Factors influencing the volatility of bitcoin returns: An empirical study

By

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Abstract

This thesis examines the bitcoin returns volatility and various factors, and formulates the following research question: ‘’*Which factors influence the volatility of bitcoin returns?’’* This study uses the GARCH (1,1) model and examines five different independent variables, namely trading volume (weekly number of bitcoin traded on Bitstamp), information demand (weekly number of searches from Google Trends), MSCI ACWI world stock market index returns, USD/EURO exchange rate and USD/JPY exchange rate. The sample consists of weekly data from the 5th of January 2014 until the 27th of December 2020, and has been split into two subsample periods due to the increased interest in bitcoin starting from 2017. The results of the variance equation within the GARCH (1,1) model finds support for a positive impact of the number of bitcoin traded on Bitstamp and the number of searches on Google Trends on bitcoin returns volatility, and supports there being no effect of the stock market returns. However, the results find no support for the positive influence of both the exchange rates. The most noticeable limitation to this study is that the results show no significance in the variance equation when testing the period from 2017 until 2020, even though this was to be expected due to it being a highly volatile period. Future research could be executed by using alternative cryptocurrencies, such as ethereum or ripple, or by using a different model for alternative insights.

Keywords: Bitcoin; digital currency; bitcoin returns; modelling volatility; GARCH (1,1)

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1. Introduction

Cryptocurrencies are an extraordinary financial and technological innovation developed over the last decade (Feng, Yiming & Zhang, 2018). Cryptocurrency is a subset of digital or virtual currency that is designed to serve as a medium of exchange, however, with very different characteristics. They are often used in a wider form within the general economic system. The currency makes use of cryptography in order to secure and verify transactions, controlling the creation of new units and making limited entries in a database called Blockchain (Cointelegraph, s.a.). The technology behind Blockchain is an open distributed ledger which records all the transactions. By doing so, it solves the problem of double-spending and gets rid of the need to have a trusted third party. Furthermore, decentralization allows the technology of blockchain to have faster settlement, increased capacity, as well as better security. As a result, cryptocurrency has become one of the most pressing topics within the financial area (Lee, Guo & Wang, 2017). Still to this day, the first and largest market capped cryptocurrency is the bitcoin. Invented in 2008 by Satoshi Nakamoto, bitcoin spurred the creation of many new cryptocoins, better known as altcoins (Nakamoto, 2008). Bitcoin was introduced by its creators in an attempt to step away from the so-called trust-based model of fiat currencies and to create a system that is based on cryptographic proof (Nakamoto, 2008). As of 2021, a total number of 8,436 cryptocoins are available on 367 exchanges (coinmarketcap, 2021a). The total market capitalization of all available cryptocurrencies combined is around $1.45 trillion, of which bitcoin dominates with a market capitalization of 60.1% (coinmarketcap, 2021a). these numbers coincide with the findings of Feng, Wang, and Zhang (2018), who also concluded that the market of cryptocurrencies is extremely volatile. In addition, Ciaian, Rajcaniova and Kancs (2016) mentioned that these extreme forms of volatility are unusual within traditional currencies, suggesting that the volatility could be caused by other determinants of factors that influence the returns of bitcoin. Moreover, Kristoufek (2013) argued that bitcoin could not be explained by traditional economic theories, such as purchasing power parity, future cash flow models or uncovered rate parity, which leads to the consideration whether economic theories could be used for explaining the returns of bitcoin. Notwithstanding, the price of bitcoin fluctuates severely and expeditiously, which results in the fact that many uncertainties remain. Though, bitcoin has the potential to serve as a stable platform for forthcoming financial innovations, regardless of if it manages to emerge as a feasible currency (Economist, 2014).

Due to the unique aspects of bitcoin, it has created a large number of headlines. One of the most interesting and common one is its high volatility. The information and expertise around bitcoin is however minimal compared to fiat currency. At the end of 2020, the database Scopus showed a number of 3,887 articles regarding bitcoin, while there are 54,093 academic articles regarding fiat currencies. Generally, this information is about the legal status of bitcoin, how to classify it and if bitcoin can be treated as a fiat currency, not so much regarding factors that could influence the bitcoin returns volatility. This inadequacy of information leads to greater risks for investors that are involved. This study engages in researching data regarding bitcoin by using financial theories, in order to present investors with knowledge and information regarding those factors. Price volatility and price formation have been broadly studied on various financial markets (e.g., Fama, 1970; Lux, 1995; Barberis, Shleifer & Vishny, 1998; Schwert, 1990), and is in general of great importance to investors, due to the fluctuations resulting in direct loss or gains of their capital. These studies and their findings have expanded the information on volatility of those assets, which helped investors better understand certain aspects on other specific financial assets. However, since the introduction of cryptocurrencies, there has always been criticism around volatility. The market of bitcoin is highly speculative, and more volatile in comparison to other currencies (Cheah & Fry, 2015). Since bitcoin has earned its place in the financial markets and within portfolio management, it is crucial that its volatility is examined (Dyhrberg, 2016). Due to the emerging stage of the bitcoin market, researchers have only just started to investigate this financial phenomenon. This particular market, which attracts attention from all directions, offers interesting research topics. The underlying causes of high price volatility of bitcoin can best be identified with wide information searches and the aid of various financial theories. In line with studies from Kristoufek (2013) and Vlastakis and Markellos (2012), this research uses financial modelling to study variables that found relevant within the theoretical investigation regarding the bitcoin returns volatility.

The purpose of this specific study is to identify various drivers behind the returns volatility of bitcoin. Bitcoin's returns volatility is much higher compared to other fiat currencies (Cheah & Fry, 2015). Joint with its unique market setting, it makes for an interesting study. A literature review consisting of theoretical paradigms as well as empirical research is conducted to analyse which variables are significant factors for price formations within other financial markets as well as the cryptocurrency market. After carefully evaluating the variables and applying them to the bitcoin market, this study aims to identify the specific variables that affect bitcoin's returns volatility. Once these variables are identified, statistical and econometric methods are applied in order to hypothesize their explanatory power. Existing economic theories are being studied in a different setting, which has the possibility to lead to new insights. Therefore, the purpose of this study is to broaden the general knowledge of the bitcoin market. Hence, by identifying the factors that influence the returns volatility of bitcoin, this study sets to benefit both scientific literature as well as the investors.

This thesis aims to identify various drivers behind the volatility of bitcoin returns. In order to reach this goal, the following research question has been formulated:

Research Question: *Which factors influence the volatility of bitcoin returns?*

There are multiple studies that have researched the effect of certain factors on the volatility of bitcoin returns (e.g., Kristoufek, 2015; Ciaian et al., 2016; Pichl & Kaizoji, 2017; Wang & Vergne, 2017; Bouoiyour et al., 2018). These studies all use different factors over a different time period and analysing the data using various methods to test which factors could influence the bitcoin returns. For example, the study of Wang and Vergne (2017) examined the effect of certain aspects of both the supply-side and demand-side factors, such as public interest and technological developments, on the weekly returns of bitcoin from September 2014 until August 2015. They mentioned that applying the same variables and methods on a different time period could lead to interesting different results. In addition, Ciaian et al. (2016) studied both the traditional factors that influence prices, such as market forces of supply and demand, as well as digital specific factors, like the attractiveness of bitcoin by investors. Their study used a derivative of the Barro model for gold over a time period from 2009 until 2015. The results showed that the effects will not hold in the short term but could better explain price changes in the long run, which could result in an interesting alternative study. this particular study seeks to contribute to existing literature by extending the sample period to achieve new insights in the effects of certain factors, by using a time period from the beginning of 2014 until the end of 2020.

Moreover, a number of studies investigated the effect of a single factor on the bitcoin returns volatility (e.g., Kristoufek, 2013; Pryzmont, 2016; Balcilar et al., 2017; Bouri et al., 2019; El Alaoui et al., 2019; Shen et al., 2019). For example, the studies of Balcilar et al. (2017), Bouri et al. (2019) and El Alaoui et al. (2019) all studied the effect of trading volume on the volatility of bitcoin returns. In general, these studies found that the bitcoin returns and changes in trading volume mutually collaborate with each other in a nonlinear way. Furthermore, Bouri et al. (2019) argued that trading volume can be seen as a useful tool to predict extreme positive and negative returns of cryptocurrencies, such as bitcoin. Additionally, the study of Kristoufek (2013) investigated the effects of search queries on Google Trends and Wikipedia with regards to the returns of bitcoin. There main findings showed that search queries are correlated to the bitcoin price and that there exists a pronounced asymmetry between the effect of a raised curiosity towards bitcoin whilst being below or above its trend value. This specific study seeks to contribute to the literature by combining previous studied factors, such as trading volume and search queries on Google Trends, in order to test the effects on the volatility of bitcoin returns.

Throughout all the research that have been conducted with regards to testing the effect of certain factors on the returns volatility of bitcoin, many different methods have been used. For example, Kristoufek (2013) used a single lag in the VAR approach, Ciaian et al. (2016) used a derivative of the Barro model for gold and Balcilar et al. (2017) used the standard linear Granger causality test. This study seeks to complement the existing literature by using a Generalized Autoregressive Heteroskedasticity Model (GARCH) in order to test the influence of certain factors. This method for explaining bitcoin returns volatility has already been used by certain researchers (e.g., Dyhrberg, 2016; Naimy & Hayek, 2018). However, this study is, to my knowledge, the only study that combines these specific factors with this specific model, during this specific time period, and therefore contributes to existing research.

The remainder of the thesis is structured as follows. In chapter 2 the theoretical framework will be discussed, and the hypotheses will be formulated. Chapter 3 introduces the research methodology and data and, chapter 4 presents the empirical results. The last chapter, chapter 5, concludes this thesis and displays the conclusions of this study and discusses the limitations and future research possibilities.

2. Theoretical framework

The purpose of this chapter is to elaborate on specific aspects of bitcoin itself, the bitcoin market, as well as the drivers behind price volatility. In addition, this chapter contains an extensive description of various theoretical concepts, such as the efficient market hypothesis, the market microstructure, and behaviour finance, as a fundamental for understanding existing research analysing the bitcoin market.

2.1 Bitcoin

In 2008, Satoshi Nakamoto introduced a peer-to-peer network better known as bitcoin. Bitcoin can be seen as a digital monetary and payment system that is available through decentralized and distributed networks, without the need for intermediaries. Having a decentralized nature means that for example bitcoin does not have a central authority, there is no central storage for bitcoin, and anybody can trade in bitcoin without the need of any approval. Bitcoin is the first cryptocurrency that has been introduced and is followed by many other digital currencies known as altcoins. Some major alternative coins are ethereum, ripple and litecoin (Coinmarketcap, 2021b). However, At the time of writing this study, bitcoin is still the largest cryptocurrency in existence, as shown by table 1.

Table 1*: Top 10 largest cryptocurrencies of 2021*

Cryptocurrency	Market Cap
1. Bitcoin	$ 872,89 billion
2. Ethereum	$ 206,65 billion
3. Tether	$ 31,60 billion
4. Cardano	$ 27,70 billion
5. XRP	$ 26,98 billion
6. Polkadot	$ 25,63 billion
7. Binance Coin	$ 20,08 billion
8. Litecoin	$ 13,47 billion
9. Stellar	$ 12,39 billion
10. Chainlink	$ 12,33 billion

Source: (Coinmarketcap, 2021a)

Bitcoin is generated as a reward of the process called mining. Mining consists of dealing with very specific, random-based numerical computations that desire significant computing power (Garcia et al., 2014). It involves identifying a certain block that yields a number that is smaller than the given difficulty target. Mining bitcoin is extremely time consuming and a costly process. The bitcoin mining process shows that the reward declines every 4 years. After being launched in 2008, mining a single block resulted in receiving 50 BTC. 4 years later, in 2012, this reward halved to 25 BTC. In 2016 the reward halved again to 12.5 BTC per mined block, and in 2020 the reward halved to 6.25, which is currently still the amount received for mining one block. Following this trend, the reward will halve every 4 years or so until the last bitcoin is mined, which will be around the year 2140. Meaning that there is a reduction in rewards for miners over time (Investopedia, 2019). Considering the unique design of bitcoin, this particular cryptocurrency cannot be generated outside the standard creation mechanism and trying to falsify bitcoin itself or its transaction will be unsuccessful (Sapuric & Kokkinaki, 2014).

The transactions of bitcoin are verified by certain network notes by using cryptography and are documented in a public ledger called blockchain. Blockchain was introduced by Satoshi Nakamoto, who used it as the peer-to-peer network for bitcoin (Nakamoto, 2008). Blockchain is an open distributed ledger that is able to efficiently document transactions between two parties in a permanent and verifiable way. Blockchain can be seen as a growing list of records, or blocks, which are linked together using cryptography. Every individual block contains an algorithm (hash) of the previous block, a certain time stamp, and transaction data (see appendix A for an overview of the bitcoin blockchain structure). Blockchain has been designed in such a way that it is resistant to any form of modification of the data, due to the fact that once documented, the specific data of any block cannot be changed retroactively without altering all following blocks (the economist, 2016).

Today, bitcoin can be used as a form of payment for both online services as well as many physical goods (Bradbury, 2014). Moreover, it is believed by venture capitalists that cryptocurrency has a lot of potential, as substantiated by the fact that an amount of 1.3 billion USD already has been invested in bitcoin related organizations over the year 2018 (Rowley, 2018). By far the most interesting aspect about bitcoin are the investment opportunities. Nonetheless, bitcoin can be used for multiple other purposes, both on- and offline. For example, it is possible to donate bitcoin to charity, use it to buy certain gift cards or spend it on games and applications developed by Microsoft. On top of that, bitcoin can also be used to spend at certain restaurants, to book a hotel via Expedia, buy a plane ticket or even use it to buy a car at a dealership. In extreme forms, it is even possible to spend bitcoin to go to space with Virgin Galactic (Coinbase, 2020). These are just a few examples, as more and more businesses are accepting bitcoin each day.

