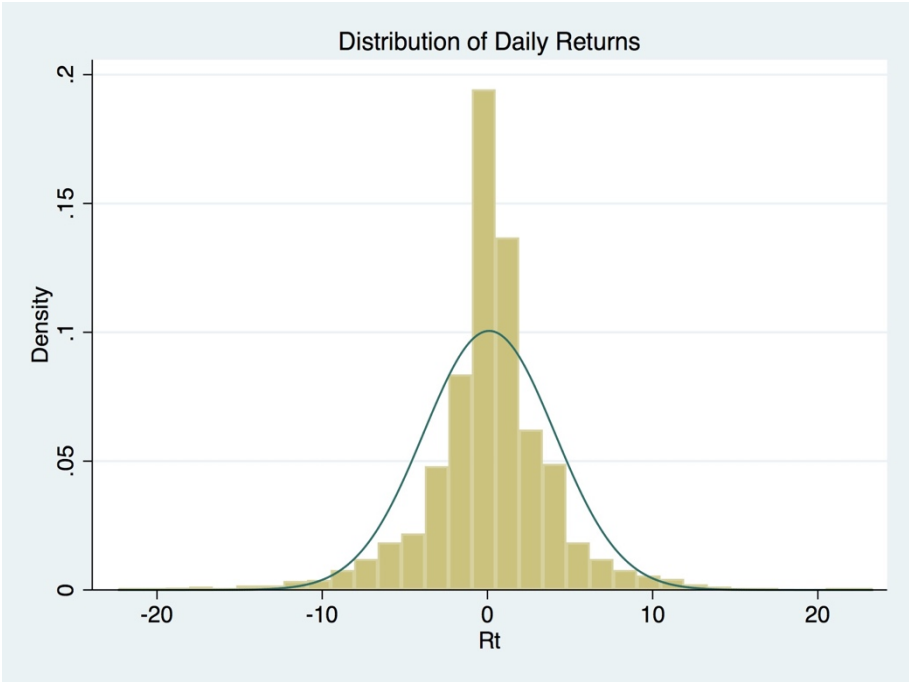


Figure 6.3: Histogram of daily returns with densities, plotted against a normal density curve for the US

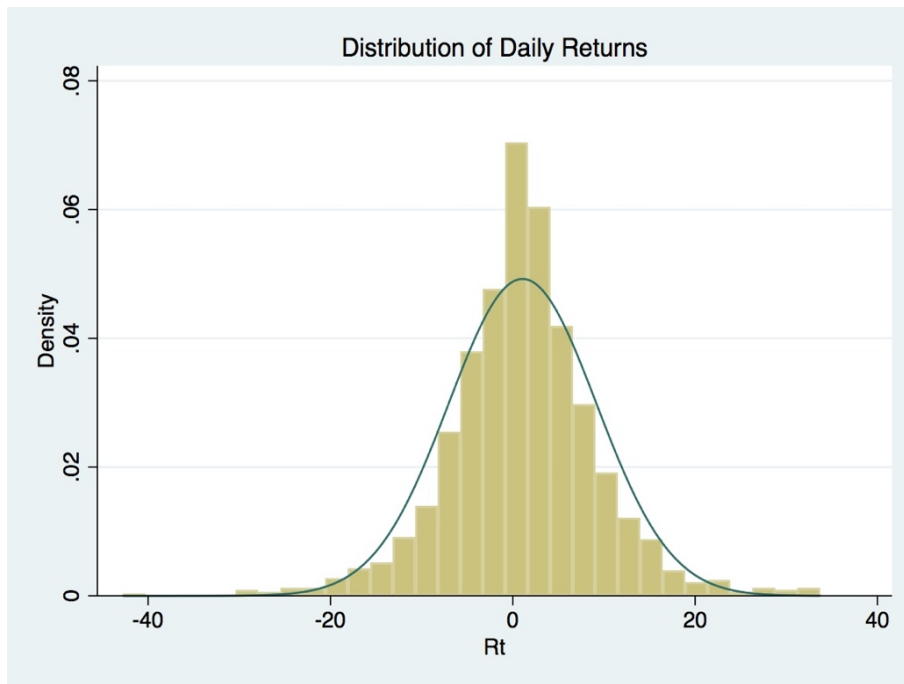


Figure 6.4: Histogram of daily returns with densities, plotted against a normal density curve for Venezuela

In summary, the descriptive statics for both the US and Venezuela, indicate some deviations from a normal distribution. This is verified by running the skewness and kurtosis test (SK-test) for normality in Stata, where the null hypothesis of the data being normally distributed, is rejected. Figure 6.1 and 6.2 shows histograms of daily returns with densities, plotted against a normal density curve. The leptokurtic behavior of the returns for both countries can clearly be observed through the density curves being more peaked than the normal distribution curves.

7. Testing the Weak Form of EMH

As described in section 4, randomness in a time series is present when the observations are serially independent, and the probability distribution is constant through time. There are several tests that can be applied to check for independently identically distributed returns in a time series. This paper is replicating the work of Urquhart (2016) where Ljung and Box test (1978), Runs test (1940), Bartels test (1982), Automatic Variance Ratio test (1999), BDS test (1996) and R/S Hurst analysis (1951) are applied to examine whether the Bitcoin market is efficient. These tests are chosen to avoid spurious results, provide robustness and to capture all the dynamics of Bitcoin (Urquhart, 2016). We apply both parametric and non-parametric tests. Ljung and Box test and AVR test are parametric tests, whilst the remaining tests are non-parametric. The main difference between these sorts of tests is that the non-parametric tests are based on less restricted assumptions regarding the underlying stochastic process (Choi, 1999).

7.1 Ljung and Box test

The Ljung and Box test (1978) is a test for the absence of autocorrelation. Under the null hypothesis, a set of L consecutive autocorrelations are simultaneously equal to zero. The test is a portmanteau test, which means that the alternative hypothesis is more loosely specified. It states that the autocorrelation (ρ) for at least one lag is significantly different from zero. The Ljung and Box test is a modified version of the Box-Pierce test for lack of fit. The application of the Ljung and Box test is often preferred, because the test statistic is adjusted, and by this expected to have better performance in small samples. (Kocenda & Cerny, 2015, s. 49).

The null- and alternative hypothesis is stated as:

$$H_0: \rho_1 = \rho_2 = \dots = \rho_L = 0$$

$H_A: \neq$ holds for at least one

Autocorrelation at lag τ can be defined as:

$$\rho_\tau = \frac{\mathbb{E}[(X_t - \mu_t)(X_{t+\tau} - \mu_t)]}{\sqrt{\mathbb{E}[(X_t - \mu_t)^2]\mathbb{E}[(X_{t+\tau} - \mu_t)^2]}} \quad (\text{Formula 7.1})$$

If the process is stationary it has the following properties:

$$\mathbb{E}[X_t] = \mu \text{ and } \mathbb{V}[X_t] = \sigma^2$$

The autocorrelation function can then be defined as:

$$\rho_\tau = \frac{\mathbb{E}[(X_t - \mu)(X_{t+\tau} - \mu)]}{\mathbb{V}[X_t]} = \frac{\mathbb{C}[X_t, X_{t+\tau}]}{\sigma^2} \quad (\text{Formula 7.2})$$

The test statistic is:

$$\hat{Q} = T(T + 2) \sum_{\tau=1}^L \frac{\hat{\rho}_\tau^2}{T - \tau} \quad (\text{Formula 7.3})$$

T is number of observations, τ reflects the number of lags and $\hat{\rho}_\tau^2$ is the estimated autocorrelation in lag τ .

Number of lags depends on the sample size and is calculated by $\min((T/2)-2, 40)$. If the null hypothesis is true, \hat{Q} follows a chi-square distribution with L degrees of freedom. The null hypothesis is rejected if $\hat{Q} \geq w_{1-\alpha}$ where $w_{1-\alpha}$ denotes the critical value at significance level, α (Jochen Jungeilges, Personal communication, 2019).

7.2 Runs test

The Runs test is developed by Wald and Wolfowitz (1940). It was first applied to examine whether two samples are from the same population. In 1943, the test was further developed to study independency of data. The null hypothesis states that the observations are stochastically independent, meaning that the data is randomly distributed over the time period. Under the alternative hypothesis, the observations are dependent. To apply the test, the data must be

categorized as above or below the median, usually denoted as + or -. If the following observation in a time series changes sign it is considered as a run. Hence, if the number of runs is small the observations tend to remain above or below the median for several observations, resulting in positive serial correlation. Negative serial correlation is associated with a high number of runs, which means that observations below the median tend to be followed by observations above the median, and contrarily (NIST/SEMATECH , 2013).

The null- and alternative hypothesis is stated as:

H_0 : The observations are stochastically independent

H_A : The observations are dependent

The test statistic is:

$$Z = \frac{R - \mathbb{E}[R]}{\sigma[R]} \quad (\text{Formula 7.4})$$

R denotes the number of runs, $\mathbb{E}[R]$ is the expected number of runs and $\sigma[R]$ is the standard deviation of the number of runs.

The expected return is denoted by:

$$\mathbb{E}[R] = \frac{2n_1n_2}{n_1+n_2} + 1 \quad (\text{Formula 7.5})$$

The standard deviation is expressed as:

$$\sigma^2[R] = \frac{2n_1n_2(2n_1n_2 - n_1 - n_2)}{(n_1+n_2)^2(n_1+n_2-1)} \quad (\text{Formula 7.6})$$

n_1 and n_2 are the numbers of positive and negative deviations from the median, respectively.

Under the null hypothesis, the test statistic, Z , follows a normal distribution. If the null hypothesis is rejected the time series is considered as dependent.

H_0 is rejected if:

$$|Z| > Z_{1-\frac{\alpha}{2}}$$

$Z_{1-\frac{\alpha}{2}}$ is the critical value from a normal distribution at the significance level α (Wald & Wolfowitz, 1943).

7.3 Bartels test

Another test for independency is the Bartels test (1982), also referred to as the rank version of von Neumann's ratio test for randomness. Bartels test is considered to be more powerful than Runs test, since it accounts for the magnitude of the observations (Cromwell, Labys, & Terraza, 1994). Similarly, with the Runs test, the null hypothesis is that the observations are stochastically independent. The alternative hypothesis states that the observations are dependent. In order to run the test, the data needs to be divided into ranks in ascending order from 1 to T (Bartels, 1982).

The null- and alternative hypothesis is stated as:

H_0 : The observations are stochastically independent

H_A : The observations are dependent

The test statistic is given by:

$$RVN = \frac{\sum_{i=1}^{T-1} (R_i - R_{i+1})^2}{\sum_{i=1}^T (R_i - \bar{R})^2} \quad (\text{Formula 7.7})$$

R_i is the rank of the i^{th} observation with T observations and \bar{R} denotes the mean rank.

The test statistic, RVN, follows an asymptotic $N(2, 4/T)$ approximation, when H_0 is true. The null hypothesis is rejected if the test statistic RVN is greater than the critical value. Critical values are given in Bartels (1982). For $10 \leq T \leq 100$, calculation of the p-value should be based on a beta approximation. The approximation for larger sample sizes ($T > 100$) can be

found by applying the asymptotic $N(2, 4/T)$ distribution. However, Bartels (1982) found that the approximation $N(2, 20/(5n + 7))$ based on σ^2 , gives a moderately improved distribution (Bartels, 1982).