2.2 Bitcoin market

The value of bitcoin is not determined by macroeconomic fundamentals of any kind, such as GDP, inflation or interest rates, or clinched against other currencies (Kristoufek, 2013). On the contrary, the exchange rate of bitcoin is entirely based on supply and demand. Hence, it is of most importance to recognize the microstructure of the bitcoin market in order to understand its price formation (Garman, 1976; Ciaian, Rajcaniova & Kancs, 2016). As of 2020, the number of investors has risen significantly throughout the last few years and have reached a number of approximately 380,000 trades per day (Blockchain, 2020). Current financial times led investors to find alternative innovative investment opportunities, where bitcoin's lack of correlation with other assets makes it an attractive market (Brière et al., 2015; Chowdhury, 2016). Moreover, Kaplanov (2012) states that the main reason for the rapidly rising popularity of bitcoin is that a lot of people are craving for alternative currencies which are not regulated by the government. No regulation results in various benefits for bitcoin users. First of all, it ensures user autonomy. Users of digital currencies are able to control the way they spend their money without having to deal with intermediary authorities, such as the government or a bank. Secondly, bitcoin purchases are discrete. This means that transactions will never be associated with the buyer's personal identity, similar to cash-only purchases, and will not be easily tracked back to the buyer. Furthermore, the bitcoin system is entirely peer-to-peer, implying that bitcoin users can send and receive payments around the world without needing the approval from any external authority. Moreover, bitcoin also eliminates traditional banking fees, such as the minimum balance fees, overdraft charges and returned deposit fees. Also, the (international) transaction costs of bitcoin are kept low since these transactions have no intermediary government or institutions involvement. In addition, bitcoin transactions happen quickly, which eliminates the inconvenience of waiting periods and authorization requirements. Lastly, bitcoin users can pay for coins anywhere they have access to the internet, meaning that it is not necessary to go to a store or bank. This means that bitcoin, in theory, is available to populations of users who do not have access to traditional banking systems or any other payment methods (Investopedia, 2020a).

Bitcoin has been gaining more attention due to the support and approval of the industry. This results in the fact that the bitcoin market is developing, and more institutional investors are open to investments, ensuring the development of bitcoin into a mature asset class (Chin, 2014). In order to further explore the market of bitcoin, two theories will be used. First of all, the efficient market hypothesis, to understand how certain information is integrated into prices and how it could influence such prices. Secondly, the market microstructure, to better understand the price formation in financial markets, and ultimately the price formation of bitcoin.

2.2.1 Efficient Market Hypothesis

The EMH, short for efficient market hypothesis, is used as the foundation for many modern financial aspects (Malkiel, 2003). Its existence presents significant implications respecting the relationship between asset prices and information (Fama, 1970). Consequently, it can be seen as an important foundation for this research. The efficient market hypothesis speculates that the market equilibrium could be declared in terms of expected returns, and that the market fully exploits the information (Fama, 1970). Ritter (2003) argued that the foundation of the EMH is formed by the ideas of rational investors together with the expected utility theory. Notwithstanding, not the ideas of all investors are mandatory, however, the market requires to be rational and adequate to make unbiased forecasts respecting the future. Jensen (1978) stated that the existence of sophisticated investors assures that certain prices will never significantly alter from its fundamental value. This ensures that the EMH serves under the conditions of a zero-profit competitive equilibrium, while performing in an uncertain and highly speculative market.

Fama (1970) classified three different forms of efficient markets that have been broadly tested by research. The prime difference between these forms is the way they interpret the information set θ_t, which is used to analyse the power of efficiency (Jensen, 1978). Firstly, the strong-form, which affirms that prices display all available information, and no one holds the monopolistic access to the information that is significant for price formation (Fama, 1970). Secondly, the semi-strong-form, which states that all available information at time t (θ_t), is counted towards the price formation, meaning less restrictions (Jensen, 1978; Fama, 1970). However, the downside to this form is the dilemma of determining what refers to as being ‘all publicly available information’. Lastly, the weak-form, which integrates the historical series of price or returns into the price formation (Fama, 1970).

The efficient market hypothesis is closely linked to the random walk theory, which speculates that prices follow a random walk. This ensures that the price of tomorrow is not related to the price of today (Malkiel, 2003). Moreover, new information is in general unstable, implying that prices are unstable as well due to all prices being reflected by all known information. Malkiel (2003) argued that new information circulates rapidly and is directly integrated into prices, ensuring that neither the fundamental nor the technical analysis can be used to forecast future prices. Hence, without acknowledging above-average risks, investors cannot realise above-average returns. Nonetheless, Shleifer (2000) stated that even though the publication of new information is causing price changes, no-arbitrage conditions assures that new information cannot be used to assume certain returns in the future.

2.2.1.1 Efficient market anomalies

During the late 1980s, questions arise regarding the efficient market hypothesis due to the discovery of more anomalies (Shiller, 2003). Lux (1995) argued that stock prices show greater volatility compared to the expected returns, as shown by empirical research. This indicates that excess volatility supports the predictability of returns (West, 1988). Moreover, Malkiel (2003) stated that other anomalies are the presence of momentum within the short-term stock prices, day-of-the-week or seasonal patterns and mean-returns annulments spread within a longer time period. However, he explained that these anomalies are challenging to gain favour of as patterns dissolve when becoming public and due to the fact that they are not trustworthy from period to period.

Shiller (2003) showed that the most problematic anomaly has proven to be excessive price volatility, compared to other financial anomalies. The volatility anomaly is much deeper compared to for example those who are represented by exchange-rate overshooting or price stickiness. The evidence concerning excessive price volatility seems to imply that price changes occur without a fundamental reason, e.g., due to mass psychology (Shiller, 2003). The constant failing to confirm the efficient market hypothesis suggests the existence of noise as a disturbance. Hence, West (1988) claims that a different model should be used, where the aim is not focussed on the rational investor. Taking this into account, this theoretical framework will consider and contrast such forms of theories to the EMH. Since bitcoin prices experience comparable extreme volatility, these theories could grant valuable insights into why this takes place. Following the three forms of efficiency markets stated by Fama (1970), these theories should consist of a strong market form, meaning that the price is based on all available information without any sort of noise disturbance. This ensures that it is not possible to adjust the price by a single person or organisation.

2.2.1.2 Efficiency of the bitcoin market

Shleifer (2000) mentioned that the efficient market hypothesis specifies that unless the logic behind adjustments in supply and demand of a certain asset is substantiated by news regarding changes of the fundamental value, there should not be any effect on the price. Since the price of bitcoin does not depend on traditional fundamentals, but rather find its value based on e.g., the cost of generating one bitcoin through the mining process, the amount said person receives as a reward for mining a bitcoin, or the number of competing cryptocurrencies, it is difficult to apply the EMH on the market of bitcoin. However, the bitcoin price has shown extreme volatility during its existence, making it interesting to examine its origin. Notwithstanding, this study does not focus on applying the EMH on the bitcoin market and test the efficiency of the market. Nevertheless, the efficient market hypothesis serves as a theoretical foundation in order to understand how information is integrated within prices, and is thus essential for any analysis of the elemental purposes of asset price volatility.

Although the efficient market hypothesis is not able to directly explain the price formation of bitcoin, there is another theory that could help to better understand this specific market and how the price of bitcoin is constructed, which is the market microstructure theory.

2.2.2 Market microstructure theory

A fundamental part of finance is acquiring knowledge about price formation. This grants insight in market regulations, in investors behaviour and in the formation of new trading mechanisms. In order to understand price formation within financial markets, the market microstructure theory is used (O'Hara, 1995). Madhavan (2000) defined this theory as a process where the underlying demands of investors are ultimately translated into the prices and volumes of a certain asset.

As mentioned by Madhavan (2000), the market microstructure theory speculates that financial asset prices are exposed to various frictions and could perhaps fail to fully reflect the accessible information. However, Biais, Glosten and Spatt (2005) argued that the theory instead concentrates on how adequately short-term prices correspond to their long-term equilibrium prices. Hence, when studying markets considering market microstructure, the microeconomic theories encounter the reality of actual markets. The original research of Garman (1976) introduced an alternative to classic economic theories regarding exchange markets. Garman's conception of market microstructure advocates a more complicated and dynamic structure compared to classic economic theories.

Madhavan (2000) specified that informational economics are a crucial issue when studying market microstructure. The study of Madhavan (2000) emphasizes that the information design and market efficiency both have important implications for investors' behaviour and therefore the market outcomes. O'Hara (1995) argued that some studies conclude that every individual trader acts competitively, whilst others mention that using private information assures that a number of investors act strategically. The different strategic models are associated with the rational expectations that investors will make assumptions about each other's information, which will lead to the equilibrium price. As mentioned by O'Hara (1995), this can further be branched into two different parts; One that targets informed traders and one that also includes uninformed traders. The first part concentrates on market makers and informed traders, while noise traders base their choice on arguments that are exogenous to the model. The second part also includes uninformed trades who base their strategies on decisions made by informed traders (O'Hara, 1995). Moreover, the trading instruments of a specific market are considered to be an essential part of the price formation process (O'Hara, 1995).

Biais et al. (2005) specified that the market microstructure research has seen a development over the last few decades due to strong market changes, such as regulatory changes, technological innovations and structural shifts. The bitcoin market shows how technological innovations encourage changes within the financial market. Its developing nature entails that research has not yet fully explored the variables of the bitcoin market microstructure and how they affect the price formation. Within the boundaries of this study, the market microstructure helps to support by understanding the logic behind investors' decisions to invest in bitcoin. This particular theory better explains the demands of bitcoin investors, and how the price of bitcoin develops accordingly.

2.2.2.1 Bitcoin trading structure

As mentioned by O'Hara (1995), the guidelines concerning the trading mechanism will serve as the basis for the price development of assets. Table 2 below shows that at the end of 2020 bitcoin has reached a circulation of approximately 16.52 million BTC. Chowdhury (2016) argued that the supply function of bitcoin depends on the rate of mining and the willingness of bitcoin holders to sell. The fixed amount of bitcoin supply is set to 21 million BTC (Nagamoto, 2008), meaning that roughly 75 percent of all bitcoin already have been mined. As of 2020, mining a single block results in receiving 6.25 BTC. Moreover, table 2 displays that the total amount of market capitalisation for bitcoin amount to approximately $607.49 billion USD, or 444.59 billion euros. This implies that the bitcoin market is growing extensively, considering that it was only introduced in 2009 (Nagamoto, 2008). Bitcoinmarket.com was the first bitcoin exchange and opened in 2010 (Bitcoin.com, 2018). By the end of 2020, the trading volume of bitcoin reached a total of around 350,000 trades per day (table 2), displaying the absurd progress of the bitcoin market.

Table 2: *Bitcoin network*

Total number of bitcoin in circulation	BTC 16.52 million
Number of transactions per day (24h)	348,877
Total Market Capitalisation USD	$ 607.49 billion
Total Market Capitalisation GBP	£ 444.59 billion
Total Market Capitalisation EUR	€ 508.81 billion
BTC reward received per block mined	BTC 6.25

Source: (Bitcoincharts, 2020a)

At this current stage, bitcoin can be traded on various exchanges over the world using numerous different currencies (Bitcoincharts, 2020a). In addition to bitcoin, the particular exchanges also offer other cryptocurrencies, such as litecoins, ripple and ethereum. Table 3 below shows that the current largest exchanges are Bitstamp, bitFlyer and Kraken, where Kraken is split into an American and European market. These markets trade in different currencies, of which two uses USD, one EUR and the other JPY. These three currencies are considered dominant, pertaining 85% of the market (Bitcoincharts, 2020b). As displayed by table 3, there is quite a variation in rates that are offered for the same currency but on different markets. For example, the 30-day average price on Bitstamp was $ 35,033/BTC, whilst the 30-day average price on Coinsbit for the same period of time was $ 35,577/BTC. Shleifer (2000) stated that such deviations in price could in theory offer arbitrage opportunities. However, Wong (2014) argued that it is quite challenging to gain favour of such arbitrage on the bitcoin market. For example, during 2014, the exchange price on the former largest bitcoin exchange (Mt. Gox) constantly showed large deviations in contrast to other exchanges. Though, in practice, bitcoin trading on Mt. Gox was blocked due to various technical complications, assuring that an arbitrage strategy would not have been successful.

Table 3: *Top 10 largest bitcoin markets*

Market	Currency	30-Day average price	BTC 30-day volume
BitStamp	USD	$ 35,033	415,935
Kraken	USD	$ 35,087	323,355
bitFlyer	JPY	¥ 3,677,821	320,951
Kraken	EUR	€ 28,936	256,581
CoinsBank	USD	$ 35,353	82,481
Coinsbit	USD	$ 35,577	71,033
CoinsBank	EUR	€ 28,966	51,151
BitBay	PLN	Zł 132,476	40,922
BitX	ZAR	R 552,691	26,194
BTCBOX	JPY	¥ 3,661,923	21,543

Source: (Bitcoincharts, 2020b)

2.2.2.2 Bitcoin market characteristics

The market of bitcoin can be seen as fully transparent, in the sense that the traders are presented with information regarding the entire state of the order book. The provided information also includes the available trading volume and corresponding price levels. In addition, the bitcoin trading platforms also offer a wide range of analysis tools, that for example show the evolution of market growth within a specific time period. Moreover, all trading platforms offer the complete history of transactions ever registered, which are accessible by every trader. Furthermore, the trading platforms do not consist of any iceberg orders or dark pools, meaning that larger single orders are not being divided into smaller limit orders to hide the actual order quantity, nor that there are any private exchanges which are not accessible by the public (Dimpfl, 2017).

Dimpfl (2017) mentioned that similar to the stock markets, bitcoin markets are associated with several trading costs. First of all, the trading platforms demand transaction fees in order to make up for their costs. Table 4 below displays the trading fee schedule of Kraken as an example, which is one of the largest trading platforms for bitcoin. The structure of fees is arranged in a way that it is cheaper when investing in multiple trades, however, only noticeable when buying bitcoin worth over 50,000 USD (as seen below). A more appealing feature of the fee structure is the fact that it makes a distinction between liquidity providers (the 'maker') and liquidity consumers (the 'taker').