7.4 AVR test

The Variance Ratio test was first introduced by Lo and MacKinlay in 1988. They stated that if the null hypothesis of returns being serially uncorrelated over time holds, “the variance of a k-period return should be equal to k times the variance of a one-period return” (Heymans & Santana, 2018). The main objective of the test is that if we fail to reject the null hypothesis the variance ratio should be equal to one, for all lag truncation points, and the data follows a normal distribution.

The variance ratio is defined as:

$$VR(k) = \frac{Var(r_t - r_{t-k})}{kVar(r_t - r_{t-1})} \quad (\text{Formula 7.8})$$

One of the inconsistencies of this test is that the results vary depending on the chosen parameter k. In later years, various researchers have done some adjustments to the original variance ratio test. Among these is Choi (1999), who found a way to avoid issues of choosing period k. This version of the test relies on a data-dependent procedure for the selection of the optimal value of k, and is called Automatic Variance Ratio test (AVR) (Charles & Darné, 2013).

The standardized test statistic is:

$$VR = \sqrt{T}/k[\widehat{VR}(k) - 1]/\sqrt{2} \quad (\text{Formula 7.9})$$

The variance ratio estimator $\widehat{VR}(k)$ is defined as:

$$\widehat{VR}(k) = 1 + 2 \sum_{i=1}^{T-1} h(i/k) \hat{\rho}(i) \quad (\text{Formula 7.10})$$

$H(x)$ denotes the Quadratic Spectral (QS) window and has the form:

$$h(x) = \frac{25}{12\pi^2 x^2} \left[\frac{\sin(6\pi x/5)}{6\pi x/5} - \cos(6\pi x/5) \right] \quad (\text{Formula 7.11})$$

(Choi, 1999)

Under the null hypothesis, the test statistic, VR, converges to a normal distribution. The null hypothesis is rejected if the test statistic is greater than the critical value of a normal distribution at a given significance level α .

7.5 BDS test

The BDS test was developed by Brock, Dechert and Scheinkman in the mid 1980s. It is a portmanteau test where the null hypothesis states that the data are independent and identically distributed (i.i.d.), whereas the alternative hypothesis is not clearly specified (Brock, Dechert, Scheinkmann, & LeBaron, 1996). The alternative hypothesis can take various forms, such as the data being linearly dependent, non-linearly dependent or chaotic. In order for the test to give adequate results, a large sample size (over 500) is required. For a univariate time series X_t , the test procedure starts by defining a distance ε . In the next step the probability that the distance between pairs of points being less than ε is considered. If the observations are i.i.d. the probability will be the same for any pair of observations. When performing the BDS test it is necessary to divide the data into m embedding dimensions (Eviews, 2019). The correlation integral is calculated as a part of the test statistic and examines whether the probability that any pairs of m -dimensional points is less than epsilon.

The correlation integral is:

$$c_{m,n}(\varepsilon) = \frac{2}{(n-m+1)(n-m)} \sum_{s=m}^n \sum_{t=s+1}^n \prod_{j=0}^{m-1} I_{\varepsilon}(X_{s-j}, X_{t-j}) \quad (\text{Formula 7.12})$$

n denotes number of observations, m reflects embedding dimensions and $I_{\varepsilon}(X_{s-j}, X_{t-j})$ is the indicator function.

If the distance between X_{s-j} and X_{t-j} is less than ε , the indicator function will have a value of one. Contrarily, the indicator function will be zero if the distance is higher than or equal to ε .

The test statistic is given by:

$$w_{m,n}(\varepsilon) = \sqrt{n - m + 1} \frac{c_{m,n}(\varepsilon) - c_{1,n-m+1}^m(\varepsilon)}{\sigma_{m,n}(\varepsilon)} \quad (\text{Formula 7.13})$$

σ is the square root of the variance which is defined as:

$$\sigma_{m,n}^2(\varepsilon) = 4 \left[k^m + 2 \sum_{j=1}^{m-1} k^{m-j} c^{2j} + (m-1)^2 c^{2m} - m^2 k c^{2m-2} \right] \quad (\text{Formula 7.14})$$

(Belaire-Franch & Contreras, 2002).

The test statistic, $w_{m,n}(\varepsilon)$, follows a normal distribution when H_0 is true. The null hypothesis is rejected when the test statistic is greater than the critical value at the significance level α , for a normal distribution.

7.6 R/S Hurst analysis

R/S Hurst analysis is a procedure developed by Harold Edwin Hurst, published in 1951. It was first developed in the context of hydrology, where the initial objective was to find an ideal level of a water reservoir. The aim was to discharge the correct amount of water from the reservoir, so that it never overflowed or emptied. To achieve this, Hurst tested whether the influx of water from rainfall followed a random walk (Peters, 1991, s. 62). The techniques developed by Hurst was expanded and refined by Mandelbrot and others. Mandelbrot introduced the procedure in an economic context in 1971, and later it has been applied to detect long memory of stock returns (Booth, Kaen, & Koevos, 1982).

R/S Hurst is a robust procedure with few assumptions about the underlying process, which makes it highly applicable to time series models.

Based on a time series t with n observations, the Hurst exponent can be obtained by the following procedure:

1. Calculation of the mean

$$\mu = \frac{1}{N} \sum_{i=1}^N X_i \quad (\text{Formula 7.15})$$

2. Calculate the cumulative deviation over N periods

$$Z_t = \sum_{i=1}^t (X_i - \mu) \text{ where } t = 1, 2, \dots, N. \quad (\text{Formula 7.16})$$

3. The difference between the maximum and minimum values of (2):

$$R_t = \text{Max} (Z_1, Z_2, \dots, Z_N) - \text{Min} (Z_1, Z_2, \dots, Z_N) \text{ where } t = 1, 2, \dots, N \quad (\text{Formula 7.17})$$

4. Calculate the standard deviation S

$$S_t = \sqrt{\frac{1}{t} \sum_{i=1}^t (X_i - \mu)^2} \quad (\text{Formula 7.18})$$

(Tzouras, Anagnostopoulos, & McCoy, 2015).

From this we attain the relationship between R/S and the Hurst exponent:

$$(R/S)_t = (a * N)^H \quad (\text{Formula 7.19})$$

$(R/S)_t$ is the rescaled range, N denotes number of observations, a is a constant, and H defines the Hurst exponent.

As shown above, the rescaled range consists of the difference between the maximum and minimum levels of the cumulative deviation, Z_t , divided by the standard deviation of the observations, S_t . Hurst applied this method by standardizing the range over the time period, and this way compensate for the fact that the fluctuations around the mean vary over time (Peters, 1991, ss. 62-63). The relationship between the Hurst exponent and R/S shows that if

H is equal to zero the rescaled range will always be one, hence the range is equal to the standard deviation. If H is one, the rescaled range is proportional to the sample size. The larger sample size, the larger ratio between R/S. When H is 0.5, R/S is equal to the square root of the proportion of the sample size. If the sample size increases, the rescaled range increases.

To obtain an estimate of the Hurst exponent, a regression analysis can be applied. By taking the log on both sides of formula 7.19, an estimate of the exponent, H, can be found.

$$\log(R/S)_t = H \log(a * N) \tag{Formula 7.20}$$

To illustrate how to find the rescaled range a simple example is provided. Hennig Olsen AS is preparing their production of ice cream for 17th of May. They have limited storage space, meaning that if they produce too much ice cream the storage will overflow, and if the production is too low they will not be able to satisfy the demand. Under the assumption that the demand for ice cream solely depends on the temperature, R/S Hurst is used to estimate an optimal production level.

Temperatures for 17th of May in Kristiansand 2009-2018 are listed below:

Years	Temperature (°C)	Z _t
t ₁	11.8	0
t ₂	10.6	1.86
t ₃	15.8	4.92
t ₄	11.4	2.78
t ₅	17.0	5.04
t ₆	14.8	1.7
t ₇	11.4	0.56
t ₈	14.2	2.82
t ₉	12.7	2.28
t ₁₀	16.9	3.24

Table 7.1: Average temperatures (°C) for 17th of May in Kristiansand (2009-2018)

Mean (μ)	13.66
St. Deviation (S _t)	2.399

Table 7.2: Mean and standard deviation

With an average temperature for the 17th of May the last 10 years of 13.7°C (table 7.2), the cumulative deviations from the mean are:

$$Z_1 = (11.8 - 13.66) + (10.6 - 13.66) + (15.8 - 13.66) + \dots + (16.9 - 13.66) = 0$$

$$Z_2 = (10.6 - 13.66) + (15.8 - 13.66) + \dots + (16.9 - 13.66) = 1.86$$

$$Z_3 = (15.8 - 13.66) + \dots + (16.9 - 13.66) = 4.92$$

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$$Z_{10} = (16.9 - 13.66) = 3.24$$

The maximum positive cumulative deviation from the mean is in the sub period that includes the last 5 years (t_5 - t_{10}) and is equal to 5.04°C. This means that the temperature in this sub period is 5.04°C higher than the average temperature.

With a minimum cumulative deviation from the mean equal to zero, which is for the full time period, the range of the complete time series is calculated to be:

$$\begin{aligned} R_{10} &= \text{Max} (0, 1.86, 4.92, 2.78, 5.04, \dots, 3.24) - \text{Min} (0, 1.86, 4.92, 2.78, 5.04, \dots, 3.24) \\ &= 5.04 - 0 = 5.04 \end{aligned}$$

With a standard deviation of 2.399°C the rescaled range equals:

$$(R/S)_{10} = \frac{5.04}{2.399} = 2.101$$

In the example above the rescaled range is approximately twice as big as the standard deviation, meaning that the deviations from the mean locally are higher than the deviations from the mean over the full time period. This implies that when Hennig Olsen is choosing which amount of ice cream to produce, an optimal production level can be difficult to attain by looking at the mean.

For the time series to be random, the present observation will not affect the future value, meaning that the correlation equals zero. This is what defines a white noise process. If the relationship between the range and the standard deviation (R/S) holds for a stochastic process, the autocorrelation function can be expressed as:

$$C = 2^{2H-1} - 1 \quad \text{(Formula 7.21)}$$

If $0 < H < 0.5$ the correlation will be negative. The behavior of the time series is in this case denoted as anti-persistent, hence it will be mean reverting. A positive observation in one period is most likely to be followed by a drop in the next period, and vice versa. Positive correlation is associated with $0.5 < H < 1$. The series is then considered as persistent, which means that an increase in the series is most likely followed by an increase in the next period and conversely. If $H=0.5$ the correlation equals zero and indicates the existence of a random series, in other words market efficiency is present (Peters, 1991, ss. 64-65).

8. Results from Testing the Weak Form of the EMH

This section covers the individual test results. For all the statistical tests, except the R/S Hurst analysis, a significance level of 5% is chosen. As for the R/S Hurst analysis, a range within the interval from 0.45 to 0.55 is consistent with a random series (Mitra, 2012). The p-values and the Hurst exponents are presented in tables associated with each of the different tests, in the following sections.

8.1 Ljung and Box test

To obtain the Q statistic and the related p-values for the Ljung and Box test, the «wntestq» command is performed in Stata. As mentioned in section 7.1, the null hypothesis states that there is no autocorrelation up to a specified lag L in the returns. In Stata, the maximum number of lags to be tested is 40 and based on the number of observations for each period, in both countries of interest, we set the number of lags equal to 40.

	p-values
01.06.2014 - 31.12.2018	0.1523
01.06.2014 - 31.12.2016	0.0121
01.01.2017 - 31.12. 2018	0.3817

Table 8.1: p-values from the Ljung and Box test for the US

Table 8.1 displays the p-values associated with the Ljung and Box test for the returns from the United States. The null hypothesis of no autocorrelation is rejected for the 1st subsample period. For the full sample period and the 2nd subsample period we fail to reject H₀. These results show that autocorrelation is observed in the 1st subsample period, which implies inefficiency. There are no significant signs of autocorrelation in the full sample period and the 2nd subsample, meaning that both of these periods are consistent with the weak form of the EMH.

	p-values
01.01.2015 - 31.08.2018	0.0000
01.01.2015 - 31.12.2016	0.0000
01.01.2017 - 31.08.2018	0.0028

Table 8.2: p-values from the Ljung and Box test for Venezuela

The p-values from the Ljung and Box test for Venezuela are displayed in table 8.2. We fail to reject H_0 for all the three sample periods. This means that there are signs of autocorrelation in the returns. In other words, there is significant evidence for inefficiency of the Bitcoin market in Venezuela.

8.2 Runs test

To obtain the results for the Runs test, the command «runtest, d» is typed in Stata. The null hypothesis states that the data is identically independently distributed. As mentioned in section 7.2, the test procedure captures how many times the data shifts between values above and below the median, counted as “runs”. It is also possible to perform the Runs test by using the mean as a threshold, although Stata uses median as a default. As shown in table 6.1, the value of the median and the mean are approximately equal. Hence, the selection does not affect our results and we chose the default option from Stata. The Z-value reflects the relationship between the observed and expected number of runs, as shown in formula 7.4. Z moves towards zero as the difference decreases, which is adequate with stronger evidence of dependency in the data. If returns are equal to the median, the «d» option in Stata ignores these values. Table 8.3 and 8.4 displays the p-values obtained when carrying out the runs test.

	p-values
01.06.2014 - 31.12.2018	.05
01.06.2014 - 31.12.2016	.06
01.01.2017 - 31.12. 2018	.63

Table 8.3: p-values from the Runs test for the US

The null hypothesis of independency in the returns is rejected for the full sample period. For the 1st and the 2nd subsample period, we fail to reject H_0 . When looking at the full sample

period there is evidence of the returns being dependent. However, the test results show evidence of the returns being stochastically independent in both of the subsample periods, thus the market has characteristics of weak form efficiency. By comparing the differences in Z-values for the three periods, a smaller value is observed for the 2nd subsample period, which is reflected in the high p-value. Hence, there is strong evidence of the data being independently identically distributed in this subsample period, in the US Bitcoin market.

	p-values
01.01.2015 - 31.08.2018	0.00
01.01.2015 - 31.12.2016	0.00
01.01.2017 - 31.08. 2018	0.01

Table 8.4: p-values from the Runs test for Venezuela

As shown in table 8.4 the null hypothesis is clearly rejected for all three sample periods for Venezuela. This means that the difference between observed and expected number of runs is small, hence there are no evidence of weak form market efficiency of the Venezuelan Bitcoin market.

8.3 Bartels test

To run the Bartels test, with the null hypothesis of stochastically independency in the returns, the «lmavon» command is typed in Stata. This procedure provides a RVN statistic as shown in formula 7.7. All sample periods for both the US and Venezuela include more than 100 observations, thus a normal approximation $N(2, 20/(5n + 7))$ is applied. For calculation of the p-value associated with the test statistic RVN, we use the « igaussiantail(m,a,x)» command in Stata, where m is the mean, a is the variance and x is the test statistic.

	p-values
01.06.2014 - 31.12.2018	0.02641
01.06.2014 - 31.12.2016	0.03526
01.01.2017 - 31.12. 2018	0.03873

Table 8.5: p-values from the Bartels test for the US

	p-values
01.01.2015 - 31.08.2018	0.02548
01.01.2015 - 31.12.2016	0.03246
01.01.2017 - 31.08. 2018	0.03838

Table 8.6: p-values from the Bartels test for Venezuela

As shown in table 8.5 and 8.6, the p-values from all sample periods, for the US and Venezuela, are below the significance level of 0.05. This means that the null hypothesis of stochastic independence of the returns is rejected, hence there is evidence against the weak form of EMH, in the Venezuelan Bitcoin market.

8.4 AVR test

Conduction of the automatic variance test is done by running the «Auto.VR» command in the statistical software, R. The null hypothesis states that returns are serially uncorrelated over time. Running the test in R provides a test statistic (VR), as described in section 7.4. H_0 is rejected if the estimated test statistic exceeds the critical value of a normal distribution at a significance level α . For this paper, we have chosen a significance level of $\alpha=0.05$, and since the test is two-tailed, this results in a critical value of $|1.96|$. Calculation of critical value is performed in R by typing «qnorm(1-($\alpha/2$))». The p-values are obtained by using the «display 1-normal(Z)» command, in Stata.

	p-values
01.06.2014 - 31.12.2018	0.7392
01.06.2014 - 31.12.2016	0.3777
01.01.2017 - 31.12. 2018	0.7803

Table 8.7: p-values from the AVR test for the US

As shown in table 8.7, we fail to reject the null hypothesis of serially uncorrelated returns for all three sample periods. This can be interpreted as evidence of the Bitcoin market, in the US, being weak form efficient.

	p-values
01.01.2015 - 31.08.2018	0.0000
01.01.2015 - 31.12.2016	0.0000
01.01.2017 - 31.08. 2018	0.9542

Table 8.8: p-values from the AVR test for Venezuela

For Venezuela, the opposite findings are observed for the full period and the 1st subsample period, as seen in table 8.8. We reject the null hypothesis for these periods, reflecting that the market shows signs of being inefficient. For the last subsample period, we fail to reject the null hypothesis, hence returns are serially uncorrelated over time, which implies presence of weak form EMH in the Bitcoin market, in Venezuela.

8.5 BDS test

For application of the BDS test, a statistical software package from EViews is used. The null hypothesis states that the returns are independent and identically distributed. Rejection of H_0 therefore means that there is no evidence of weak form market efficiency in the data. As mentioned in section 7.5, the test statistic depends on selection of the free variables, ε and m . Brock et. Al (1996) suggests choosing an ε between 0.5 and 1.5 standard deviations of the data. In this paper, an ε equal to the standard deviation has been used. In order to make sure that the test results are consistent, the test have been performed with different values of ε . The embedding dimensions, m , depends on the dataset. Literature that includes approximately the same amount of data as in this study, proposes a value of m between 6 and 10. Based on this we have chosen to conduct the test with an embedding dimension of 8.

	Embedding dimensions	Z-statistics	p-values
01.06.2014 - 31.12.2018	2	9.2906	0.0000
	3	12.2204	0.0000
	4	14.7499	0.0000
	5	17.4390	0.0000
	6	20.4902	0.0000
	7	23.9150	0.0000
	8	27.8457	0.0000
01.06.2014 - 31.12.2016	2	7.1879	0.0000
	3	8.5620	0.0000
	4	9.6955	0.0000
	5	11.2379	0.0000
	6	12.6873	0.0000
	7	14.1217	0.0000
	8	15.6761	0.0000
01.01.2017 - 31.12. 2018	2	3.4093	0.0007
	3	5.0495	0.0000
	4	6.4832	0.0000
	5	7.6772	0.0000
	6	9.4364	0.0000
	7	11.4253	0.0000
	8	13.5401	0.0000

Table 8.9: BDS test statistics, Z, and p-values for each time period in the US

	Embedding dimensions	Z-statistics	P-values
01.01.2015 - 31.08.2018	2	14.3086	0.0000
	3	14.6480	0.0000
	4	15.3884	0.0000
	5	15.9486	0.0000
	6	16.5432	0.0000
	7	17.6810	0.0000
	8	19.2012	0.0000
01.01.2015 - 31.12.2016	2	11.8823	0.0000
	3	12.1215	0.0000
	4	13.0455	0.0000
	5	13.8227	0.0000
	6	14.3757	0.0000
	7	15.5021	0.0000
	8	17.0372	0.0000
01.01.2017 - 31.08.2018	2	8.7023	0.0000
	3	8.6981	0.0000
	4	8.7640	0.0000
	5	8.8177	0.0000
	6	9.0560	0.0000
	7	9.6434	0.0000
	8	10.3004	0.0000

Table 8.10: BDS test statistics, Z, and p-values for each time period in Venezuela

As shown in table 8.9 and 8.10, above, the null hypothesis of i.i.d. returns is rejected for all three periods in both countries, regardless of the selection of the embedding dimension, m . This means that the data shows no signs of being independent and identically distributed. Thus, no indications of weak form market efficiency, in the Bitcoin returns for the US and Venezuela, are detected by running the BDS test.

8.6 R/S Hurst analysis

The Hurst analysis starts by dividing the data into non-overlapping sub groups of equal length n . This is done to decrease the correlation and make sure that the observations are independent. To obtain an adequate estimate of H , the test will be conducted several times with different values of n . For this paper, the data is divided into subgroups starting at $n=10$, with increments of 10, up until each sub group consists of 810 data points, hence two sub groups. As n increases the stability of the results is expected to decrease, due to the large number of observations in each sub group (Peters, 1991, s. 82). To find the rescaled range, the procedure described in section 7.6 is carried out for each value of n . The R/S used to obtain the Hurst exponent, is calculated by averaging the different estimated values.

Hurst exponent	
01.06.2014 - 31.12.2018	0.6154
01.06.2014 - 31.12.2016	0.5279
01.01.2017 - 31.12. 2018	0.5414

Table 8.11: Hurst exponent for each time period in the US

Hurst exponent	
01.01.2015 - 31.08.2018	0.5580
01.01.2015 - 31.12.2016	0.5035
01.01.2017 - 31.08. 2018	0.6067

Table 8.12: Hurst exponent for each time period in Venezuela

Figure 8.1, 8.2 and 8.3 shows the log/log plot of the full sample period and the two subsample periods in the United States.