Table 4: *Fee schedule of Kraken*

Volume (USD)	**Maker**	**Taker**
$0 – $50,000	0.16%	0.26%
$50,001 – $100,000	0.14%	0.24%
$100,001 – $250,000	0.12%	0.22%
$250,001 – $500,000	0.10%	0.20%
$500,001 – $1,000,000	0.08%	0.18%
$1,000,001 – $2,500,000	0.06%	0.16%
$2,500,001 – $5,000,000	0.04%	0.14%

Source: (Kraken, 2019)

Table 4 shows that the fees for using a market order, thus providing liquidity ('maker'), are less, meaning that there is an incentive towards customers to forsake immediacy as an advantage of lower transaction costs. The difference in transaction fees is due to the means of increasing the supply of liquidity. However, not all fee structures are similar to the schedule of Kraken. Some trading platforms will only involve one schedule and do not make a distinction between liquidity consuming and liquidity provision (Dimpfl, 2017). Another cost related to bitcoin transactions is adverse selection cost (Braido, Da Costa & Dahlby, 2011). These costs are associated with a situation in which the seller has more information compared to the buyer, or the other way around, regarding a certain aspect. These costs often occur when asymmetric information is being used. In general, the seller has the extensive information, which causes the buyer to be at a disadvantage. Furthermore, bitcoin is anonymous, which generates certain counterparty risks if any trader acquires private information. Due to the fact that the trading platforms do not function as market makers, the costs of inventory holding are non-existent.

The structure of a stock market is somewhat formed around the rules and regulations published by the regulatory authorities. However, in the case of bitcoin, there are no specific regulations. The European Union ruled in 2015 that bitcoin will be treated as a verified currency from a tax point of view, meaning that trading in bitcoin is seen as a service, and therefore not subjected to VAT. The EU specifically mentioned that a bitcoin transaction is seen as similar to transactions involving bank notes and coins that are used as legal tender (ECJ, 2015).

2.2.3 The investors of bitcoin

The foundation of the bitcoin market is not limited to one country, and its value is not defined by any commodity (Grinberg, 2011). Therefore, bitcoin has no macroeconomic foundation that determines its value. Instead, the value is substantially based on self-fulfilling expectations. In addition, the value is mainly driven by short-term fluctuations and long-term upward trends, both highly linked to speculations. Supply and demand, specific events, number of exchanges and specific regulations all influence the value of bitcoin (Bouoiyour, Selmi, Tiwari & Olayeni, 2018). As specified before, the absolute supply of bitcoin is fixed, yet the supply daily traded alter each day corresponding to the willingness of investors to trade. Regarding the demand of bitcoin, it fluctuates according to the faith investors have in its perpetual growth (Kristoufek, 2013). Hence, investors and the drivers of investor demand are crucial in order to understand the price volatility of bitcoin.

It has been said that the bitcoin exchange markets are dominated by speculators, trend chasers, short-term investors, and noise traders (Kristoufek, 2013; Corbet et al., 2018). Hence, primarily individual, uninformed investors engage in this market. Notwithstanding, as the bitcoin exchange market remains to grow, more institutional investors begin to show interest (Corbet et al., 2018). Thus, the behavioural and cognitive aspects of investors willing to invest in bitcoin are essential in order to understand the bitcoin market. Grinberg (2011) argued that bitcoin is greatly affected by bubbles and investors' loss of confidence, assuring that the bitcoin demand disintegrates relative to the supply.

2.3 Bitcoin price behaviour

Kristoufek (2015) argued that the fluctuations of bitcoin prices are proven to be quite a controversial matter since bitcoin gained popularity and accessibility to the wider public. Despite it being relatively difficult to identify direct factors that could drive the value of bitcoin, Garcia et al. (2014) stated that the economy of bitcoin is primarily affected by social factors.

However, in order to better understand the price behaviour of bitcoin, it is best to first understand the behaviour of investors and the behaviour of investors that specifically trade in bitcoin, by exploring behavioural finance. Once clarified, the price volatility of bitcoin is further analysed, and drivers of price volatility are presented.

2.3.1 Behavioural Finance

Trades take place based on the varying preferences of investors, their beliefs or on certain endowments (Grossman & Stiglitz, 1980). In general, economists assume that investors are solely rational in their decisions and that the various markets accurately exhibit these views (Fama, 1970). Nevertheless, continuous aberrations from both the random walk as well as the EMH has led to researchers looking for different explanations regarding price formation (Ritter, 2003). All of this has caused the emergence of behavioural finance. Behavioural finance is based on certain concepts of cognitive psychology, and is limited to arbitrage (Ritter, 2003). Certain beliefs or choices assures that not all investors are entirely rational, which creates inefficient markets. Therefore, the focal point of behavioural finance is the importance of researching the fundamental reasons behind the investor's decision-making process. In regard to this study, behavioural finance can strengthen both the EMH and the market microstructure by contributing deeper insights into the roots of investor demand.

The roots of behavioural finance can be tracked back to Tversky and Kahneman (1989) and to Simon (1955). Tversky and Kahneman (1989) argued that the power, scope, and simplicity of a rational choice model is challenging to equal for alternative models. Nonetheless, they further stated that adding psychological considerations is also needed despite the normative and mathematical complexity. Furthermore, Ritter (2003) mentioned that behavioural finance will progressively be included within mainstream financial research and operation, and stated that it should not be considered as an autonomous discipline, but rather as an additional source of information for defining the financial market. These statements were supported by Wilkinson and Klaes (2017), who argued that behavioural economics solely seek to contribute to the framework of classic economical theories. Taking this into account, behavioural considerations should be considered when evaluating the bitcoin market.

2.3.1.1 Decision-making process

Illeditsch (2011) argued that investors neither know the realisation of a certain asset's payoff (risk), nor the probability of its occurrence (ambiguity) when evaluating an investment opportunity. Within these circumstances, investors are not able to form a logic and rational estimation of chance (Tversky & Kahneman, 1989). For that reason, Tversky and Kahneman (1989) developed the Prospect Theory, which implies that the outlining of a certain situation will affect the capability of an investor to act rationally and maximize decisions. Furthermore, Illeditsch (2011) mentioned that in general investors try to evade ambiguity, and by hedging against these situations, the investors establish excess volatility and portfolio inertia. Combining the particular conclusions, in ambiguous, non-transparent circumstances, investors tend to make non-rational choices. Nevertheless, when the circumstances are transparent and clear, e.g., having access to all available information, investors can form a rational and well-informed decision.

The decision process within the prospect theory exists of two stages. It starts with subjecting the available perspectives to an initial evaluation and arranging them into simplified forms that are easier to analyse. This process of constructing the perspectives within the outer limits of its acts, outcomes and contingencies differs between the various investors based on their personal expectancies, habits, and norms (Tversky & Kahneman, 1989). Within the second stage, the previously formed perspectives are assessed and the perspective with the highest value is being picked. This selection is based upon the believes that one perspective overshadows the other, or as a result of the comparison of their monetary principles. Moreover, Prospect Theory explains that dissimilarities between the preferences of investors arise from the first stage of decision making (Tversky & Kahneman, 1989). Hence, the decisive decision revolves around the approach in which the perspectives have been formed.

2.3.1.2 Behaviour of investors

Simon (1955) developed the fundamentals for the beliefs of bounded investor rationality. When being confronted with uncertainties, the steps of making a decision are affected by investors using plain rules of thumb, i.e., heuristics, which forms various biases within conclusions. Therefore, when the sentiment of investors is leading over facts, the decision-making process will generally be hardly fulfilling and not optimal (Wilkinson & Klaes, 2017). The paper of Tversky and Kahneman (1974) showed the first sights of cognitive biases that derived from the dependence on judgemental heuristics. First of all, Tversky and Kahneman (1974) mentioned the term ‘representativeness heuristics’, which is a frequent issue amongst investors. Representativeness heuristics defines the way in which people in general concentrate excessively on recent events when determining the probability of a certain future, rather than focussing on long-term averages. This leads to certain biases, e.g., the misunderstanding of chance, failing to acknowledge former probabilities of outcomes, and not understanding that the size affects the level of representativeness of said sample size within the population. Secondly, Tversky and Kahneman (1974) specified ‘availability heuristics, which assures that commonly appearing events are in general remembered faster and better. Moreover, investors add more value to an abundance of reoccurring smaller sized events rather than concentrating on a few large events. Finally, Tversky and Kahneman (1974) mentioned ‘anchoring heuristics’, which describes how certain people determine the initial value for the fundamental of their decision-making process. However, this chosen initial value is in general insufficiently modified in order to be representative. In addition, there is also the risk of moderation bias, where an investor has too much confident in the past.

The research of Stambaugh, Yu and Yuan (2012) further add that the effect of sentiment on the price is asymmetric, implying that a higher sentiment, or optimism, more regularly leads to over-pricing compared to lower sentiment, or pessimism, leads to under-pricing. Therefore, Stambaugh et al. (2012) argued that this conclusion supports proof that mispricing can, to an extent, define the existence of market anomalies. Additionally, Baker and Wurgler (2007) determined that younger, more volatile stocks that are presumably more subjected to financial stress, are likely to be most afflicted by sentiment.

2.3.1.3 Bubbles and herd behaviour

Throughout the history of financial markets there have been various bubbles and volatility outbreaks, such as the stock market crash in October 1989 (Schwert, 1990), the internet bubble during the late 90s (Scheinkman & Xiong, 2003) and the more recent financial crisis during 2007-2008 (Mendel & Shleifer, 2012). A bubble can be seen as a certain time period in which the price level considerably differs from its intrinsic value, as a result of investors being overconfident and having heterogeneous beliefs (Fama et al., 1969; Scheinkman & Xiong, 2003). The contemplating trading of these investors develops such bubbles, which are usually characterized with high trading volume, high prizes, and high volatility. The heterogeneous beliefs of investors have different reasons for each individual and often leads to discussions (Schwert, 1990; Scheinkman & Xiong, 2003).

Lux (1995) mentioned that not every single investor is always completely provided with information regarding the market fundamentals. This could lead to the idea that less experienced investors will structure their expectations based on expectations and behaviour of other traders. Therefore, behaviour and individual opinions can result in systematic herding behaviour. The research of Schwert (1990) showed that if new information is released regarding the over-pricing/under-pricing of a certain asset, this could encourage investors to make identical assumptions regarding its future price, and therefore buy/sell accordingly. As mentioned before by Scheinkman and Xiong (2003), this overestimation of the value of this newly obtained information is what ultimately creates a bubble. Furthermore, investors frequently establish their investing decisions based on beliefs of other investors by monitoring market price changes. This way it is possible to socially transmit price movements, which creates a bubble or a contagiously volatile price (Topol, 1991). Mimetic contagion takes place when investors modify their prices conform the average prices of the closest buyers and sellers. Prices will maintain to increase up until the behaviour of investors will again be uncorrelated and the bubble bursts (Topol, 1991).

Bikhchandani, Hirshleifer and Welch (1992) presented a model showing that even a modest quantity of information could lead to a descend in investor's behaviour. They implemented a term regarding this behaviour, called 'informational cascades'. Their model implied that investor's behaviour can be idiosyncratic and fragile, indicating that there is a possibility for systematic conformity between investors. In addition, they mentioned that severe changes in behaviour without a clear reason, i.e., fads, can arise as a result of slight alterations within the underlying meaning of alternative decisions. Therefore, if the newly acquired information only convinces a handful of investors to act a certain way, other investors may follow these actions, thus accumulating this information and generating an informational cascade (Bikhchandani et al., 1992).

2.3.1.4 Behaviour of bitcoin investor

The constantly changing and developing bitcoin market with its uncommon characteristics separates itself from other further matured financial markets. The lack of regulation, the associated higher risks and its anonymity further expand the unpredictability for investors. For that reason, theories that are based on the existence of irrational investors who are subjected to biases, sentiment and heuristic, are of most importance in order to analyse the bitcoin price volatility (e.g., Simon, 1955; Tversky & Kahneman, 1974). Accordingly, following the prospect theory of Tversky and Kahneman (1979), it is essential to formulate bitcoin as a possible investment opportunity in the decision-making process of an investor. Moreover, other characteristics of the bitcoin market, such as its low market capitalisation and its highly volatile prices, implies that there is an increased awareness towards investor’s sentiment (Baker & Wurgler, 2007).

The bitcoin price has shown bubble behaviour on various moments throughout its existence, e.g., at the beginning of 2014 and at the end of 2017. Researchers have linked these situations to informational events (e.g., Brière et al., 2015). Following the frame of mind of Scheinkman and Xiong (2003), it is expected to be caused by less experienced investors who are overreacting to newly acquired information. Moreover, Bikhchandani et al. (1992) explained that it is only needed to convince some investors to react conform this new information in order to generate an informational cascade. As trading in bitcoin is still relatively new, it is more likely that investors can cause bubble behaviour regarding the price of bitcoin. Furthermore, herding behaviour, fads, and mimetic contagion can all be seen as important factors when trying to explain the bitcoin price volatility.

2.3.2 Bitcoin price volatility

Research of Brière et al. (2015) and Chowdhury (2016) both argue that the price volatility of bitcoin is much larger than the volatility of bonds, stocks, and commodities. On top of that, the market of bitcoin is highly speculative, and more volatile in comparison to other currencies (Cheah & Fry, 2015). Moreover, the lack of regulation and fundamental value regarding bitcoin suggest different characteristics compared to traditional assets. Since bitcoin has earned its place in the financial markets and within portfolio management, it is crucial that its volatility is examined (Dyhrberg, 2016). The renowned efficient market hypothesis of Fama (1970) states that information is instantaneously integrated into prices, whereas behavioural finance argues the importance of underlying psychology of investors and the limited attention span (Tversky & Kahneman, 1974).