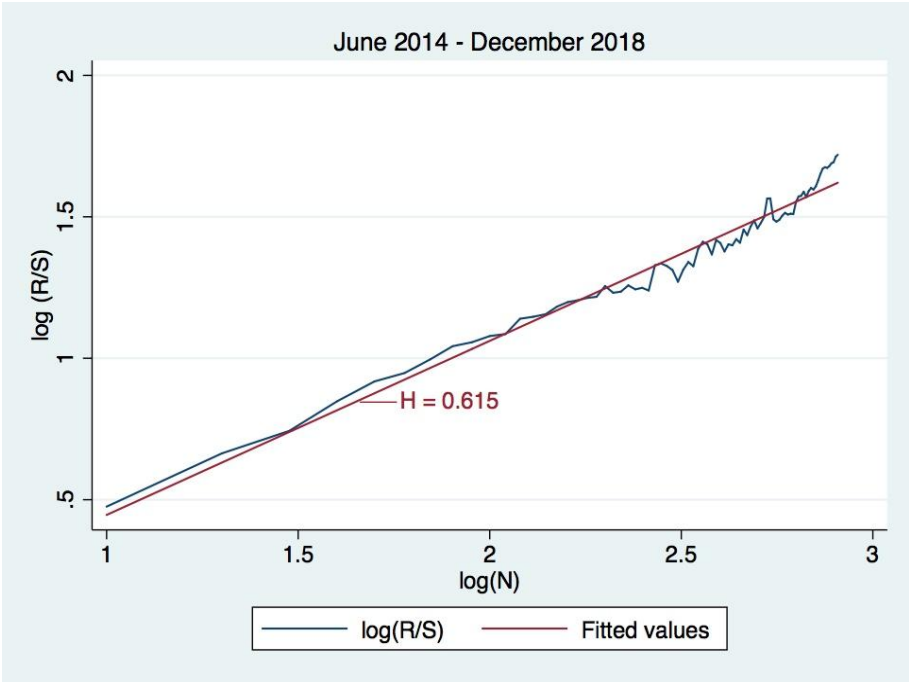


Figure 8.1: Log/log plot of the full sample period in the US

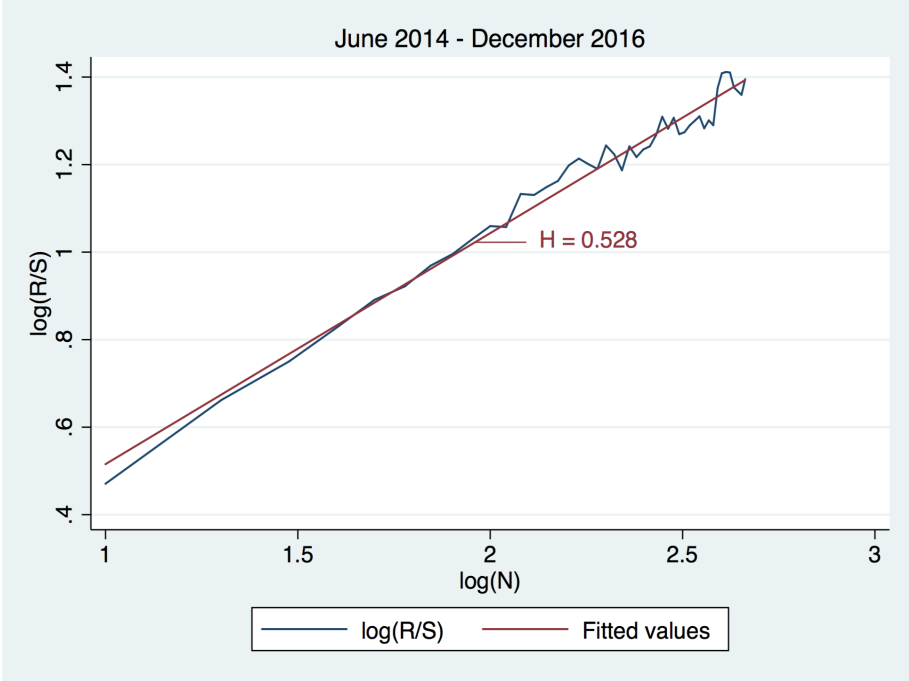


Figure 8.2: Log/log plot of the first subsample period in the US

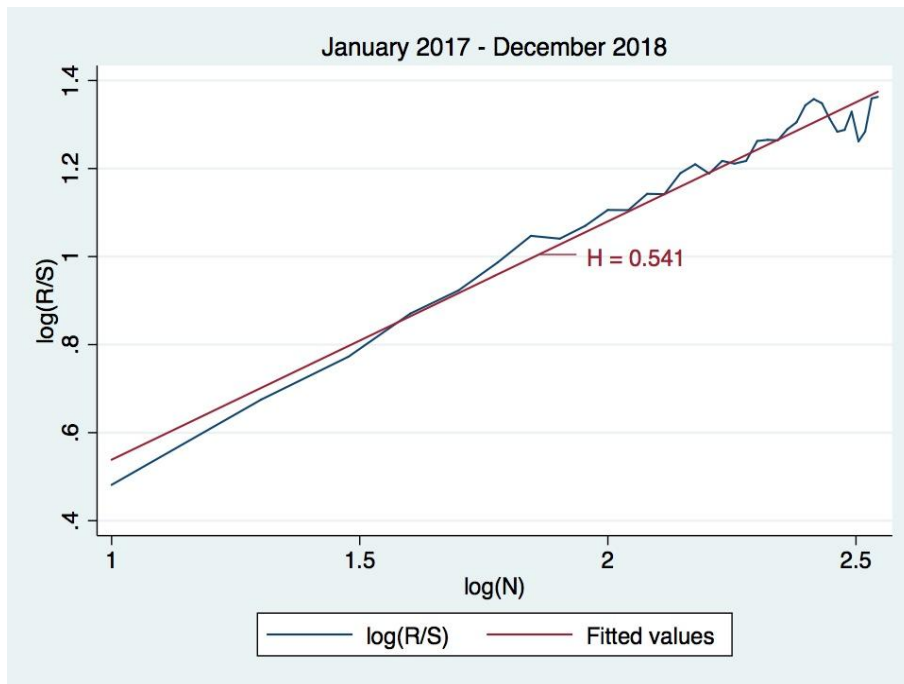


Figure 8.3: Log/log plot of the second subsample period in the US

For the full period a Hurst exponent of 0.615 is obtained. As discussed in section 7.6, $0.5 < H < 1$ is evidence of a persistent time series, where the level of persistence depends on how close H is to one. Thus, if the previous observation in the time series is positive there is a 61.5% probability that the next observation will be positive (Peters, 1991, s. 76). This shows signs of a trend reinforcing behavior, which is inconsistent with the efficient market hypothesis. The Hurst exponent of the first and the second subsample period is 0.528 and 0.541, respectively. This is within a 0.05 range from 0.5, and some authors claim that this qualifies as evidence of the data following a random walk, see for instance Mitra (2012). These findings reflect that the Bitcoin market in the US shows tendencies of being weak form efficient for the subsample periods, with the first subsample period having stronger evidence than the second subsample period. As mentioned, for the full time period the returns have a persistent behavior and do not correspond with the weak form efficient market hypothesis.