Figure 1: *Bitcoin price chart in USD (bitcoincharts, 2021)*

Figure 1 displays the price chart of bitcoin throughout its existence. It shows some extreme forms of volatility during 2017-2018, and again at the end of 2020. Fluctuations in bitcoin prices resulted in various periods of high volatility (coinmarketgap, s.a.). Taking a closer look at news reports during the time of large swings, it is possible to discover some interesting effects.

Starting from 2009, the bitcoin price shows little development up until 2017. The year 2017 started with a bitcoin price of just 900 USD. Late January showed one of the defining regulatory moments of the year: The People's Bank of China tightened their oversight of the country's ten most dominant bitcoin exchanges. This tightening led to a drop in trading volume due to the imposition of new trading fees. In March 2017, the bitcoin price dropped by nearly 30%. This depreciation was a result of the rejection of a bitcoin exchange-traded fund, firstly filed by investors Cameron and Tyler Winklevoss, by the U.S. Securities and Exchange Commission (SEC). However, the bitcoin price was back above its pre-exchange-traded fund (ETF) within a few days after this ruling. Despite the unwillingness of the SEC at the time, other firms filed to create a bitcoin ETF, focusing on particular funds tied to crypto valuta futures. The period between May and September of 2017 showed significant rise in bitcoin prices and it surpassed every successive milestone with ease. Arguably the most noteworthy development in this time period was the entry of considerable Wall Street analysts to the bitcoin markets. This resulted in the bitcoin price expanding to 4,000 USD and even reaching 5,000 USD in the first week of September. Despite the fact that China was pending to close their three largest exchanges and a global repression towards unregulated initial coin offerings (ICO), the bitcoin price broadly continued its upward trajectory, peaking at a price of 19,783.21 USD for 1 bitcoin on December the 17th. However, just days after reaching this point, the price of bitcoin dropped by another

30%. This resulted in one of the biggest market corrections seen to date, leaving bitcoin's price at just a mere 11,000 USD (coindesk, 2017).

The year 2018 saw a reversal trend regarding the bitcoin price compared to 2017. The year started with an increase of 36%, resulting in a bitcoin price of 17,527 USD, which would be the highest market price it would see for the rest of the year. Maintaining a downward spiral, the price dropped to approximately 7,000 USD by the end of February, which is a loss of 60%. During this month, the transaction fee fell significantly from 26 USD to 3 USD on average. By the beginning of April these transaction fees were some of the lowest since 2011. This improvement could be credited to the reduced interest in bitcoin after the end of the market bull run it underwent in 2017. During 2018, a study by Diar, a cryptocurrency research firm, showed that one percent of the crypto wallets held up to 55% of all the bitcoin, meaning that certain individuals hold a large amount of bitcoin. These individuals are called cryptocurrency Whales (Hackernoon, 2019). The bitcoin's price had a modest increase in value in the first weeks of March. During this month, the US Marshals Service auctioned 2,170 bitcoins, which were worth around 25 million USD at the time. These bitcoins were seized due to their connection with criminal, federal and civil cases (TNW, 2018).

The price of bitcoin was relatively stable from January to March 2019, ranging between 3,500 USD and 4,000 USD. However, the month June showed a strong increase in value, reaching its yearly high of almost 14,000 USD at the end of the month. During this month, Facebook also introduced their cryptocurrency project, called Libra, which is a controversial stable coin that is pegged to the value of USD. According to market analysts, using the technology of blockchain by large companies such as Facebook has helped improve the creditability of bitcoin (Medium, 2019). Bitcoin showed a value of 11,815.04 USD on the 7th of August, but merely a week later this value decreased by 14%, stabilizing at around 10,000 USD for the rest of the month before dropping back to 7,994 USD at the end of September. One of the most pressing things that happened during September was the launch of Bakkt. Bakkt is a bitcoin futures trading platform by the Intercontinental Exchange (ICE), which are also the owner of the New York Stock Exchange. Many people believed that this could lead institutions to bitcoin, which was briefly expressed in a price increase. However, these increases were negligible, and the value of bitcoin decreased to almost 8,000 USD (Cryptopotato, 2019). Bitcoin continued to fluctuate during the last months of 2019, showing a value of 9,160 USD by the end of October. However, during October 2019, bitcoin showed an increase in value of 41% in less than 24 hours. This increase was due to an announcement of the Chinese president, stating that the country should invest more effort into the development of blockchain-based technology (Cryptopotato, 2019). The remaining months showed again relatively stable prices with a value of 7,265 USD at the beginning of December and finishing the year just hovering over 7,100 USD (TNW, 2020).

The year 2020 marked for an interesting year worldwide, as well as for the bitcoin market, due to the globally pandemic of COVID-19. The year started with a value of bitcoin of 6,965 USD before reaching 9,501 USD at the end of January. However, it did not take long before the bitcoin market started to suffer from the pandemic. Bitcoin managed to reach a value of 10,500 USD in March, before falling below 8,000 USD. On the 12th of March, bitcoin had one of the swiftest and deepest selloffs in the history of global markets, showing a decrease of 39% in value in a single day, hitting 3,850 USD. In order to help the financial system from freezing up due to the pandemic, authorities such as the Federal Reserve, the European Central Bank, and the Bank of Japan decided to pump trillions of dollars into markets as a stimulus to the economy (Coindesk, 2020). As a result, the value of bitcoin doubled to 8,600 USD at the end of April. On the 11th of May 2020, the indicated ''halving'' process for mining bitcoin was executed, leading to a reward of 6.25 BTC instead of 12.5 BTC per mined block. This process happened every four years, which is why it let to few surprises in general. Despite all the speculations with regards to the halving process, it proved to be anticlimactic, and the value of bitcoin never climbed above 9,000 USD following this event. The following months showed relatively stable bitcoin prices up until the last months of 2020. At the beginning of October, bitcoin was trading around 10,800 USD, which was impressive considering the fact that the global economy had suffered its worst since the great depression. These months also showed that major institutions were starting to embrace bitcoin. E.g., MicroStrategy shifted 425 million USD into bitcoin, whilst Square put 50 million USD, or 1% of its assets into the cryptocurrency. Moreover, PayPal announced that they would allow their customers to hold and to use bitcoin and various other cryptocurrencies. The interest of major institutions further spurred the price of bitcoin, with values reaching past 20,000 USD. On December 31st, the value of bitcoin reached 28,768 USD, an increase of 224% compared to the start of 2020 (Coindesk, 2020).

2.4 Drivers of bitcoin price volatility

Despite there being multiple factors that could influence the volatility of bitcoin returns, this study will only focus on a few of these factors in order to provide a clear study. The factors are chosen based on previous research and are seen as most important when explaining bitcoin volatility. The specific factors are trading volume, information demand and world stock market index returns, which will be further elaborated on within this study.

2.4.1 Trading volume

Trading volume can be described as the total number of shares with regards to a specific security or asset that were traded within a certain time period. It is often used to show the presence, or continuation, of a certain trend. Essentially, it can be used to legitimize the price movements of an asset or security, which then helps investors in their decision whether to buy or sell (Investopedia, 2020b). The study of Gervais, Kaniel and Mingelgrin (2001) tested an efficient market hypothesis to test the predictive power of trading volume. Their results stated a positive correlation between extremely high trading volume and the return premium on prices. Moreover, they mentioned that an increase in volume over time will result in a larger effect. The results stated in their study suggests that trading volume has some sort of predictive power. O'Hara (1995) argued that increasing trading volume will also lead to an increased liquidity. However, liquidity is not only affected by investors, but can also be affected by trading mechanisms. The market microstructure theory of Li and Wu (2011) suggests that liquidity has a negative correlation with price volatility. These results indicate that increasing the trading volume will most likely lead to a decrease in volatility.

Testing certain effects of trading volume on the price of bitcoin has been done by some researchers as well (e.g., Balcilar et al., 2017; Bouri et al., 2019; El Alaoui et al., 2019). Their studies showed that bitcoin returns and alterations within trading volume mutually collaborate with each other in a nonlinear way. Moreover, their studies suggested that trading volume can be seen as a useful tool in order to predict the extreme positive and negative returns of bitcoin, which is supported by Kristoufek (2015), who agrees that the standard and fundamental economic factors such as trading volume indeed influence the bitcoin economy. Alaoui, Bouri and Roubaud (2019) studied the price-volume cross-correlation within the bitcoin market throughout a specific time period. Their main results display that the price of bitcoin and the trading volume interact mutually in a non-linear way and being subjected to multifractality, which benefits investors and traders in their decision-making process. Evidence of such non-linear dependency indicates that bitcoin trading volume could help foresee the underlying motion of the bitcoin price, meaning that an inference established of the bitcoin price cannot be accomplished without being accompanied by an inference of bitcoin trading volume. Additionally, Bouri, Lau, Lucey and Roubaud (2019) also examined the predictability of trading volume on the returns and volatility within the cryptocurrency market. They argued that trading volume is able to predict the price volatility of bitcoin, but only when a proxy within the GARCH Model is being employed. Moreover, their findings suggested that the predictability of trading volume is only present when the price volatility is low. The study of Balcilar, Bouri, Gupta and Roubaud (2017) displayed similar outcomes. However, they have added the fact that trading volume will not be able to predict price volatility in extreme low, or extreme high market regimes.

2.4.2 Information demand

Information is a valuable and highly sought asset with regards to the financial markets. The importance of demand for information as an explanatory variable to price movements and changes has been examined by multiple researchers. Vlastakis and Markellos (2012) transformed the demand of information into a variable, called information demand, to test the effect on stock market volatility. their study used a proxy regarding the effect of information on prices, which has been approximated from a time series regarding weekly internet search volume drawn from Google Trends. Google Trends shows how often a particular term is put into the search engine of Google during a specific time period respective of the total search volume of the website (Wordstream, s.a.). This study will use Google Trends to search for the frequency of searches regarding the word 'bitcoin' within the time period. Google Trends adds a value between 0 and 100 to a certain week within the sample period based on the number of times a specific word has been searched for, in this case 'bitcoin', compared to the overall number of searches within the complete sample period. In other words, the week with the highest number of searches within the sample will be allocated with a value of 100, and the week with the least amount of searches with a 0. Moreover, Google accounts for 87.35% of the total global search queries as of 2019 (Statista, 2019). The ''search volume index'' (SVI) of Google is therefore a reasonable representative of the behaviour of internet searches regarding the common population. The study of Vlastakis and Markellos (2012) mentioned that there is a strong theoretical link between information and financial markets. Their approach noticed the fact that internet has remodelled the way in which information within the financial industry is produced, interfered with, and consumed by users. The main findings in the study of Vlastakis and Markellos (2012) regarding information demand is that this variable has a significant positive effect on price volatility, implied volatility, and trading volume.

Early work of Kristoufek (2013) showed a positive bi-directional correlation between bitcoin and the number of searches on Google Trends and Wikipedia, indicating that the price of bitcoin may directly be influenced by information and that the number of searches regarding bitcoin is directly linked to the price changes during depreciations and appreciations. Moreover, Kristoufek (2015) later research showed that the correlation between the price of bitcoin and the level of information is not only directional, but also asymmetric, meaning that the effects are higher during price deflations compared to price inflations, forming an environment that is suitable for frequent emergence of bubble behaviour which indeed has been identified for bitcoin.

Shen, Urquhart and Wang (2019) studied the link between information demand and bitcoin returns, volume and volatility. They found that the number of searches has a positive significant effect on both trading volume and bitcoin price volatility, but not on returns. In line with these findings, Ciaian, Rasjcaniova and Kancs (2016) also reported that information demand has a positive impact on the price of bitcoin. Their findings suggested that the impact of information demand was much larger for the first period of existence, when bitcoin was still fairly unknown, compared to a later stadium of bitcoin, when bitcoin became more established within the financial market.

2.4.3 World stock market index returns

A world market index can be seen as a hypothetical portfolio of various investment holdings, such as stocks, that represents a part of the financial market. The index value is based on the prices of the underlying holdings. Some of the market indexes are based on revenue-weighting or market-cap weighting, whilst others are based on float-weighting or fundamental-weighting. These weighting methods are a way of adjusting the individual effect of items within an index (Investopedia, 2020c). This study will use the MSCI ACWI world stock market index, which is a stock index involving around 3,000 stocks, that is designed to track broad global equity-market performance. The MSCI ACWI stock market index is often used as a benchmark to measure for example performance of a certain portfolio, or to compare risk-adjusted returns (Investopedia, 2020c). The study of Bekaert, Harvey and Ng (2005) showed that returns and volatility both move between markets and different countries. This implies that there are close ties between the markets, meaning that volatility in one market has the potential to affect other markets simultaneously. Due to the many countries being connected with one another by trades and investments, any changes within the fundamentals of a specific country will most likely lead to changes within other countries as well. Moreover, correlations within prices could possibly be due to market contagion, which suggests that there is a connection that cannot be explained by the fundamentals of a market (Bekaert et al., 2005).

However, applying this knowledge on bitcoin, the study of Chowdhury (2016) suggested that bitcoin has an extremely low correlation with other assets, which indicates that bitcoin's resistance to other factors that affect the traditional assets is unique. It suggests that the price of bitcoin is not affected by market events and also possibly not by the current state of the market. This ensures that it is interesting to examine the effect of a world stock market index, which will represent the overall state of the market, on the price volatility of bitcoin. Chowdhury (2016) suggests that if it is shown that bitcoin has a negative correlation, or no correlation at all, with the world market index, this would offer more protection to potential investors that want to limit their exposure of risk.

The studies of Chowdhury (2016), Dyhrberg (2016), and Hong (2017) tested the effect of the bitcoin price with regards to a stock market index. They stated that investing in bitcoin can be seen as an alternative to trading on financial markets such as the financial times stock exchange (FTSE) or the S&P 500 stock exchange. Moreover, Hong (2017) mentioned that combining a portfolio of bitcoin with a stock exchange portfolio leads to much higher returns. In addition, both the study of Dyhrberg (2016) as well as the study of Hong (2017) argued that it is possible to see a drop in the returns within a stock exchange leading to an increase in the returns of bitcoin, which can be tested by looking at the causality amongst the returns of bitcoin and the returns of the stock exchange.