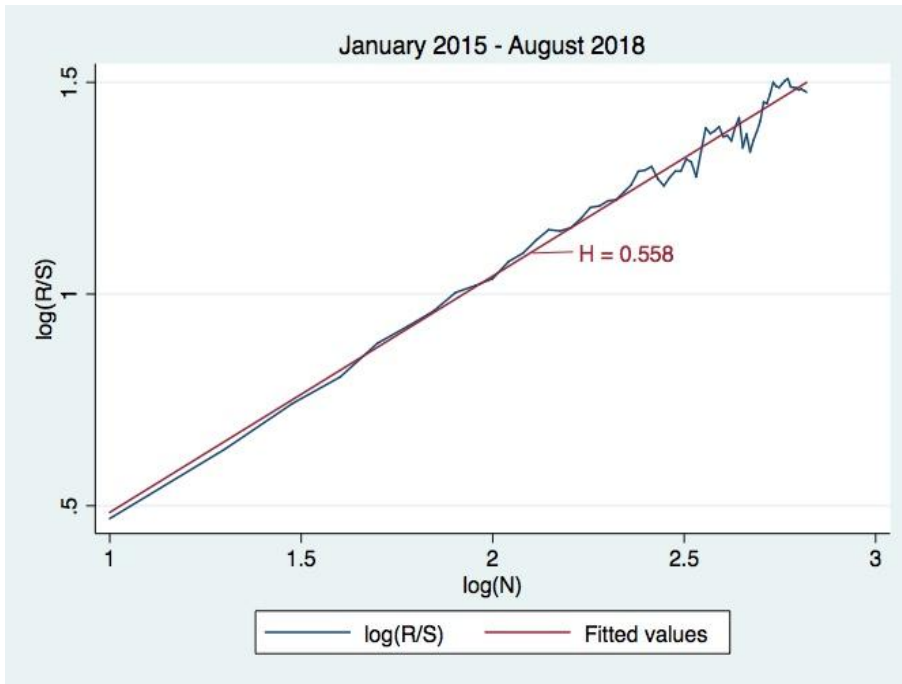


Figure 8.4: Log/log plot of the full sample period in Venezuela

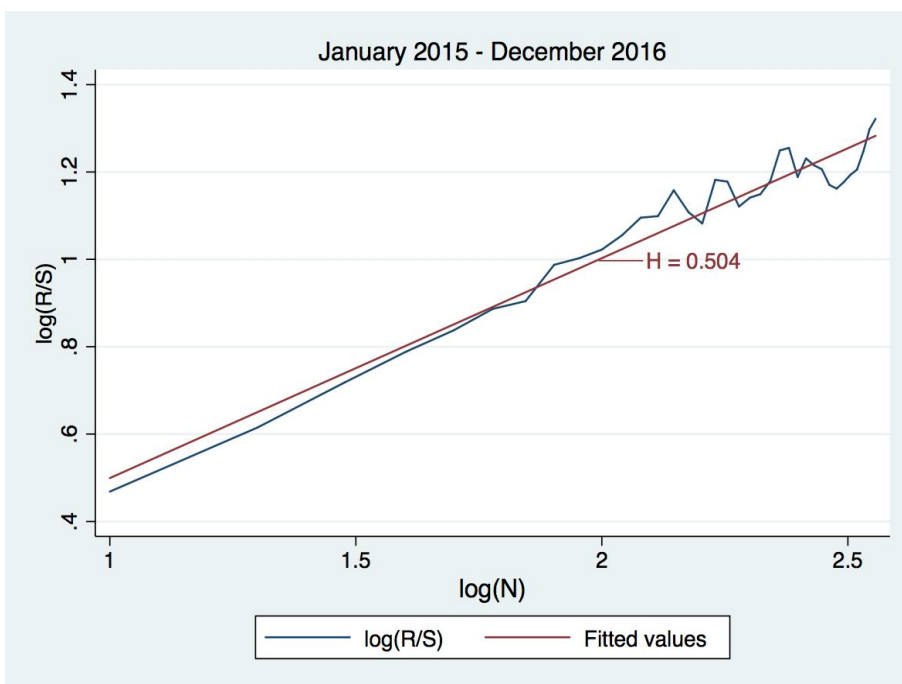


Figure 8.5: Log/log plot of the first subsample period in Venezuela

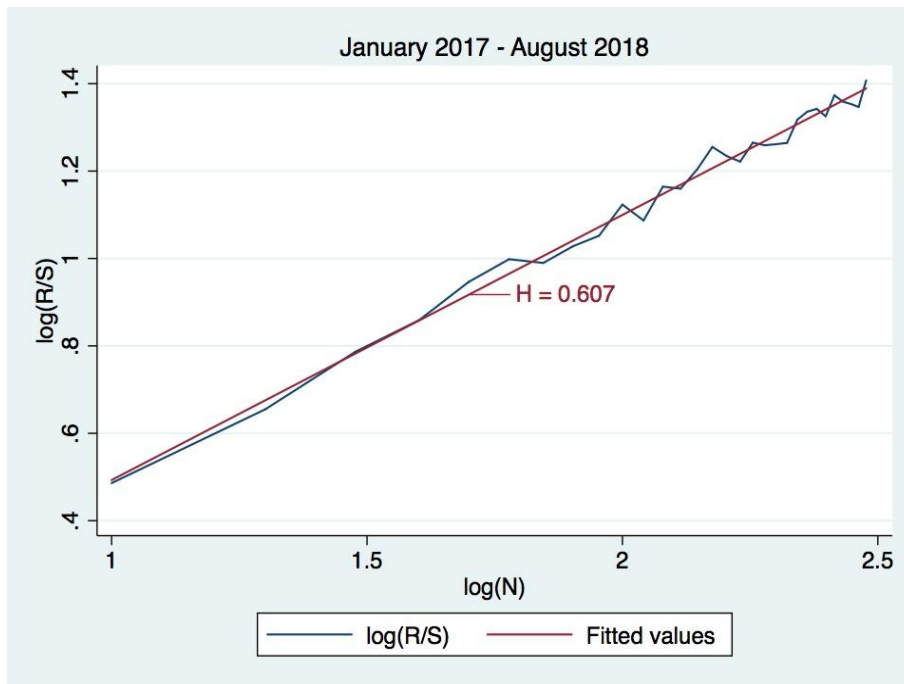


Figure 8.6: Log/log plot of the second subsample period in Venezuela

Looking at the log/log plots for Venezuela for the first subsample period, in figure 8.5, a Hurst exponent of 0.504 is obtained. This value is approximately equal to 0.5, which shows evidence of a random series. For the full and the last subsample period, in figure 8.4 and 8.6, the Hurst exponent is equal to 0.558 and 0.607, respectively. Hence, there are indications of persistency in the Venezuelan Bitcoin returns. The H in the full sample period however, is close to being within the range of 0.05, and only implies weak evidence of persistency. The findings imply that the returns become less efficient over the time period. Hence, the Bitcoin market in Venezuela shows signs of becoming less efficient in the recent years. However, looking at the full period, the Bitcoin market in Venezuela is considered to be weak form efficient.

9. Discussion

As done in Urquhart (2016), we have conducted six different statistical tests to detect weak form market efficiency, with the purpose of obtaining robust results in the statistical sense. Table 9.1 and 9.2 display the p-values from performing the different tests, by using the associated software. R/S Hurst does not provide a p-value, thus the Hurst exponent is reported in the table.

9.1 USA

	Ljung and Box	Runs	Bartels	AVR	BDS	R/S Hurst
01.06.2014 – 31.12.2018	0.1523	0.05*	0.0264*	0.7392	0.0000*	0.6154
01.06.2014 – 31.12.2016	0.0121*	0.06*	0.0353*	0.3777	0.0000*	0.5279
01.01.2017 – 31.12.2018	0.3817	0.63	0.0387*	0.7803	0.0000*	0.5414

Table 9.1: Summary of p-values from all tests for the US

The test results for the full period, for the US, show some inconclusive results. We fail to reject the null hypothesis of independently identically distributed random returns when running the Ljung and Box test and the AVR test, pointing in the direction that the Bitcoin market in the US is efficient. However, the R/S Hurst exponent is significantly higher than 0.5, which indicates that we are dealing with a persistent time series. Based on the overall results from the six statistical tests, there is stronger evidence against i.i.d. returns, hence the US market for Bitcoin returns for the full period show signs of being inefficient.

For the 1st subsample period, more contrary results are observed. We reject the null hypothesis of i.i.d. for the Ljung and Box test, Bartels test, and the BDS test, which can be interpreted as evidence against weak form EMH. Nevertheless, the Hurst exponent is approximately equal to 0.5 and can be considered as evidence against long memory in the Bitcoin returns. Although we fail to reject H_0 for the Runs test, the results show a p-value of 0.06, which is close to the significance level of $\alpha=0.05$. As mentioned in section 7.3, Bartels test is considered to be more powerful than the Runs test, due to its consideration of the magnitude of the observations. Based on this we put more emphasis on Bartels test, than Runs

test. Consequently, most of the tests reject the null hypothesis, indicating that the Bitcoin market in the US is inefficient, for the 1st subsample period. However, the results from the tests are not consistent, and some signs of the market being weak form efficient are observed. For the 2nd subsample period, Bartels and BDS test reject the null hypothesis of i.i.d. returns, pointing towards inefficiency of the Bitcoin market. The remaining tests fail to reject H_0 , meaning that there is stronger evidence of the Bitcoin market in the US to be weak form efficient in this period.

Based on the findings presented above the overall conclusion for the Bitcoin market in the US is that the market is inefficient. However, we have observed strong signs of the Bitcoin market moving towards being weak form efficient. As described in section 5, Urquhart studied a period from August 2010 to July 2016 and his last subsample period had a time frame from August 2013 to July 2016. His results were that the Bitcoin market appears to become more efficient over time. Our 1st subsample period overlaps with Urquhart's last subsample period, and gives approximately the same conclusion of the Bitcoin market in the US showing signs of moving towards efficiency. The 2nd subsample period of our study includes recent data, and it is by including this period, 1st of January 2017 to 31st of December 2018, we examine whether Urquhart's prediction holds. Through studying this period, we are able to confirm his implications. We find that the majority of the six statistical tests fail to reject the null hypothesis of i.i.d. in Bitcoin returns for our 2nd subsample period. Thus, our study shows that weak form of market efficiency is present in the US Bitcoin market when we include more recent data.

For the same sample periods as Urquhart, Nadarajah and Chu (2016) concluded that the Bitcoin market in the US is weak form efficient, see section 5. However, our results are supported by Kristoufek (2018) and Bariviera (2017), in addition to Urquhart (2016). Kristoufek applied an efficiency index and found that the market was inefficient in the time period from 18th of July 2010 to 31st of July 2017. Bariviera applied the R/S Hurst analysis and the DFA method on Bitcoin returns from 18th of August 2011 to 15th of February 2017, with the conclusion of the market being inefficient up until 2014 and that it moves towards efficiency in the following years. This implies that although the sample periods of Bitcoin returns differ, most of the previous literature available supports our findings, for the Bitcoin market in the US.

9.2 Venezuela

	Ljung and Box	Runs	Bartels	AVR	BDS	R/S Hurst
01.01.2015 – 31.08.2018	0.0000*	0.00*	0.0255*	0.0000*	0.0000*	0.5580
01.01.2015 – 31.12.2016	0.0000*	0.00*	0.0325*	0.0000*	0.0000*	0.5035
01.01.2017 – 31.08.2018	0.0028*	0.01*	0.0384*	0.9542	0.0000*	0.6067

Table 9.2: Summary of p-values from all tests for Venezuela

The findings for Venezuela are more coherent, relative to the results for the US. We reject the null hypothesis of i.i.d., for all of the tests in the full sample period. The Hurst analysis supports this result. This means that the Bitcoin market in Venezuela for the full period shows no signs of weak form EMH. We have the same scenario for the 1st subsample period, with exception of the Hurst analysis that shows an exponent close to 0.5. For the 2nd subsample period the only test that fails to reject H_0 is the AVR test. From these findings we can conclude that the Bitcoin market in Venezuela is inefficient.

According to United Nations, Venezuela is defined as a developing country and it is known through various research that emerging markets are less efficient (United Nations, 2014). An example is a study by Di Matteo, Aste and Dacorogna in 2008, who applied the Hurst approach to “study the scaling properties of daily foreign exchange rates, stock market indices and fixed income instruments”. They concluded that the inefficiency of markets is positively correlated with the degree of development (Matteo, Aste, & Dacorogna, 2008). Another example is a research paper published by Lee, Lee and Lee in 2009. This paper examines “whether the efficient market hypothesis holds in stock markets under different economic development levels” by performing a panel data stationarity test. The conclusion of their paper is that all of the 26 developing countries tested, show signs of market inefficiency (Lee, Lee, & Lee, 2009). Furthermore, Bitcoin is a relatively new phenomenon in Venezuela, and as Urquhart points out in his paper, investment assets in their infancy can be associated with emerging markets. As described in section 3.4, the economy of the country has been unstable and characterized by hyperinflation, in the recent years. Our study confirms these implications, and the test results for Venezuela are therefore not unexpected.

9.3 Short comings of our approach

As we are replicating Urquhart (2016) the ideal test procedure would be conducted by using data from the same exchange platform. He uses bitcoinaverage.com, which provides a volume weighted average of Bitcoin prices from several accessible Bitcoin exchanges from all over the world (Urquhart, 2016). However, access to this data set is costly, thus we were not able to collect data from this platform. As mentioned in section 6.1, we collect Bitcoin prices from the exchange platforms Bitfinex and LocalBitcoins. The main difference between our data and Urquhart's data is that our prices for the US are obtained from one specific platform, Bitfinex. Our data does not reflect the average market price, as done by Urquhart, who used average market prices from Bitcoinaverage.com. The price of Bitcoin varies across platforms, which limits the basis for comparison.

The results could also be improved by including a longer time period. We chose time periods for the US that overlapped with the last subsample of Urquhart's paper to check whether his statement about the market moving towards efficiency holds. For Venezuela, there were no historical prices available from the chosen exchange platform LocalBitcoins, until January 2015. These elements caused limitations for the length of the time period.

As for the tests, Urquhart does not go into detail in his description of the test procedures. Some of the tests require a selection for the value of different parameters, and specifications in the test procedure. Examples are the BDS test where embedding dimension and the distance ϵ needs to be decided, and determining increments when conducting the R/S Hurst analysis. The potential of inconsistency in the test procedure may cause inadequate results, relative to Urquhart (2016).

Section 4 describes how the presence of market efficiency makes it impossible for investors to make profit from investments. Our overall findings show that the Bitcoin returns in both the US and Venezuela, are inconsistent with weak form EMH. However, this does not necessarily mean that it is possible for investors to beat the market index. They still need to develop a suitable trading strategy in order to take advantage of the possible arbitrage opportunities. This concern is not covered in this thesis, however this thesis aims to facilitate for further research.

10. Conclusion

In this thesis, the presence of weak form market efficiency in the Bitcoin market, for the US and Venezuela, has been tested statistically. We have replicated the work of Urquhart (2016) and expanded the research by adding more recent data for the US. Urquhart studied a time period from 1st of August 2010 to 31st of July 2016, while our study period is from 1st of June 2014 to 31st of December 2018. Hence, our study consists of 29 months of recent data that is not included in Urquhart's study. Additionally, we have done a comparison of the weak form of market efficiency in the US and Venezuela, with the objective of examining two countries where the functions and use of Bitcoin differ. In the US, Bitcoin is a popular investment object, particularly as a diversifier, because its return properties differ from other investment assets. The functionality of Bitcoin in Venezuela is quite different. Due to the financial situation in the country, hyperinflation has characterized the domestic economy. This has led to an increasing part of the population using Bitcoin as a currency, and mining has also become more widespread over the recent years.

The weak form of EMH has been examined by performing six different statistical tests to detect whether daily Bitcoin returns are indeed independently identically distributed. Our findings for the US are that the Bitcoin returns are inefficient for the full period. However, we found evidence of efficiency in the last subsample period, which indicates that Urquhart's statement of the Bitcoin market moving towards efficiency, holds. In Venezuela, the findings are more coherent. We conclude that the market shows no signs of weak form EMH.

Our findings facilitate for further research on development of trading strategies, in order to examine whether it is possible to beat the market. Another interesting field of interest is to include a larger number of developed and developing countries, in order to check whether our findings can be applied as a general conclusion for such economies.