2.5 Hypotheses

As mentioned before, trading volume is able to predict the returns volatility of bitcoin in certain circumstances. This study will test the effect of trading volume on the volatility of bitcoin over a specific period of time. Based on previous research I believe that trading volume will have the same significant effect. Therefore, the following hypothesis can be used:

H1: *Trading volume has a positive effect on the returns volatility of bitcoin.*

Empirical evidence shows that the information demand factor has a positive significant effect on the price volatility of stock markets, as well as the volatility of bitcoin. Due to the similarities between stocks and cryptocurrencies, I believe that information demand will have the same significant positive influence on the returns volatility of bitcoin. Moreover, previous studies conducted regarding the effects of information demand on the returns volatility of bitcoin acknowledge this effect. Therefore, the first hypothesis can be formed as follows:

H2: *Information demand has a positive effect on bitcoin returns volatility.*

Empirical evidence has shown that the predictive power of market index for the bitcoin returns volatility is difficult to determine. Within regular financial markets it is established that the market index has a significant effect on volatility. However, as studied by Chowdhury (2016), the price of bitcoin has an extremely low correlation with other assets, implying that the price of bitcoin will not be affected by market events. Based on the suggestions of Chowdhury (2016) it is possible to conduct the following hypothesis regarding the returns volatility of bitcoin and the market index:

H3: *Stock market index has no effect on the returns volatility of bitcoin.*

3. Research methods

This empirical study consists of a deductive approach to clarify how bitcoin returns reacts to different factors. To answer the research question, this study uses quantitative methods in order to collect and analyse the particular data relevant to this subject. This chapter discuss the research methodology that is used in similar research and explains the chosen research method within this study. Furthermore, it will discuss the measurement of variables, methods for data collection, sampling, and analysis.

3.1 Time series analysis

This study examines the influence of certain factors on the returns volatility of bitcoin within a certain period of time. Due to the fact the there is one dependent variable, being bitcoin returns, studied over a longer period of time, it is possible to use a form of time series analysis. Time series analysis can be described as a statistical method that handles with series data, or trend analysis over a series of specific time periods or intervals (Statistics Solutions, s.a.). These analysis study series of data points indexed over time, which could be done in many ways, such as by using regression analysis. The studies of Hayes (2017), Wang and Vergne (2017), and Blau (2017) all used a certain form of regression analysis. For example, the study of Hayes (2017) used a least-squares (OLS) multiple regression model to test the effects of the factors on the price of bitcoin. However, there are a few limitations with regards to using regression analysis. First of all, the analysis assumes that the cause-and-effect relationship between the dependent and independent variables remains unchanged over time, which is not always the case. This could lead to erroneous and misleading results. Secondly, the model will not be good at explaining the relationship between the dependent variable and independent variables if these are not linear. Thirdly, regression analysis could suffer from multicollinearity, which is a phenomenon where two or more independent variables are highly correlated with each other. This means that the variables basically measure the same aspect, resulting in one independent variable explaining most of the variance within the dependent variable, leaving little variance to be interpreted by the second variable (Csulb, s.a.).

Due to there being some limitations to regression analysis, studies such as Ciaian et al. (2016), and Ciaian et al. (2018) used different methods to test the effect of various factors on bitcoin returns volatility. They started with testing for stationarity, which is of most importance in time series analysis and will be elaborated on at a later stage in this study, within the time series in order to avoid spurious regression results. They used four different unit root tests, being the Zivot Andrews test, the Clement Montañés test, the Dickey-Fuller test and the Dickey-Fuller GLS test. The results of these test where further divided into three different outcomes, namely all variables are non-stationary, all variables or stationary, or the variables are mixed. If all the variables turn out to be non-stationary, a Vector autoregression (VAR) model is most suitable. However, when all variables are stationary, it is best to use a Vector error correction (VEC) model. When the variables are both stationary and non-stationary, the auto regressive distributed lag (ARDL) model is most appropriate (Ciaian et al., 2016; Ciaian et al., 2018). The study of Ciaian et al. (2016) used the VAR, VEC and ARDL model to test the influence of the factors, whilst their later study of 2018 solely focussed on using the ARDL model. However, these models are quite challenging and could not be executed using the software SPSS. Hence, this study used a method that better explains the influence of the factors on the returns volatility of bitcoin compared to a regression analysis, but is less complicated than the methods used by Ciaian et al. (2016), Which is a GARCH model.

3.1.1 (G)ARCH Model

Clustering is one of the characteristics concerning the volatility of financial assets (Cont, 2007). It implies that the volatility of financial assets is not constant over time, which would be a characteristic that is clear to see within daily data, but rather tends to dissolve in monthly/yearly data. These anomalies are often referred to as heteroscedasticity, and are captured by using the Autoregressive Conditional Heteroscedasticity model (ARCH). This model was first introduced in 1982 by Engle (Engle, 2001), and models the volatility by weighting and including prior observations. However, the ARCH model is fairly complex to some extent due to the incorporation of various lags, which creates complications in estimating the parameters (Tsay, 2010). Therefore, Bollerslev developed the General Autoregressive Conditional Heteroscedasticity model (GARCH) in 1986, which still uses declining weights, but compared to the ARCH model never lets the weighted values go down to zero (Engle, 2001). This resulted in a model that is straightforward and that has demonstrated to be notably successful in forecasting conditional variances within the financial market. GARCH is a statistic model that can be used to examine different forms of time series data in finance and economics, such as macroeconomic data. However, it is most used to measure the volatility of financial assets. The aim of this model is to provide volatility measures for heteroscedastic time series data, which is similar to how standard deviations are interpreted in basic models. The general procedure of the GARCH model consist of three steps. Firstly, it estimates the best fit with regards to an autoregressive model. Secondly, the model calculates autocorrelations of the error terms. Lastly, the GARCH model will test for statistical significance (Francq & Zakoian, 2019).

The GARCH model has been thoroughly modified and extended since its existence. However, Engle (2001) mentioned that the GARCH (1,1) model, which is the basic model, is still believed to be the most powerful model. The '(1,1)' implies that the variance of the model is calculated using the latest observation of the squared residual along with the latest estimate of the variance. Furthermore, Engle (2001) concluded that the model is favourable in predicting volatility of auto related returns. In addition, Hansen and Lunde (2005) compared various models that test volatility, which resulted in there being no indication that the GARCH (1,1) model is surpassed by any other model that also uses exchange rate data. Moreover, many researchers are curious about the difference between GARCH models and implied volatility models, such as Pilbeam and Langeland (2015). They investigated the difference between the traditional GARCH (1,1) model, two asymmetric GARCH models and the implied volatility model from call and put options. Their results have shown that the implied volatility model outperforms all GARCH models. However, all models are significantly less accurate during periods of high volatility, and the output of all models is further away from the realised volatility. Additionally, Dyhrberg (2016) tested whether the GARCH (1,1) model is able to predict the volatility of bitcoin. The analysis showed that bitcoin reacts surprisingly well to all variables within the model, resulting in significant outcomes. Furthermore, Naimy and Hayek (2018) investigated various forms of the GARCH model, such as the EGARCH (1,1), EWMA and GARCH (1,1), and their predictability towards bitcoin price volatility. The results mentioned that all three models excel in their own specific tested variables. Looking at the predictability of the GARCH models, the traditional GARCH (1,1) model shows the smallest prediction error, whereas the EGARCH model (1,1) has the largest errors. Overall, the EWMA model is seen to be the least favourable model to use when estimating the volatility of bitcoin. In general, the traditional GARCH (1,1) model is adequate enough to test the price volatility of bitcoin. Hence, this model will be used within this study.

The GARCH (1,1) model is established using two different equations. The first one is the conditional mean. This equation determines the behaviour of the particular returns and the error term (ε_t), which displays the unexpected returns (Cermak, 2017). This value is calculated using the following equation:

Equation 1: *Conditional mean*

$$r_t = \beta_0 + \beta_1 r_{t-1} + \varepsilon_t$$

Source: (Cermak, 2017)

r_t = Return

r_{t-1} = Return last period

β_0 = Constant

ε_t = Error term

β_1 = Parameter

The conditional mean equation shows an estimation of the error term, which uses information specified by previous period returns (Cermak, 2017). This value is then used in the second equation; the conditional variance equation. Using the variance of the previous period it is possible to then estimate the variance of the following period.

Equation 2: *Conditional variance*

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

Source: (Cermak, 2017)

σ_t^2 = Conditional variance

ε^2_{t-1} = Residuals previous period

α_0= weighted long run average variance

σ^2_{t-1} = Variance previous period

α, β = Parameters GARCH

Where: $\alpha_1 + \beta_1 < 1$ is the stationary condition; $\alpha_1 > 0$, $\beta_1 > 0$ must hold

To be able to test whether the various variables influence the volatility of bitcoin returns, the GARCH (1,1) model is adjusted by adding the explanatory variables to both the conditional mean and conditional variance equation, similar to the models used in the studies of Vlastakis and Markellos (2012), Dyhrberg (2016), and Cermak, (2017). This results in the following mean and variance equations:

Equation 3: *Modified mean equation*

$$r_t = \beta_0 + \beta_1 r_{t-1} + \beta_2 Trade_{t-1} + \beta_3 Info_{t-1} + \beta_4 World_{t-1} + \beta_5 USDEUR_{t-1} + \beta_6 USDJPY_{t-1} + \varepsilon_t$$

Source: (Vlastakis & Markellos, 2012; Dyhrberg, 2016; Cermak, 2017)

Equation 4: *Modified variance equation*

$$\sigma_t^2 = \exp(\lambda_0 + \lambda_1 Trade_{t-1} + \lambda_2 Info_{t-1} + \lambda_3 World_{t-1} + \lambda_4 USDEUR_{t-1} + \lambda_5 USDJPY_{t-1}) + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

Source: (Vlastakis & Markellos, 2012; Dyhrberg, 2016; Cermak, 2017)

Trade = Weekly number of bitcoin traded on Bitstamp
Info = Weekly number of Google Trends searches
World = MSCI ACWI World stock market index
USDEUR = US Dollar to Euro exchange rate
USDJPY = US Dollar to Japanese Yen exchange rate

The mean equation within the GARCH (1,1) model tries to explain the impact on the returns of a specific variable. However, this particular study wants to test the impact on the volatility of a certain variable, rather than its returns. Therefore, the main focus of this study will be the variance equation within the GARCH (1,1) model, which will provide the most important data. Nevertheless, the mean equation will be used in order to help perform the variance equation.

Literature recommends modifying the mean equation by adding internal explanatory variables whilst the variance equation should be complemented with exogenous explanatory variables. However, bitcoin has no internal variables besides intervention events such as governmental regulations, and halving periods, which cannot be used as a function of returns. Dyhrberg (2016) argued that the best solution with regards to bitcoin is to modify the mean equation similar to the variance equation, by using exogenous explanatory variables, which will also be done within this study.

Before it is possible to estimate the GARCH (1,1) model, it is necessary to examine the statistical properties with regards to the mean equation. Figure 1 shown in section 2.3.2 of this study displayed that bitcoin price is sensitive to specific shocks, might have a positive time trend and shows a clear image of stationarity. This results in bitcoin displaying a random walk behaviour. Figure 1 presented periods of extremely high volatility as well as periods of relative tranquillity, which is often observed within financial assets. These particular observations are heteroscedastic, indicating that the GARCH (1,1) model is applicable to the price of bitcoin.

By implementing the classified variables within the model, this study desires to identify if the variables significantly contribute to the bitcoin price volatility. The model will be utilized using the statistical programs SPSS and STATA. By using SPSS and STATA, it is possible to estimate the parameters and produce a p-value. The p-value will acknowledge whether the parameters are statistically significant or not.

3.2 Measurement

3.2.1 Dependent variable

The dependent variable within this study is the bitcoin returns. Campbell and Shiller (1988) and Siddikee (2018) mentioned that researchers either use arithmetic return or logarithmic return when calculating for returns. The studies of Kristoufek (2013), Pichl and Kaizoji (2017) and of Chan et al. (2017) all logged their bitcoin returns. In addition, Pichl and Kaizoji (2017) mentioned that the advantage of logarithmic returns over certain price data is that it is a symmetric description of the increase and decrease in price by the equivalent multiple, which only differs with regards to the sign of the corresponding log return. Moreover, the fixed price levels are expressed by the zero return, and, in contrary to the non-stationary price process, the specific time series of a logarithmic return over certain prices can generally be seen as stationary. Thus, this study will use the logarithmic return.

3.2.2 Independent variables

The independent variables within this study are trading volume, information demand, and the world stock market index returns.

It is reasonable to incorporate trade volume as an explanatory variable to test the volatility of the bitcoin price, as mentioned before. The studies of Kristoufek (2015), Garcia and Schweitzer (2015), Ciaian et al. (2016), Ciaian et al. (2018) and Wang and Vergne (2017) all showed that trading volume has a positive significant effect on bitcoin returns. The trading volume variable will consist of the weekly number of bitcoin traded on the largest exchange 'Bitstamp'. This data will then be logged using natural logarithms as well in order to deal with the problems regarding the many outliers and high skewness that are often related to financial variables (Georgoula et al., 2015).

As specified before, multiple studies such as the studies of Vlastakis and Markellos (2012) and Kristoufek (2013) have shown the practicalities of information demand as an explanatory variable for price movements when using search frequencies on Google Trends involving specific key words. The information demand variable consists of weekly data from Google Trends with regards to the amount of ‘bitcoin’ searches. This provided absolute data is normalized and uses a scale from 0 to 100, where 100 is the week with the most amount of searches and 0 the week with the least amount of searches within the sample period. Additionally, the data will be logged using natural logarithms to eliminate outliers and high skewness (Georgoula et al., 2015).