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12. Appendix

12.1 Stata do-files

// DATA USD - DESCRIPTIVE STATISTICS

```
clear all
import excel "/Users/Kaja/Dropbox/UIA/Master/Data/Data-USD STATA.xlsx",
sheet("BITFINEX-BTCUSD-2") firstrow
drop High Low Mid Bid Ask Volume
tsset Date // Declare data to be time series
format Date %dd/n/CY // Format date to dd.mm.yyyy
gen Rt=log>Last[_n]/Last[_n-1])*100 // Generate log returns
summarize Rt // Summary of lnr statistics for log returns
summarize Rt,d // Detailed summary of lnR statistics for log returns
```

// DATA VEF - DESCRIPTIVE STATISTICS

```
clear all
import excel "/Users/Kaja/Dropbox/UIA/Master/Data/Data-VEF STATA.xlsx",
sheet("Ark1") firstrow
gen Date = dofc(Timestamp) // Generate Date without including the time
tsset Date // Declare data to be time series
format Date %dd/n/CY // Format date to dd.mm.yyyy
drop High Low Open VolumeBTC VolumeCurrency WeightedPrice Timestamp
gen Rt=log(Close[_n]/Close[_n-1])*100 // Generate log returns
replace Rt = 20.8451138 in 1326
summarize Rt // Summary of lnr statistics for log returns
summarize Rt,d // Detailed summary of lnR statistics for log returns
```

// LJUNG BOX TEST USA

```
clear all
import excel "/Users/Kaja/Dropbox/UIA/Master/Data/Data-USD STATA.xlsx",
sheet("BITFINEX-BTCUSD-2") firstrow
drop High Low Mid Bid Ask Volume
tsset Date
format Date %dd/n/CY
gen t=_n
tsset t
gen Rt=log>Last[_n]/Last[_n-1])*100
wntestq Rt
```

// LJUNG BOX TEST USA - FIRST PERIOD

```
clear all
import excel "/Users/Kaja/Dropbox/UIA/Master/Data/Data-USD STATA.xlsx",
sheet("BITFINEX-BTCUSD-2") firstrow
drop High Low Mid Bid Ask Volume
drop in 923/1636
tsset Date
format Date %dd/n/CY
gen t=_n
```

```

tsset t
gen Rt=log>Last[_n]/Last[_n-1])*100
wntestq Rt

```

// LJUNG BOX TEST USA - SECOND PERIOD

```

clear all
import excel "/Users/Kaja/Dropbox/UIA/Master/Data/Data-USD STATA.xlsx",
sheet("BITFINEX-BTCUSD-2") firstrow
drop High Low Mid Bid Ask Volume
drop in 1/922
tsset Date
format Date %dd/n/CY
gen t=_n
tsset t
gen Rt=log>Last[_n]/Last[_n-1])*100
wntestq Rt

```

// LJUNG BOX TEST VENEZUELA

```

clear all
import excel "/Users/Kaja/Dropbox/UIA/Master/Data/Data-VEF STATA.xlsx",
sheet("Ark1") firstrow
gen Date = dofc(Timestamp) // Generate Date without including the time
tsset Date // Declare data to be time series
format Date %dd/n/CY // Format date to dd.mm.yyyy
drop High Low Open VolumeBTC VolumeCurrency WeightedPrice Timestamp
gen t=_n
tsset t
gen Rt=log(Close[_n]/Close[_n-1])*100
replace Rt = 20.8451138 in 1326
wntestq Rt

```

// LJUNG BOX TEST VENEZUELA - FIRST PERIOD

```

clear all
import excel "/Users/Kaja/Dropbox/UIA/Master/Data/Data-VEF STATA.xlsx",
sheet("Ark1") firstrow
gen Date = dofc(Timestamp) // Generate Date without including the time
tsset Date // Declare data to be time series
format Date %dd/n/CY // Format date to dd.mm.yyyy
drop High Low Open VolumeBTC VolumeCurrency WeightedPrice Timestamp
drop in 730/1337
gen t=_n
tsset t
gen Rt=log(Close[_n]/Close[_n-1])*100
wntestq Rt

```

// LJUNG BOX TEST VENEZUELA - SECOND PERIOD

```

clear all
import excel "/Users/Kaja/Dropbox/UIA/Master/Data/Data-VEF STATA.xlsx",
sheet("Ark1") firstrow
gen Date = dofc(Timestamp) // Generate Date without including the time

```

```

tsset Date // Declare data to be time series
format Date %dd/n/CY // Format date to dd.mm.yyyy
drop High Low Open VolumeBTC VolumeCurrency WeightedPrice Timestamp
drop in 1/729
gen t=_n
tsset t
gen Rt=log(Close[_n]/Close[_n-1])*100
replace Rt = 20.8451138 in 597
wntestq Rt

```

// RUNS TEST USA

```

clear all
import excel "/Users/Kaja/Dropbox/UIA/Master/Data/Data-USD STATA.xlsx",
sheet("BITFINEX-BTCUSD-2") firstrow
drop High Low Mid Bid Ask Volume
tsset Date
format Date %dd/n/CY
gen t=_n
tsset t
gen Rt=log>Last[_n]/Last[_n-1])*100
runtest Rt, d //ignore values equal to median

```

// RUNS TEST USA - FIRST PERIOD

```

clear all
import excel "/Users/Kaja/Dropbox/UIA/Master/Data/Data-USD STATA.xlsx",
sheet("BITFINEX-BTCUSD-2") firstrow
drop High Low Mid Bid Ask Volume
drop in 923/1636
tsset Date
format Date %dd/n/CY
gen t=_n
tsset t
gen Rt=log>Last[_n]/Last[_n-1])*100
runtest Rt, d //ignore values equal to median

```

// RUNS TEST USA - SECOND PERIOD

```

clear all
import excel "/Users/Kaja/Dropbox/UIA/Master/Data/Data-USD STATA.xlsx",
sheet("BITFINEX-BTCUSD-2") firstrow
drop High Low Mid Bid Ask Volume
drop in 1/922
tsset Date
format Date %dd/n/CY
gen t=_n
tsset t
gen Rt=log>Last[_n]/Last[_n-1])*100
runtest Rt, d //ignore values equal to median

```

// RUNS TEST VENEZUELA

```
clear all
import excel "/Users/Kaja/Dropbox/UIA/Master/Data/Data-VEF STATA.xlsx",
sheet("Ark1") firstrow
gen Date = dofc(Timestamp) // Generate Date without including the time
tsset Date // Declare data to be time series
format Date %dd/n/CY // Format date to dd.mm.yyyy
drop High Low Open VolumeBTC VolumeCurrency WeightedPrice Timestamp
gen t=_n
tsset t
gen Rt=log(Close[_n]/Close[_n-1])*100
replace Rt = 20.8451138 in 1326
runtest Rt, d
```

// RUNS TEST VENEZUELA - FIRST PERIOD

```
clear all
import excel "/Users/Kaja/Dropbox/UIA/Master/Data/Data-VEF STATA.xlsx",
sheet("Ark1") firstrow
gen Date = dofc(Timestamp) // Generate Date without including the time
tsset Date // Declare data to be time series
format Date %dd/n/CY // Format date to dd.mm.yyyy
drop High Low Open VolumeBTC VolumeCurrency WeightedPrice Timestamp
drop in 730/1337
gen t=_n
tsset t
gen Rt=log(Close[_n]/Close[_n-1])*100
runtest Rt
```

// RUNS TEST VENEZUELA - SECOND PERIOD

```
clear all
import excel "/Users/Kaja/Dropbox/UIA/Master/Data/Data-VEF STATA.xlsx",
sheet("Ark1") firstrow
gen Date = dofc(Timestamp) // Generate Date without including the time
tsset Date // Declare data to be time series
format Date %dd/n/CY // Format date to dd.mm.yyyy
drop High Low Open VolumeBTC VolumeCurrency WeightedPrice Timestamp
drop in 1/729
gen t=_n
tsset t
gen Rt=log(Close[_n]/Close[_n-1])*100
replace Rt = 20.8451138 in 597
runtest Rt
```

// BARTELS TEST USA

```
clear all
import excel "/Users/Kaja/Dropbox/UIA/Master/Data/Data-USD STATA.xlsx",
sheet("BITFINEX-BTCUSD-2") firstrow
drop High Low Mid Bid Ask Volume
tsset Date
format Date %dd/n/CY
```

```

gen t=_n
tsset t
gen Rt=log(Last[_n]/Last[_n-1])*100
lmavon Rt
display igaussiantail(2,0.00244439,2.0442) //calculate p-value

```

// BARTELS TEST USA - FIRST PERIOD

```

clear all
import excel "/Users/Kaja/Dropbox/UIA/Master/Data/Data-USD STATA.xlsx",
sheet("BITFINEX-BTCUSD-2") firstrow
drop High Low Mid Bid Ask Volume
drop in 923/1636
tsset Date
format Date %dd/n/CY
gen t=_n
tsset t
gen Rt=log(Last[_n]/Last[_n-1])*100
lmavon Rt
display igaussiantail(2,0.00433651,1.9816)

```

// BARTELS TEST USA - SECOND PERIOD

```

clear all
import excel "/Users/Kaja/Dropbox/UIA/Master/Data/Data-USD STATA.xlsx",
sheet("BITFINEX-BTCUSD-2") firstrow
drop High Low Mid Bid Ask Volume
drop in 1/922
tsset Date
format Date %dd/n/CY
gen t=_n
tsset t
gen Rt=log(Last[_n]/Last[_n-1])*100
lmavon Rt
display igaussiantail(2,0.0055991,2.0821)

```

// BARTELS TEST VENEZUELA

```

clear all
import excel "/Users/Kaja/Dropbox/UIA/Master/Data/Data-VEF STATA.xlsx",
sheet("Ark1") firstrow
gen Date = dofc(Timestamp) // Generate Date without including the time
tsset Date // Declare data to be time series
format Date %dd/n/CY // Format date to dd.mm.yyyy
drop High Low Open VolumeBTC VolumeCurrency WeightedPrice Timestamp
gen t=_n
tsset t
gen Rt=log(Close[_n]/Close[_n-1])*100
replace Rt = 20.8451138 in 1326
lmavon Rt
display igaussiantail(2,0.00299088,2.6278) //calculate p-value

```


// BARTELS TEST VENEZUELA - FIRST PERIOD

```
clear all
import excel "/Users/Kaja/Dropbox/UIA/Master/Data/Data-VEF STATA.xlsx",
sheet("Ark1") firstrow
gen Date = dofc(Timestamp) // Generate Date without including the time
tsset Date // Declare data to be time series
format Date %dd/n/CY // Format date to dd.mm.yyyy
drop High Low Open VolumeBTC VolumeCurrency WeightedPrice Timestamp
drop in 730/1337
gen t=_n
tsset t
gen Rt=log(Close[_n]/Close[_n-1])*100
lmargin Rt
display igaussiantail(2,0.005483959,2.8404) //calculate p-value
```

// BARTELS TEST VENEZUELA - SECOND PERIOD

```
clear all
import excel "/Users/Kaja/Dropbox/UIA/Master/Data/Data-VEF STATA.xlsx",
sheet("Ark1") firstrow
gen Date = dofc(Timestamp) // Generate Date without including the time
tsset Date // Declare data to be time series
format Date %dd/n/CY // Format date to dd.mm.yyyy
drop High Low Open VolumeBTC VolumeCurrency WeightedPrice Timestamp
drop in 1/729
gen t=_n
tsset t
gen Rt=log(Close[_n]/Close[_n-1])*100
replace Rt = 20.8451138 in 597
lmargin Rt
display igaussiantail(2,0.00657462,2.4325 ) //calculate p-value
```