Brière et al. (2013) mentioned that bitcoin features an uncommon resistance against various elements that do affect traditional assets, implying that the price of bitcoin is not affected by any market events or possibly the state of the market. The world market index returns proxy will be created by using the weekly MSCI ACWI stock market index returns (NASDAQ, 2019). This index offers a fully integrated approach for measuring the full equity set without any gaps or overlap. It covers over 13.000 securities across small, medium, and large caps and styles, and is active in 23 developed and 24 emerging markets (MSCI, 2019). Given the mentioned advantages of the logarithmic return by Pichl and Kaizoji (2017), it is also applicable to the MSCI ACWI world stock market index returns in order to deal with outliers and high skewness (Georgoula et al., 2015).

3.2.3 Control variables

In general, data regarding cryptocurrency is displayed in US Dollars. Notwithstanding, currencies could depreciate or appreciate against other currencies, e.g., the US Dollar against the Euro. The study of Ciaian et al. (2016) mentioned that this affects the returns of bitcoin. Moreover, they argued that if the US Dollar appreciates against the Euro, it is most likely to appreciate against bitcoin as well. This results in there being less Dollars needed to acquire bitcoin, thus resulting in a decline of bitcoin returns. This study will test whether the exchange rate of USD/EURO will have an effect on the bitcoin returns by using the weekly change in prices of this particular exchange rate. Engelbarts (2019) showed that from February 2019 the Japanese Yen surpassed the US Dollar as being the largest fiat currency that is used with regards to buying bitcoin. In addition, the cryptocurrency market of Japan is better regulated by the regulation authority of Japan (Financial Services Authority) compared to the United States of America (SEC), which could be an essential aspect. Hence, this study will also test if the exchange rate of USD/JPY has an effect on bitcoin returns by using the weekly change in prices of this particular exchange rate. Both variables will be logged using natural logarithms in order to deal with the outliers, skewness, but mostly the non-stationarity of the control variables (Georgoula et al., 2015).

3.3 Sample and data collection

Bitcoin price data used in this study consists of weekly closing prices from the largest bitcoin exchange, Bitstamp, over a time period of seven years, from the 1st of January 2014 until December 31st, 2020. This resulted in a total number of 365 observations. Weekly data has been chosen in order to increase the reliability of this particular study, since it is conducted over a longer period of time. The bitcoin price data has been retrieved from coindesk.com. In order to prevent measurement errors and to ensure that all variables are measured on the same data, weekly data will be used for every individual variable. The weekly data of trading volume is also retrieved from coindesk.com, and is available for the entire sample. The information demand variable is based on weekly searches that can be subtracted from Google Trends. The data regarding the world market index returns variable is retrieved from investing.com, which also provided the data of both the USD/EURO and USD/JPY exchange rates.

This study used mostly secondary data, such as articles retrieved from Google Scholar, Scopus, and the digital library of the university. Typical for these types of sources is the fact that they all possess documentary aspects and that they all have primarily been gathered by someone else. However, Saunders et al. (2012) argued that this type of data is included in almost every study and can, when combined with a fitting archival research strategy, also act as a main data source. Keywords used when searching for articles were: volatility, cryptocurrency, bitcoin, BTC, bitcoin returns, price volatility and returns volatility. By constantly following the sources of literature, and building on from the foundation, it is possible to assemble a complete theoretical framework. Secondary literature generally consists of publications from firsthand sources, addressed to a broader audience compared to primary literature, thus easier to access (Saunders et al., 2009). When using literature published by eminent journals it is possible to assure a certain level of quality, due to it first being reviewed and authorized by academic peers previous to it being published. This study has prioritised these articles and journals that are reviewed by academic peers.

3.4 Data analysis

3.4.1 Statistical Stationarity

Ruppert (2004) mentioned that there is a possibility of time invariant properties within time series, which is better known as statistical stationarity. Knowing the existing invariant properties benefits the conclusion whether changes within a certain time series variable affects another. Due to stationarity, one could model a process using a certain equation consisting of fixed coefficients, which could be estimated by using historical data (Pindyck & Rubinfeld, 1981). Due to the fact that this particular research concerns about modelling volatility, it is of most importance to determine the condition of stationarity within the data.

In order for the data to contain statistical stationarity, it is not necessary to have fixed values over a set period of time, but rather show consistent statistical properties (Ruppert, 2004). Within the financial sector, it is in general considered that asset returns show a weak form of stationarity, implying that only the first and second stages are constant (Tsay, 2010). Empirically verifying stationarity can be done by using a unit root test. Palachy (2019) mentioned that there are multiple methods regarding a unit root test, but the most common and extensive one is the Augmented Dickey-Fuller test (ADF). This particular unit root test will also be used within this study. Dickey and Fuller (1979) mentioned that the time series drifts, when time expires (increasing t), towards stationarity when $\alpha<1$. The time series will show a random walk when $\alpha=1$. When $\alpha>1$, the time series expands rapidly, which implies a certain case of non-stationary time series. Using the Augmented Dickey-Fuller test it is possible to test the null hypothesis (H0); $\alpha=1$, against the alternative hypothesis (H1); $\alpha<1$ (Tsay, 2010).

Tsay (2010) mentioned that evaluating this test can be done by comparing the results to the critical values. If the results are higher than the critical values, H0 of the unit root will be rejected, implying that the specific time series is stationary. However, if the time series turn out to be non-stationary, it is possible to carry out a so-called differencing. Differencing helps by transforming non-stationary time series stationary by computing the differences between observations (Kwiatkowski, Philips, Schmidt & Shin, 1992).

3.4.2 GARCH model evaluation

3.4.2.1 Ljung-box Test

After the various parameters of the GARCH (1,1) model being determined, it is possible to evaluate the model. Hull (2012) mentioned that the evaluation of the GARCH (1,1) model is according to how adequately this model discards autocorrelation of the squared returns. This is as a result of the prime assumption of volatility persistence, meaning that a certain period displaying great volatility is most likely followed by a time period showing comparable high volatility. Assuming that a GARCH (1,1) model is functioning sufficiently, the model is able to discard such autocorrelations. Autocorrelation could also lessen the accuracy of a certain time-based model with predictive power, such as a GARCH (1,1) model. Hull (2012) showed that it is possible to test a GARCH (1,1) model for autocorrelation by using a Ljung-box test statistic. This statistic tests the null and alternative hypothesis where H0: there is no correlation, meaning that the data is randomly distributed, and H1: the used data is not independently distributed.

3.4.2.2 Durbin-Watson Test

Saunders et al. (2012) showed a different statistic of testing for autocorrelation within a time-based predictive model, being the Durbin-Watson test statistic (Durbin & Watson, 1951). This test statistic will always display a value between 0 and 4. A value of 2 indicates that the sample does not show any autocorrelation. Moreover, a value between 0 and 2 signifies that there is a positive autocorrelation and values between 2 and 4 signifies a negative correlation. This shows that if the bitcoin price displays a positive autocorrelation, it would indicate that the bitcoin price of a certain day has a positive correlation on the bitcoin price of the following day. Meaning that if the price rises a certain day, it is most likely to rise the following day as well. A bitcoin price with a negative autocorrelation will show negative influences over time, meaning that if the bitcoin price has risen a certain day, it is most likely to fall the following day.

3.4.3 Correlation coefficient

When studying the relation between variables, it is needed to expose the collected data to a correlation test (Saunders et al., 2009). By doing so, it is possible to analyse the strength of association of the variables seen from a statistical angle. Moreover, testing the correlation is also important as correlation between independent variables, which is called collinearity, could lead to problems when executing regression analysis (Saunders et al., 2007). Considering that the objective of this study is to investigate whether a described variable has an effect on the price volatility of bitcoin, it is of most importance that there is no collinearity present that could affect the evaluation of the regression parameters. Due to the specified variables being numerical with interval characteristics, it is best to use the Pearson's Product Moment Correlation Coefficient (PPMCC) (Wright, 1921).

Bryman and Bell (2007) mentioned that the correlation coefficient will always have a value between -1 and 1. If the correlation between two variables equals a value of 1, they will have a perfect positive correlation and will display the exact same movements. If the correlation coefficient equals a value of -1, there is a perfect negative correlation between the variables, moving with identical amplitude but in opposite direction. When the correlation coefficient displays a value of 0, there will be no relation at all between the two variables.

3.4.3.1 Limitations of analysing correlation

As mentioned before, it can be helpful to collect information using a correlation test when researching a relation between different variables. However, it is crucial to keep in mind that there could be limitations inherent within the data (Moore, 2009). This involves the interpretation of the results. For example, interpreting the results as true for other data than the data being studied should be done carefully. Moreover, it is possible that the data is linear but part of a non-linear relation. The relation between the variables that are used in a correlation test could also be affected by other, incidental, variables that are not used within the study. These variables are called ‘’ lurking variables’’ (Moore, 2009). These lurking variables could explain a relation between variables and therefore interfere with the correlation test, which is why this should be done carefully. Another argument regarding carefulness is the possibility of being influenced by outliers, which could lead to a significant difference of the correlation coefficient. In order to keep the outliers to a minimum, it is helpful to create scatterplots of the data for visualisation.

3.5 Robustness

3.5.1 Time Periods

Ciaian et al. (2016) and Ciaian et al. (2018) have split their sample into two different time periods to analyse if the specific variables have the same effects or rather show dissimilarities at a certain time period. For example, the information demand variable will show a positive but not significant effect in the first period, a positive significant effect in the second period and a positive significant effect in the overall period. Hence, if the research would only take the overall period of time into account, it will show inaccurate conclusions with regards to the first period of time. By studying not only the overall time period but also add two subsample periods, it is possible to draw trustworthy conclusions with regards to differences and similarities. Thus, this study will not only focus on the complete dataset between January 2014 and December 2020, but will also split the sample into two subsamples. Looking at the price of bitcoin overtime (see figure 1), it is possible to conclude that the price does not show many fluctuations since its introduction up until the start of 2017. After this period, the price of bitcoin started to display more volatile data and an increase in interest, making it interesting to see whether the effects of the variables remain the same, or show dissimilarities during this period of time. Hence, the first time period will be from the 5th of January 2014 until the 25th of December 2016, and the second time period will be from the 1st of January 2017 until the 27th of December 2020.

4. Results

The following chapter shows the findings of this report. It displays the descriptive statistics, followed by the Pearson's correlation matrix and the Augmented Dickey-Fuller test. Moreover, it shows the results of the GARCH (1,1) model within the full sample period, as well as the results of the robustness tests using the GARCH (1,1) model within two additional periods of time.

4.1 Descriptive statistics

Before taking a closer look at the results of the statistical tests and displaying the volatility of bitcoin returns, it is helpful to embark on the selected variables and their characteristics in order to accomplish a better understanding of said variables.

The descriptive statistics shown in table 5 below display the number of weeks, the minimum and maximum values, and the mean and standard deviation of the (in)dependent variables within the time period from the beginning of 2014 until the end of 2020, resulting in 365 observations. Moreover, it also shows whether the variables display any form of skewness or kurtosis in the data. The variables bitcoin returns, MSCI ACWI, USD/EURO and USD/JPY all show values measured in percentages. The variables trading volume and information demand show absolute values in this table in order to better understand these specific variables.

Table 5: *Descriptive statistics*

Variables	Min	Max	Mean	SD	Skewness	Kurtosis
Bitcoin returns	-.536	.363	.010	.107	-.278	2.464
Trading volume	2,232	48,815	10,678	6,938	1.898	5.235
Information demand	2	100	14.82	16.374	2.009	5.605
MSCI ACWI	-.146	.109	.001	.023	-1.150	9.474
USD/EURO	-.041	.039	.000	.011	.192	1.148
USD/JPY	-.050	.042	.000	0.12	-.237	1.561

Note. N=365.

The mean weekly returns of bitcoin was 1%, with a standard deviation of 10.7%. The bitcoin returns showed a minimum value of -.536, implying that the returns dropped 53.6% in one week compared to the following week. Moreover, the maximum increase in value within consecutive weeks was 36.3%. Looking at the skewness and kurtosis of the data, acceptable values are between -3 and 3 for skewness and values between -10 and 10 for kurtosis (Kline, 2011). Skewness refers to the degree of asymmetry that is being observed within a probability distribution, where kurtosis differentiates the extreme values in either tails of the distribution (Kline, 2011). When the data displays a skewness of around 0 with a kurtosis around 3, it implies that this data is normally distributed. The bitcoin returns does not show extreme values of skewness and kurtosis, but rather shows a skewness close to 0 with a kurtosis close to 3, meaning that the variable is normally distributed, which is substantiated by the histogram shown in appendix B. The study of Pichl and Kaizoji (2017) display similar outcomes regarding the bitcoin returns values. They studied the daily returns of bitcoin from August 2012 until April 2013, showing values ranging from -.372 (-37.2%) to 0.308 (30.8%). Moreover, they also find that their daily returns data of bitcoin is normally distributed, which is in line with this study. However, the data of bitcoin returns is not always normally distributed, as shown by previous research. For example, the study of Chan et al. (2017) analysed the statistical properties of various large cryptocurrencies, such as bitcoin, from June 2014 until February 2017. Analysing the daily returns of bitcoin, their study showed a minimum value of -.159 (-15.9%) and a maximum value of 0.205 (20.5%), which are less excessive compared to this study. Additionally, showing a high value of Kurtosis and illustrated by a histogram, they stated that their daily bitcoin returns data is non-normally distributed, which is contradictory to this study.