// RS HURST ANALYSIS USA

```
clear all
import excel "/Users/Kaja/Dropbox/UIA/Master/Data/Data-USD STATA.xlsx",
sheet("BITFINEX-BTCUSD-2") firstrow
drop High Low Mid Bid Ask Volume
tsset Date
format Date %dd/n/CY
gen t=_n
tsset t
gen Rt=log>Last[_n]/Last[_n-1])*100
gen lRt = L1.Rt //lag (x_t-1)
regress Rt lRt
gen Xt = Rt- (.1095346+(-.0220458*lRt)) // generates residual returns (bruker alpha og beta)
```

```
gen RS = . // generates an empty variable where R/S values is placed as they are computed
gen N = . // generates an empty variable where the length of the sub-periods is placed as
they are generated
```

```
forvalues i =10(10)816 {
```

```

egen float n`i' = seq(), from(1) to(1636) block(`i') // generates the non-overlapping
subperiods
sort n`i'
by n`i' : egen mean`i' = mean(Xt) // computes the mean of the sub-periods
by n`i' : egen ss`i' = sum((Xt-mean`i')^2) // computes the variance of the sub-periods
by n`i' : gen sd`i' = (ss`i'/'i')^0.5
gen cXt`i' = (Xt-mean`i') // generates the accumulative depatures from the
mean
by n`i': gen scXt`i' = sum(cXt`i' )
by n`i': egen min`i' = min(scXt`i')
by n`i': egen max`i' = max(scXt`i')
gen Range`i' = max`i' - min`i' // generates the range
by n`i': gen rs`i' = (Range`i'/sd`i') if n`i' <= floor(1636/'i') // generates the R/S values of
the sub-periods, drop period which is not equal to the length n
egen mrs`i' = mean(rs`i') // calculates the mean R/S of the sub-
periods
by n`i' : gen ersl`i' = 1/(sqrt(((`i'-0.5)/'i')*((`i'*_pi)/2))) // line 31-33 computes the
expexted R/S values
by n`i' : gen sqnr`i' = sqrt((`i'-t)/t)
by n`i' : egen ssqnr`i' = sum(sqnr`i')
replace RS = mrs`i' in `i' // places the mean R/S of the sub-periods in
variable RS
replace N = `i' in `i' // places the length n of the sub-periods in
variable N
}
gen logRS = log10(RS)
gen logN = log10(N)
twoway (line logRS logN)
regress logRS logN
twoway (line logRS logN)(lfit logRS logN)

```

// RS HURST ANALYSIS USA - FIRST PERIOD

```

clear all
import excel "/Users/Kaja/Dropbox/UIA/Master/Data/Data-USD STATA.xlsx",
sheet("BITFINEX-BTCUSD-2") firstrow
drop High Low Mid Bid Ask Volume
drop in 923/1636
tsset Date
format Date %dd/n/CY
gen t=_n
tsset t
gen Rt=log(Last[_n]/Last[_n-1])*100
gen lRt = L1.Rt //lag (x_t-1)
regress Rt lRt
gen Xt = Rt-(.0393795+(.0099234*lRt)) // generates residual returns (bruker alpha og beta)

gen RS = . // generates an empty variable where R/S values is placed as they are computed
gen N = . // generates an empty variable where the length of the sub-periods is placed as
they are generated

```

```

forvalues i =10(10)461 {

egen float n`i' =seq(), from(1) to(922) block(`i') // generates the non-overlapping
subperiods
sort n`i'
by n`i' : egen mean`i' = mean(Xt) // computes the mean of the sub-periods
by n`i' : egen ss`i' = sum((Xt-mean`i')^2) // computes the variance of the sub-periods
by n`i' : gen sd`i' =(ss`i'/`i')^0.5
gen cXt`i' = (Xt-mean`i') // generates the accumalative depatures from the
mean
by n`i': gen scXt`i' = sum(cXt`i' )
by n`i': egen min`i' = min(scXt`i')
by n`i': egen max`i' = max(scXt`i')
gen Range`i' = max`i' - min`i' // generates the range
by n`i': gen rs`i' = (Range`i'/sd`i') if n`i' <= floor(922/`i') // generates the R/S values of the
sub-periods, drop period which is not equal to the length n
egen mrs`i' = mean(rs`i') // calculates the mean R/S of the sub-
periods
by n`i' : gen ers1`i' = 1/(sqrt(((`i'-0.5)/`i')*((`i'*_pi)/2))) // line 31-33 computes the
expexted R/S values
by n`i' : gen sqnr`i' = sqrt(`i'-t)/t)
by n`i' : egen ssqnr`i' = sum(sqnr`i')
replace RS = mrs`i' in `i' // places the mean R/S of the sub-periods in
variable RS
replace N = `i' in `i' // places the length n of the sub-periods in
variable N
replace ERS = (ers1`i'*ssqnr`i') in `i' // // places the Expected R/S of the sub-
periods in variable ERS
}

gen logRS = log10(RS)
gen logN = log10(N)
twayway (line logRS logN)
regress logRS logN
twayway (line logRS logN)(lfit logRS logN)

// RS HURST ANALYSIS USA - SECOND PERIOD
clear all
import excel "/Users/Kaja/Dropbox/UIA/Master/Data/Data-USD STATA.xlsx",
sheet("BITFINEX-BTCUSD-2") firstrow
drop High Low Mid Bid Ask Volume
drop in 1/922
tsset Date
format Date %dd/n/CY
gen t=_n
tsset t
gen Rt=log(Last[_n]/Last[_n-1])*100
gen IRt = L1.Rt //lag (x_t-1)
regress Rt IRt
gen Xt = Rt- (.1965925+(-.040508*IRt)) // generates residual returns

```

```

gen RS = . // generates an empty variable where R/S values is placed as they are computed
gen N = . // generates an empty variable where the length of the sub-periods is placed as
they are generated

```

```

forvalues i =10(10)356 {

```

```

egen float n`i' =seq(), from(1) to(712) block(`i') // generates the non-overlapping
subperiods
sort n`i'
by n`i' : egen mean`i' = mean(Xt) // computes the mean of the sub-periods
by n`i' : egen ss`i' = sum((Xt-mean`i')^2) // computes the variance of the sub-periods
by n`i' : gen sd`i' =(ss`i'/'i')^0.5
gen cXt`i' = (Xt-mean`i') // generates the accumalative depatures from the
mean
by n`i': gen scXt`i' = sum(cXt`i' )
by n`i': egen min`i' = min(scXt`i')
by n`i': egen max`i' = max(scXt`i')
gen Range`i' = max`i' - min`i' // generates the range
by n`i': gen rs`i' = (Range`i'/sd`i') if n`i' <= floor(712/'i') // generates the R/S values of the
sub-periods, drop period which is not equal to the length n
egen mrs`i' = mean(rs`i') // calculates the mean R/S of the sub-
periods
by n`i' : gen ers1`i' = 1/(sqrt(((`i'-0.5)/'i')*((`i'*_pi)/2))) // line 31-33 computes the
expexted R/S values
by n`i' : gen sqnr`i' = sqrt((`i'-t)/t)
by n`i' : egen ssqnr`i' = sum(sqnr`i')
replace RS = mrs`i' in `i' // places the mean R/S of the sub-periods in
variable RS
replace N = `i' in `i' // places the length n of the sub-periods in
variable N
}

```

```

gen logRS = log10(RS)
gen logN = log10(N)
tway (line logRS logN)
regress logRS logN
tway (line logRS logN)(lfit logRS logN)

```

// RS HURST ANALYSIS VENEZUELA

```

clear all
import excel "/Users/Kaja/Dropbox/UIA/Master/Data/Data-VEF STATA.xlsx",
sheet("Ark1") firstrow
gen Date = dofc(Timestamp) // Generate Date without including the time
tsset Date // Declare data to be time series
format Date %dd/n/CY // Format date to dd.mm.yyyy
drop High Low Open VolumeBTC VolumeCurrency WeightedPrice Timestamp
gen t=_n
tsset t
gen Rt=log(Close[_n]/Close[_n-1])*100
replace Rt = 20.8451138 in 1326

```

```

gen lRt = L1.Rt //lag (x_t-1)
regress Rt lRt
gen Xt = Rt-(1.409802+(-.3129124*lRt)) // generates residual returns (bruker alpha og beta)

gen RS = . // generates an empty variable where R/S values is placed as they are computed
gen N = . // generates an empty variable where the length of the sub-periods is placed as
they are generated

forvalues i =10(10)668 {

egen float n`i' =seq(), from(1) to(1337) block(`i') // generates the non-overlapping
subperiods
sort n`i'
by n`i' : egen mean`i' = mean(Xt) // computes the mean of the sub-periods
by n`i' : egen ss`i' = sum((Xt-mean`i')^2) // computes the variance of the sub-periods
by n`i' : gen sd`i' =(ss`i'/'i')^0.5
gen cXt`i' = (Xt-mean`i') // generates the accumulative depatures from the
mean
by n`i': gen scXt`i' = sum(cXt`i' )
by n`i': egen min`i' = min(scXt`i')
by n`i': egen max`i' = max(scXt`i')
gen Range`i' = max`i' - min`i' // generates the range
by n`i': gen rs`i' = (Range`i'/sd`i') if n`i' <= floor(1337/'i') // generates the R/S values of
the sub-periods, drop period which is not equal to the length n
egen mrs`i' = mean(rs`i') // calculates the mean R/S of the sub-
periods
by n`i' : gen ers1`i' = 1/(sqrt(((`i'-0.5)/'i')*((`i'*_pi)/2))) // line 31-33 computes the
expexted R/S values
by n`i' : gen sqnr`i' = sqrt((`i'-t)/t)
by n`i' : egen ssqnr`i' = sum(sqnr`i')
replace RS = mrs`i' in `i' // places the mean R/S of the sub-periods in
variable RS
replace N = `i' in `i' // places the length n of the sub-periods in
variable N
}

gen logRS = log10(RS)
gen logN = log10(N)
tway (line logRS logN)
regress logRS logN
tway (line logRS logN)(lfit logRS logN)

// RS HURST ANALYSIS VENEZUELA - FIRST PERIOD
clear all
import excel "/Users/Kaja/Dropbox/UIA/Master/Data/Data-VEF STATA.xlsx",
sheet("Ark1") firstrow
gen Date = dofc(Timestamp) // Generate Date without including the time
tsset Date // Declare data to be time series
format Date %dd/n/CY // Format date to dd.mm.yyyy
drop High Low Open VolumeBTC VolumeCurrency WeightedPrice Timestamp