The trading volume variable showed a mean value of 10,678 and a standard deviation of 6,938. On top of that, the minimum and maximum values are 2,232 and 48,815 respectively. These absolute values show that during one week within the sample period the minimum amount of bitcoin that have been traded on the exchange ‘Bitstamp’ was 2,232. The maximum amount of bitcoin traded within a week during this period on this exchange was 48,815. Furthermore, the displayed values in both the skewness and kurtosis imply that the data is not normally distributed. Comparing this data with prior studies, such as the study of Wang and Vergne (2017), it is possible to conclude that the data differs quite a bit. These differences are mainly due to the fact that Wang and Vergne (2017) for example studied trading volume by using the variable ‘’liquidity’’, which uses data from all major online exchanges rather than just focussing on the largest exchange Bitstamp. Moreover, they studied the effect of trading volume on the weekly bitcoin returns from September 2014 until August 2015, which is a much smaller time period compared to this study.

The variable information demand displayed a minimum value of 2 and a maximum value of 100. Moreover, the mean statistic of information demand is 14.82 with a standard deviation of 16.374. As mentioned before, this variable consists of the weekly number of searches with regards to the word ‘bitcoin’ on Google Trends normalized with a scale from 0 to 100. The maximum value of 100 has been given to the week within the sample with the most amount of searches. The study of Vlastakis and Markellos (2012) showed that the value of information demand varies considerably across the various stocks that they have studied within the period from 2004 until 2009, making it difficult to compare these specific values. However, they mentioned that the majority of their stock’s information demand is positively skewed, which is similar in this study ($r = 2.009$). Additionally, Vlastakis and Markellos (2012) showed that most of their information demand data is non-normally distributed, which is comparable to the information demand variable in this study, as demonstrated by the histogram shown in Appendix B.

To test the effects of a certain exchange rate on the volatility of bitcoin returns, both the USD/EURO and USD/JPY exchange rates are being studied. The USD/EURO exchange rate for example showed a minimum drop in value of 4.1% ($r = -.041$), where the maximum increase in value is 3.9% ($r = .039$). Furthermore, the mean value and standard deviation associated with this variable are .000 and .011 respectively. The study of Ciaian et al. (2018) also studied the effect of various exchange rates on the volatility of bitcoin returns. The main differences compared to this study are that they investigated daily bitcoin returns data instead of weekly data, and that they studied the time period of 2013 until 2016 instead of 2014 until 2020. Moreover, they did not log their exchange rate variables but rather kept them as absolute values, resulting in very different values. However, it is possible to conclude that, similar to this study, their USD/EURO exchange rate values are also quite close to each other. Their study displayed a minimum value of 1.055, a maximum value of 1.395, with a mean of 1.232 and a standard deviation of just 0.108.

4.2 Correlation matrix

Table 6 displays the Pearson’s correlation matrix, which shows how the variables relate to each other. Looking at the results, it is possible to conclude that the MSCI ACWI world stock market index returns displays a negative significant correlation with the USD/EURO exchange rate ($r = -.173$, $p<0.01$), and a positive significant correlation with the USD/JPY exchange rate ($r =$

.170, p<0.01). Moreover, the USD/JPY exchange rate shows a positive significant correlation with USD/EURO exchange rate (r = .464, p<0.01). All the other variables do not show any significant correlation between each other. Due to the relatively high value of correlation between the USD/EURO exchange rate and the USD/JPY exchange rate, the data could suffer from multicollinearity. In order to account for this phenomenon, the variance inflation factor (VIF) test have been used (see appendix C). These tests displayed that there is no severe form of multicollinearity, since all VIF values are below 5 (Hair et al., 2014). However, due to there still being correlation between these independent variables, it is best to still test them separately. Hence the data will be tested using 3 models, where model 1 will test both the USD/EURO and USD/JPY exchange rates, model 2 the USD/EURO exchange rate separately, and model 3 the USD/JPY exchange rate.

Table 6: *Pearson's correlation matrix*

	Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1)	Bitcoin returns	1					
(2)	Trading volume	.029	1				
(3)	Information demand	.075	.072	1			
(4)	MSCI ACWI	.005	.002	.026	1		
(5)	USD/EURO	.022	.046	-.097	-.173**	1	
(6)	USD/JPY	.056	-.022	-.058	.170**	.464**	1

Note. *p<0.05, Correlation is significant at the 0.05 level (2-tailed), **p<0.01, Correlation is significant at the 0.01 level (2-tailed).

Analysing the scatterplots created and presented in appendix D, it is possible to conclude that the strongest correlation is between the USD/EURO exchange rate and the USD/JPY exchange rate, which corresponds to the highest significant value shown in table 6 (r = .464). The various dots within this specific scatterplot display an uphill pattern from left to right, indicating a positive relationship between the variables. This implies that if one of the variables increases, the other variable tends to increase as well. However, the dots are rather dispersed, implying that there is a weak relationship. The scatterplot of the MSCI ACWI world stock market index and the USD/JPY exchange rate displayed a significantly weaker relationship, showing a high clustering of dots in a half circle construction. However, these dots are scattered slightly towards the right of the scatter plot, which corresponds to the positive value displayed in table 6 (r = .170), implying a weak relationship.

4.3 Statistical stationarity

In order to test the time series using a GARCH (1,1) model, it is necessary to first test the specific data for stationarity. Table 7 below shows the results of the unit root test used within this study, which is the augmented Dickey-Fuller test. Using the statistical program SPSS, it is possible to test the variables by analysing whether the alternative hypothesis (H_1 = stationary) should be accepted or rejected, by using the corresponding p-values. All variables display a p-value of 0.01, which is smaller than the normal critical threshold of 5% (0.05). This implies that the test rejects the null hypothesis (H_0) and accepts the alternative hypothesis (H_1), concluding that all variables are stationary. Thus, there is no need to perform differencing on any of the variables.

Table 7: *Augmented Dickey-Fuller test*

Variable	Alternative Hypothesis (H_1)	P-value
Bitcoin returns	Stationary	0.01
Trading volume	Stationary	0.01
Information demand	Stationary	0.01
MSCI ACWI	Stationary	0.01
USD/EURO	Stationary	0.01
USD/JPY	Stationary	0.01

Note. H_0 = non-stationary, H_1 = stationary

4.4 GARCH (1,1) model

4.4.1 Testing for heteroscedasticity

Before it is possible to estimate the GARCH (1,1) model, it is necessary to examine the statistical properties of the mean equation, by meeting two preconditions. These specific preconditions are clustering volatility and displaying an ARCH effect.

Figure 2 below displays a closer look at the logarithmic returns of the variables, which offers a different angle regarding the movements within the time period. Using this figure, it is possible to determine the effect of clustering that is generally known within financial assets, as mentioned before. The chart displays a clear spread in for example the bitcoin returns, with great volatile time periods. It shows periods of low volatility that are followed by periods of low volatility, and vice versa. This implies that small returns are followed by small returns, and large returns by large returns. This phenomenon is also known as clustering volatility, which indicates that the variable is heteroskedastic.

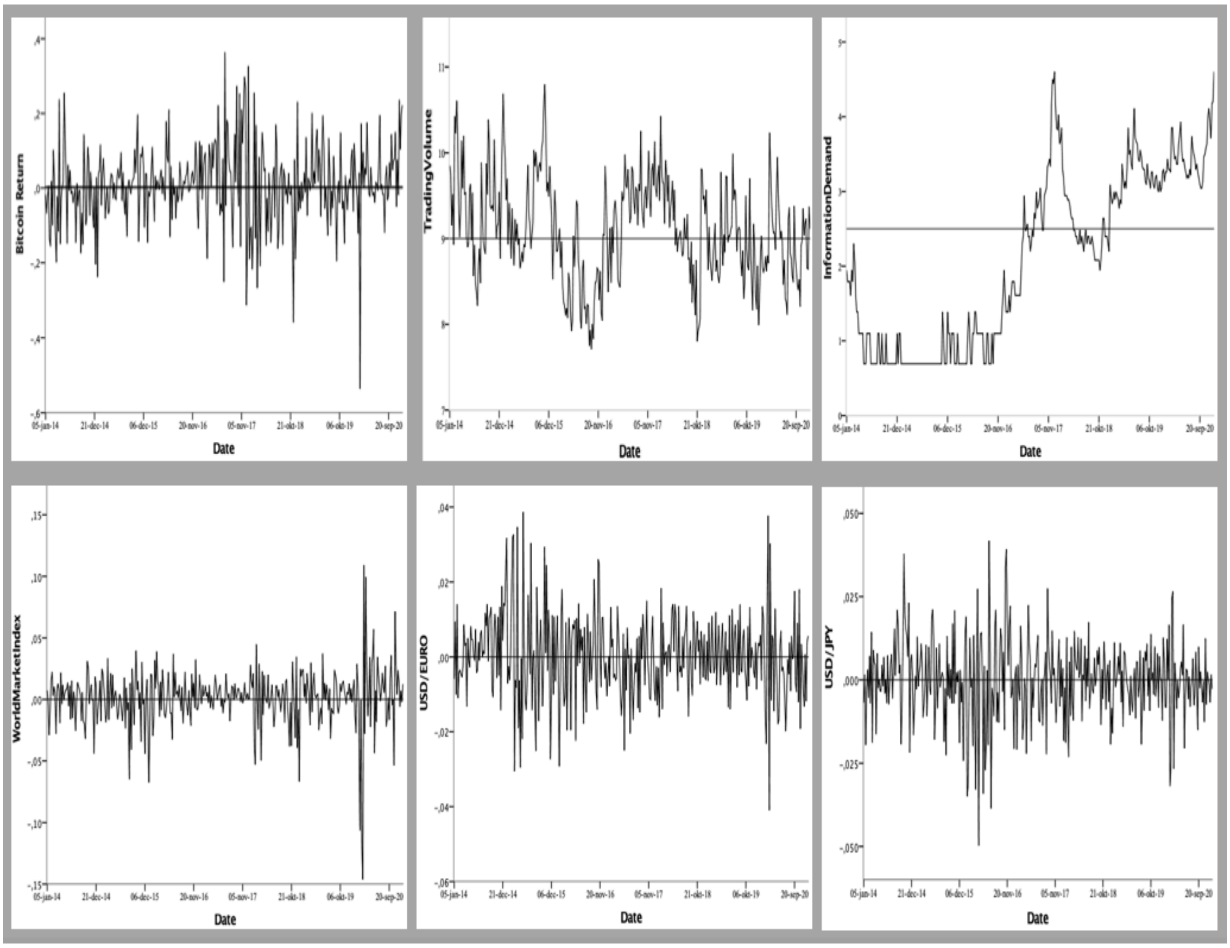

Figure 2: *Logarithmic returns*

These observations can be complemented by using Engle's Lagrange multiplier test (LM Test) in SPSS, which determines whether there exists an ARCH effect in the conditional volatility of bitcoin returns to test for serial correlation of the heteroscedasticity. The null hypothesis (H_0) within this test states that there is no ARCH effect in the conditional volatility of bitcoin returns, where the alternative hypothesis (H_1) claims that there is an ARCH effect. The findings displayed in table 8 below provides strong evidence that the null hypothesis (H_0) can be rejected ($p<0.05$), implying that there is an ARCH effect. Therefore, the data satisfies both preconditions, which ensures the validity to run the GARCH (1,1) model.

Table 8: *Engle's Lagrange multiplier test*

Lags (p)	ChiSquare	D.f	Prob >ChiSquare
1	9.777	1	0.002

Note. H_0 = no ARCH effect in the conditional volatility of bitcoin returns, H_1 = ARCH disturbance.

4.4.2 Results GARCH (1,1) model

The results of the GARCH (1,1) model are displayed in table 9 below. The model shows the mean equation as well as the variance equation, with the coefficient values, standard error values and corresponding p values for every variable. Models 2 and 3 can be found in appendix E. However, testing USD/EURO and USD/JPY exchange rates separately did not display any significant differences.

Table 9: *GARCH (1,1) model 1*

	Mean equation			Variance equation		
Variable	Coef.	Std. Err.	P-value	Coef.	Std. Err.	P-value
Trading volume	-.0045	(.0076)	.560	.5346	(.2353)	$.023^{**}$
Information demand	.0055	(.0048)	.256	.3550	(.1145)	$.002^{***}$
MSCI ACWI	.0323	(.3002)	.914	-3.0645	(11.6044)	.792
USD/EURO	-.1648	(.5108)	.747	4.0142	(25.4791)	.875
USD/JPY	.2373	(.4414)	.591	-5.6386	(23.0591)	.807
L. arch α				.1318	(.0585)	$.024^{**}$
L. garch β				.6217	(.1300)	$.000^{***}$
Constant	.0400	(.0676)	.554	-11.6659	(2.0572)	$.000^{***}$
Observations		365			365	

Note. Dependent variable = Bitcoin returns, $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

The mean equation displays that all the explanatory variables are statistically insignificant, which is an outcome that is expected and to be desired. However, as mentioned before, these results are not important with regards to explaining the volatility of bitcoin returns. Those values will be elaborated on with using the variance equation. Nonetheless, the results of this mean equation concludes that none of the variables of the previous period could significantly forecast the bitcoin returns of the current period. In other words, the returns of bitcoin is independent from the effects of all the analysed explanatory variables. Comparing this mean equation to the values of the GARCH (1,1) model used in the study of Cermak (2017), it is possible to conclude that overall the results are similar. However, Cermak (2017) did find one explanatory variable to be significant in the mean equation, and stated that if one or more explanatory variables were to be significant, this could be accounted for by running a separate regression for that specific variable to verify or refute that relationship.

The variance equation on the other hand shows that the variable trading volume has a statistically significant effect on the volatility of bitcoin returns at a 5% level ($p<0.05$). As described by the coefficient value of .5346, when the volume of trading is increased, the volatility of bitcoin returns will slightly increase simultaneously. Wang and Vergne (2017) studied the variable liquidity to explain the effect of trades on the volatility of bitcoin. As mentioned before, they have used the weekly trading volume of all major exchanges regarding bitcoin, over a time period of almost a year. They have used various models to test the effects of multiple variables on the volatility of bitcoin, of which the GARCH (1,1) model was one of them. Comparing those values to the values of this study, it is possible to conclude that their findings suggested that trading volume is positively and significantly associated with bitcoin returns ($r = 0.044$), which is similar to this study. They mentioned that these findings are to be expected, due to the fact that if only a few assets, read bitcoin, are being traded every day, sellers have to keep lowering the price in order to find enough investors to buy their product. Hence, influencing the volatility. This phenomenon is better known as price slippage.