```

```

drop in 730/1337
gen t=_n
tsset t
gen Rt=log(Close[_n]/Close[_n-1])*100
gen lRt = L1.Rt //lag (x_t-1)
regress Rt lRt
gen Xt = Rt-(.7691109+(-.4210771*lRt)) // generates residual returns (bruker alpha og beta)

gen RS = . // generates an empty variable where R/S values is placed as they are computed
gen N = . // generates an empty variable where the length of the sub-periods is placed as
they are generated

forvalues i =10(10)365 {

egen float n`i' =seq(), from(1) to(729) block(`i') // generates the non-overlapping
subperiods
sort n`i'
by n`i' : egen mean`i' = mean(Xt) // computes the mean of the sub-periods
by n`i' : egen ss`i' = sum((Xt-mean`i')^2) // computes the variance of the sub-periods
by n`i' : gen sd`i' =(ss`i'/'i')^0.5
gen cXt`i' = (Xt-mean`i') // generates the accumalative depatures from the
mean
by n`i': gen scXt`i' = sum(cXt`i' )
by n`i': egen min`i' = min(scXt`i')
by n`i': egen max`i' = max(scXt`i')
gen Range`i' = max`i' - min`i' // generates the range
by n`i': gen rs`i' = (Range`i'/sd`i') if n`i' <= floor(729/'i') // generates the R/S values of the
sub-periods, drop period which is not equal to the length n
egen mrs`i' = mean(rs`i') // calculates the mean R/S of the sub-
periods
by n`i' : gen ers1`i' = 1/(sqrt(((`i'-0.5)^(`i')*(`i'*_pi)/2))) // line 31-33 computes the
expected R/S values
by n`i' : gen sqnr`i' = sqrt((`i'-t)/t)
by n`i' : egen ssqnr`i' = sum(sqnr`i')
replace RS = mrs`i' in `i' // places the mean R/S of the sub-periods in
variable RS
replace N = `i' in `i' // places the length n of the sub-periods in
variable N
}

gen logRS = log10(RS)
gen logN = log10(N)
tway (line logRS logN)
regress logRS logN
tway (line logRS logN)(lfit logRS logN)

// RS HURST ANALYSIS VENEZUELA - SECOND PERIOD
clear all
import excel "/Users/Kaja/Dropbox/UIA/Master/Data/Data-VEF STATA.xlsx",
sheet("Ark1") firstrow

```

```

gen Date = dofc(Timestamp) // Generate Date without including the time
tsset Date // Declare data to be time series
format Date %dd/n/CY // Format date to dd.mm.yyyy
drop High Low Open VolumeBTC VolumeCurrency WeightedPrice Timestamp
drop in 1/729
gen t=_n
tsset t
gen Rt=log(Close[_n]/Close[_n-1])*100
replace Rt = 20.8451138 in 597
gen lRt = L1.Rt //lag (x_t-1)
regress Rt lRt
gen Xt = Rt-(2.049811+(-0.2141565*lRt)) // generates residual returns (braker alpha og
beta)

gen RS = . // generates an empty variable where R/S values is placed as they are computed
gen N = . // generates an empty variable where the length of the sub-periods is placed as
they are generated

forvalues i =10(10)304 {

egen float n`i' =seq(), from(1) to(608) block(`i') // generates the non-overlapping
subperiods
sort n`i'
by n`i' : egen mean`i' = mean(Xt) // computes the mean of the sub-periods
by n`i' : egen ss`i' = sum((Xt-mean`i')^2) // computes the variance of the sub-periods
by n`i' : gen sd`i' =(ss`i'/'i')^0.5
gen cXt`i' = (Xt-mean`i') // generates the accumulative depatures from the
mean
by n`i': gen scXt`i' = sum(cXt`i' )
by n`i': egen min`i' = min(scXt`i')
by n`i': egen max`i' = max(scXt`i')
gen Range`i' = max`i' - min`i' // generates the range
by n`i': gen rs`i' = (Range`i'/sd`i') if n`i' <= floor(608/'i') // generates the R/S values of the
sub-periods, drop period which is not equal to the length n
egen mrs`i' = mean(rs`i') // calculates the mean R/S of the sub-
periods
by n`i' : gen ers1`i' = 1/(sqrt(((`i'-0.5)/'i')*((`i'*_pi)/2))) // line 31-33 computes the
expexted R/S values
by n`i' : gen sqnr`i' = sqrt((`i'-t)/t)
by n`i' : egen ssqnr`i' = sum(sqnr`i')
replace RS = mrs`i' in `i' // places the mean R/S of the sub-periods in
variable RS
replace N = `i' in `i' // places the length n of the sub-periods in
variable N
}
gen logRS = log10(RS)
gen logN = log10(N)
tway (line logRS logN)
regress logRS logN
tway (line logRS logN)(lfit logRS logN)

```

12.2 Reflection note – Anne Line Berge Wiersdalen

This paper discusses and reflects upon our master thesis, which main theme is statistical analysis of Bitcoin. We have studied whether the weak form of the efficient market hypothesis is present in the Bitcoin market for the US and Venezuela. For this purpose we have applied six different statistical tests to detect randomness in returns, within a time frame from 2013 up until 2018. The idea for this thesis came from reading articles provided by our supervisor. Especially, we thought a paper written by Andrew Urquhart in 2016 about the (in)efficiency of Bitcoin was appealing. Based on this we decided to replicate his work by including newer data and comparing the results with the same study of the Venezuelan Bitcoin market. The process of writing this thesis has been challenging and educational. In the following sections I am going to discuss how our thesis relates to the concepts; internationalization, innovation and accountability.

When it comes to internationalization, an obvious property of this thesis is that we have written it by using the English language. Furthermore, all communication with our supervisor has been in English. I think this has been useful, and feel that I am better prepared for stepping into the working life by practicing English to this extent. The topic of our thesis is linked to internationalization in the way that Bitcoin is an international currency and investment asset. It is used worldwide and its use differs across countries. In the US its main application area is as an investment asset, while in Venezuela, and other emerging economies, it has been used as a currency. By having the property of being an international investment asset some countries have developed regulations on Bitcoin. As mentioned in section 2.3, the Chinese government has decided to ban all trading of cryptocurrencies from their country. Another example, discussed in this thesis is Venezuela, where there have been cases of people going to jail due to mining Bitcoin. However, one of the main purposes of Bitcoin has been to avoid the need for third parties in transactions and avoiding costly government regulations. Making restrictions and requiring transaction fees will therefore somehow destroy the concept.

When it comes to the term innovation, I have gained a lot of knowledge about the newest methods within statistical analysis, amongst other the Hurst exponent. This method can be applied in several contexts to discover the behavior of time series data. Hurst first used it to examine the optimal amount of water in a water reservoir. A rolling window Hurst exponent

can be used to develop trading strategies in inefficient markets. It has also been applied to study the behavior of nature phenomena, such as sun spots. Additionally, I have learned a lot about the blockchain technology, which is a new and innovative invention. The blockchain technology is highly relevant in future businesses that operates within the field of economy. Some of the largest international audit firms operating in Norway are working on implementing this new technology as a way of sharing financial information for companies, such as financial statements. The blockchain technology facilitates for sharing this information continuously, without any unwanted parties having access. Blockchain technology also have potential of being used in contracting, regulatory compliances and in general as a tool to code and secure exchange of information.

As for accountability I have gained knowledge on how the mining of Bitcoin is affecting the environment. It is stated that mining of Bitcoin today requires the same amount of electricity as a small country. Some argue that this is unsustainable and that Bitcoin mining is not viable and has to stop. Other concerns related to the accountability of bitcoin is that there have been platforms where it has been used to trade illegal goods, like drugs. Bitcoin has also been related to a number of Ponzi schemes and frauds, so that the ethical aspects around the currency has been challenged several times.

However, in some countries Bitcoin is more a more accountable currency, than their country currency. This is especially in emerging markets, amongst others, in some of the countries in Latin-America, such as Venezuela. Due to failing financial systems, with high transaction fees, and in some countries hyperinflation, citizens of these countries use Bitcoin and other cryptocurrencies as a more stable alternative. The paradox of this is that in the developed part of the world Bitcoin is defined as a highly risky and volatile investment asset.

As discussed in this reflection note, this thesis relates to all three terms; internationalization, innovation and accountability. It has been an educational process and it feels like I have gained some more insight and reflected upon important themes that I hope will be useful when stepping into the working life.

12.3 Reflection note – Kaja Aslaksen

During my last semester at the University of Agder, I have been working on my master thesis about the efficiency in the Bitcoin market. Urquhart (2016) concluded that the Bitcoin market in the United States was inefficient, but it also showed signs of moving towards weak form efficiency in the future. A total of six different statistical tests were run, on more recent data, to duplicate the work of Urquhart. The objective was to test if his statement holds true, or not. Additionally, the thesis aims to find out if the results would vary between countries which use Bitcoin in different ways. For this part, the United States and Venezuela were chosen as pilots. In the US, Bitcoin is for the most part used as an investment asset, whilst it in Venezuela is commonly traded as a currency. Our findings show that the market in the United States is inefficient when considering the full time period. However, the last subsample has indications of being weak form efficient, hence Urquhart's statement holds. For Venezuela, the results of our work show that the market is clearly considered inefficient.

Bitcoin is for sure an international phenomenon and holds no borders. Most people have heard or read about Bitcoin in one shape or form. However, very few fully understand the underlying concept of this cryptocurrency. As described in the thesis, Bitcoin differs from fiat money by not being backed up by central banks or governments, hence it has no intrinsic value. This means that the value of Bitcoin is not necessarily influenced by the same factors as fiat money, such as inflation rates and monetary policies. A question that springs to mind is which international factors that influence the price of Bitcoin. From my experience with the subject, I would say that there is probably not one correct answer to this question and that the opinions are many. However, market demand and the introduction of new innovative technologies probably have an influence on the price. Also, the regulatory environment will make a difference. If Bitcoin is not accepted by a country, the price tends to go down, and vice versa, if it is accepted, the price goes up. As discussed, international factors can have an impact on the price of Bitcoin, but on the other side, Bitcoin could also influence international trade. In today's world, it is business as usual that countries trade with each other. The amount of import and export of goods and services in general is not decreasing. However, different currencies and changing exchange rates represent a challenge and risk in international transactions. Bitcoin makes the use of one common currency possible and takes complexity out of the trade equations. As shown in the thesis, the Use of Bitcoin does not

require a third party. There are no transaction fees involved, hence the costs of imports and exports go down.

Upon its introduction, Bitcoin received some critique. The sceptics struggled to see the need for the new cryptocurrency and questioned whether it brought any value to the table. Even though it has gained more acceptance today, some still fail to see the full potential of Bitcoin. It often takes time for markets to recognize the potential and need for new innovations. The same was the case for the internet when introduced many years ago. Whether Bitcoin is a new innovation, or not, can be discussed. According to the Cambridge Dictionary, innovation is a new idea or a better solution, which is so good that people want to use it. In my opinion, Bitcoin by itself is not an innovation. I believe that the real innovative part is the underlying concept of Bitcoin, namely the blockchain technology.

Bitcoin and the area of responsibility have been widely discussed. There is evidence of Bitcoin transactions linked to illegal businesses. Some criminals use Bitcoin, as well as other cryptocurrencies, as a method of payment for illegitimate items and substances, like drugs. By nature, it is difficult to monitor and control all Bitcoin transactions. That would defeat its purpose of a highly efficient and bureaucracy free currency. Therefore, responsibility on an individual level is critical. It is important not to misuse the concept. The legislation about Bitcoin varies from country to country. In some, there are no regulations or restriction on the use of Bitcoin. Others, like China, ban it entirely.

In my opinion, authorities should work together, through already existing international fora's, to agree on common worldwide regulations of digital currencies. If it is a change for the better, there is no holding back.