The most significant finding within the variance model is that the explanatory variable information demand is statistically significant at a 1% level ($p<0.01$) to forecast the next day's bitcoin volatility, implying that the volatility of bitcoin is reacting to the number of searches on Google Trends. When examining this variable, it is interesting to analyse the information provided by the coefficient value. Information demand displays a rather large positive value of 3.550, indicating that it has a considerable effect on the volatility of bitcoin returns. This value implies that when the number of searches on Google Trends increases, the volatility of bitcoin returns increases as well. The study of Wang and Vergne (2017) also studied the effects of information demand on the volatility of bitcoin returns. They have created the explanatory variable ''public interest'' that uses the search volume index (SVI) of Bing, rather than the SVI of Google trends used in this study. Their GARCH model found a significant positive effect of the number of searches on Bing on the returns volatility of bitcoin, however, with a rather small coefficient value (r = 0.25) compared to this study. This difference could be due to several reasons, such as the use of a different search platform, but provides a similar positive outcome compared to this study. Moreover, the study of Kristoufek (2013) also stated significant effects of the demand for information on the bitcoin returns. However, he used a VAR (1) model instead of a GARCH (1,1) model to test for significance, which makes it difficult to compare the values with this study. Notwithstanding, Kristoufek (2013) argued that the demand for information strongly effects the returns volatility of bitcoin, similar to the results of this study. Additionally, he found that an increase in bitcoin returns also results in an increase of information demand not only for investors, but also for the general public.

The MSCI ACWI world stock market index returns did not show a significant effect on the returns volatility of bitcoin within the variance model of this study. However, when comparing this outcome with the results of e.g., Dyhrberg (2016) and Cermak (2017), the conclusion can be made that a world market index could significantly influence the volatility of bitcoin returns, as displayed in their research. The difference between this study and those of Dyhrberg (2016) and Cermak (2017) however is that they have used a different world market index over a different time period, which could explain the dissimilarities in results. Dyhrberg (2016) studied the effect of the FTSE index on the volatility of bitcoin returns from July 2010 until May 2015, and found a small significant effect of this particular stock market index. This implies that a positive shock to this stock market could lead to investors seeking more risk and therefore invest in alternative assets such as bitcoin. Cermak (2017) has studied the effects of multiple stock market indices, such as the S&P 500 and the Shanghai Stock Index, from August 2010 until March 2017. His study found that all the used world market indices show a strong significant effect on the volatility of bitcoin returns.

The effects of both the USD/EURO and USD/JPY exchange rates on the volatility of bitcoin returns displayed no significant values. However, the study of Dyhrberg (2016) tested the USD/EURO exchange rate as well, and showed a significant effect on the volatility of bitcoin returns, implying that in different circumstances the exchange rate could show significance. He mentioned that this significant result implies that there are regional or country specific effects present. Additionally, this shows that bitcoin could also be effective in hedging against the US Dollar.

Lastly, the variance equation model shows that the ARCH (α) term is significant, which indicates that the returns information of bitcoin of the previous day does affect the volatility of bitcoin today (ARCH). Moreover, the equation also displays the statistical significance of the GARCH (β) term, implying that the volatility of bitcoin of the previous day does influence the volatility of bitcoin today. Additionally, it is noteworthy to mention that due to $\beta > \alpha$, it is possible to conclude that past volatility effects are preferred over past shock effects, meaning that past volatility effects should be considered when forecasting the volatility of bitcoin. Compared to the mean equation, additional explanatory variables show statistical significance within the variance model regarding explaining the volatility of bitcoin, which is a desirable result.

4.4.3 Fitness of Model

In order to test the GARCH (1,1) model for autocorrelation, it is possible to use the Durbin-Watson test as described in section 3.4.2. This test will tell whether there exists positive autocorrelation, negative autocorrelation, or no autocorrelation at all. Table 10 displays a value of 2.032, indicating that the autocorrelation within this model is removed.

Table 10: *Durbin-Watson test*

	D-statistic
Durbin-Watson	2.032

Another way to test for autocorrelation within the model is by using the Ljung-Box test. This statistical test checks whether any of the autocorrelations within a time series is different from zero. However, instead of testing the randomness at each distinct lag, it rather tests the ''overall'' randomness based on a certain number of lags, which means that it is a portmanteau test (where the null hypothesis (H_0) is well specified, but the alternative hypothesis (H_1) is rather generally specified). The null hypothesis (H_0) of the Ljung-Box test is that the residuals of the model are independently distributed, where the alternative hypothesis (H_1) is that the residuals are not independently distributed; exhibiting serial correlation. Table 11 displays that the tests are non-significant for all the lag values, meaning that the test fails to reject the null hypothesis (H_0), implying that the residuals for the time series are independent. Testing for no lag, or multiple lags, compared to the 1 lag used within this model show no difference in value, meaning that the GARCH (1,1) model is sufficient.

Table 11: *Ljung-Box test*

	No lag Portmanteau (Q) statistic	1 lag Portmanteau (Q) statistic	2 lags Portmanteau (Q) statistic	3 lags Portmanteau (Q) statistic
Ljung-Box test	35.2692 (p=.683)	.1616 (p=.688)	2.5544 (p=.279)	3.8664 (p=.276)

4.4 Robustness test results

To test whether the specific independent variables have the same effect on the volatility of bitcoin returns at a specific time period, the data has been split into two subsamples. Table 12 displays the results of the GARCH (1,1) model for the first time period that runs from the 5th of January 2014 until the 25th of December 2016. The data associated with this time period, i.e., descriptive statistics, correlation matrix, VIF test, Durbin-Watson test and Ljung-Box test, are all included in appendix F. The correlation matrix again displayed a semi-strong significant correlation between the USD/EURO exchange rate and the USD/JPY exchange rate (r =.495, p<0.01), and a significant correlation between the USD/JPY exchange rate and the MSCI ACWI world stock market index (r = .384, p<0.01). However, the variance inflation factor (VIF) test showed that the values remained around 1, similar to the full sample period, confirming that multicollinearity is not an issue. All other data did not display any concerning values.

The mean equation of the first time period model displays that the variable information demand became significant compared to the full sample period. However, as explained before, this implies that the previous period number of searches on Google Trends significantly impacts the bitcoin returns of the current period rather than the bitcoin returns volatility, which is therefore not of value to this specific study. Looking at the variance equation, it shows that the trading volume variable remains significant, but compared to the full sample period, the significance level decreased to a 10% level (p<0.1) instead of a 5% (p<0.05) significance level displayed within the full sample period. An additional noteworthy difference to the full sample period is the fact that this specific time period did not show a significant effect of the information demand variable on the volatility of bitcoin returns, despite this variable displaying a highly significant effect in the full sample period. Moreover, in contrast to the results of the full sample period, the value for the ARCH (α) term did not display a significant result for this specific period.

Furthermore, the model again shows a significant value for the GARCH (β) term, similar to the full period of time, which implies that the volatility of bitcoin of the previous day does influence the volatility of bitcoin today within this time period. All other explanatory variables remain insignificant in the first period of time.

Table 12: *GARCH (1,1) model first time period*

	Mean equation			Variance equation		
Variable	Coef.	Std. Err.	P-value	Coef.	Std. Err.	P-value
Trading volume	-.0033	(.0092)	.718	.7733	(.4189)	$.065^{*}$
Information demand	-.0473	(.0236)	$.045^{**}$	1.0774	(.7908)	.173
MSCI ACWI	.0514	(.3505)	.883	-21.7533	(38.7030)	.574
USD/EURO	-.0079	(.5565)	.989	21.6395	(48.9629)	.659
USD/JPY	-.2056	(.4942)	.677	40.2878	(42.7554)	.346
L. arch α				.0210	(.0521)	.221
L. garch β				.7981	(.0827)	$.000^{***}$
Constant	.0742	(.0814)	.362	-15.2784	(4.1240)	$.000^{***}$
Observations		156			156	

Note. Dependent variable = Bitcoin returns, N=156 from 05/01/2014 – 25/12/2016, $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

Table 13 displays the results of the GARCH (1,1) model for the second time period that runs from the 1st of January 2017 until the 27th of December 2020. The data associated with this time period, i.e., descriptive statistics, correlation matrix, VIF test, Durbin-Watson test and Ljung-Box test, are all included in appendix G. Again, the correlation matrix displayed a semi-strong significant correlation between the USD/EURO exchange rate and the USD/JPY exchange rate (r =.413, p<0.01), and this time a significant correlation between the USD/EURO exchange rate and the MSCI ACWI world stock market index (r = -.404, p<0.01). However, the variance inflation factor (VIF) test showed that the values regarding the second time period remained around 1, similar to the full sample period and the first time period, confirming that multicollinearity is again not an issue. All other data did not display any concerning values.

The results of the mean equation for the second period of time shows that none of the explanatory variables are significant, which is desired and in line with the results of the full sample period. By closely examining the variance equation of this particular time period, it is possible to conclude that the ARCH (α) term is again significant, similar to the full sample period, and that the GARCH (β) term remain significant, which is in line with the previous periods of time. However, all the explanatory variables within the variance equation show no significant effects on the volatility of bitcoin returns within the tested second time period, which is contradictory to the results of both the full sample as well as the first time period. Looking at the price changes overtime within the sample period (figure 1), it is clear to see that from 2017 until the end of 2020 the bitcoin returns fluctuates much more compared to the beginning of the sample. As the literature suggested, the variables could influence such fluctuations. However, table 13 below does not show these significant effects. This could be due to several causes. For example, Cermak (2017) mentioned that significance could be achieved by testing the effect of every variable separately on the volatility of bitcoin returns. Moreover, Wang and Vergne (2017) mentioned that there could be another version of the GARCH (1,1) model that better fits the data of this specific study. Looking specifically at the trading volume variable, Balcilar et al. (2017), Alaoui et al. (2019), and Bouri et al. (2019) all mentioned that the predictive power of trading volume is only present when the volatility of bitcoin returns is considered low, implying that trading volume will not be able to predict returns volatility in extremely low or extremely high circumstances. Comparing these statements to this particular study, it might be possible that the volatility is too high during the second period of time, thus displaying insignificant results.

Table 13: *GARCH (1,1) model second time period*

	Mean equation			Variance equation		
Variable	Coef.	Std. Err.	P-value	Coef.	Std. Err.	P-value
Trading volume	.0037	(.0147)	.803	.0823	(.6312)	.896
Information demand	.0051	(.0116)	.663	-.1115	(.3525)	.752
MSCI ACWI	.1551	(.5373)	.773	-18.4421	(17.7948)	.300
USD/EURO	.6235	(1.0205)	.541	-70.3693	(52.5755)	.181
USD/JPY	.2807	(1.0047)	.780	9.9189	(56.1594)	.860
L. arch α				.1719	(.0869)	.048**
L. garch β				.6542	(.1658)	.000***
Constant	-.0312	(.1303)	.811	-6.5798	(4.8882)	.178
Observations		209			209	

Note. Dependent variable = Bitcoin returns, N=209 from 01/01/2017 – 27/12/2020, $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

When comparing the full period of time and the split subsample periods, it is possible to conclude that there are a few differences. For example, the variable trading volume is positive significant in both the full sample period as well as the first time period, but insignificant in the second time period. On top of that, the variable shows to be significant at a 5% significance level within the full sample period, whilst decreasing the significance in the first time period to a 10% significance level. Arguably the most noticeable difference between the various time periods is the fact that the explanatory variable information demand displayed a strong highly significant effect ($p<0.01$) on the volatility of bitcoin returns within the full sample, but no significant effect in both the tested subsamples, which is surprising. These results imply that when information demand is tested over the complete sample data combined with the other explanatory variables, it is able to significantly affect the returns volatility of bitcoin. However, when being tested during a different time period, these effects do not hold their significance. Another noteworthy dissimilarity between the time periods is the ARCH(α) term. This specific term displays a significant value in both the full sample and the first time period, but an insignificant value in the second period of time. This implies that in the first time period the returns information of bitcoin of the previous day does not significantly affect the volatility of bitcoin today.

4.5 Results Hypotheses

The first hypothesis of this study suggested that trading volume would have a positive effect on the returns volatility of bitcoin. Looking at the results of the GARCH (1,1) model it is possible to conclude that trading volume has a positive significant effect on bitcoin returns volatility in the full sample period as well as the first time period. This explanatory variable does not show significance within the second period of time. However, sufficient significant evidence has been provided by the model to conclude that trading volume has a positive effect on the returns volatility of bitcoin, meaning that the first hypothesis can be accepted. These results are in line with the study of Alaoui et al. (2019) as well as the study of Bouri et al. (2019). The second hypothesis stated that the explanatory variable information demand would also have a positive significant effect on the volatility of bitcoin returns. The results of the GARCH (1,1) model showed that the variable indeed has a strong positive significant effect on the returns volatility of bitcoin in the full sample period, but an insignificant effect in both subsamples. However, sufficient significant evidence has been provided by the model to conclude that information demand has a positive effect on the returns volatility of bitcoin, implying that this hypothesis can be accepted as well. These findings are in line with the studies of Vlastakis and Markellos (2012), Ciaian et al. (2016), and Shen et al. (2019), who all mentioned positive effects of information demand. Finally, the third hypothesis suggested that the MSCI ACWI world stock market index returns would have no effect on the volatility of bitcoin returns. The results of the GARCH (1,1) model displays a positive effect of the world market index variable in the full sample period and the first time period, and a negative effect in the second period of time. However, none of these effects are significant, implying that the MSCI ACWI world stock market index variable has no effect on the returns volatility of bitcoin, thus accepting the hypothesis. This conclusion is in line with the study of Chowdhury (2016), who also mentioned that if it is shown that bitcoin has no correlation with the world market index, this would offer more protection to potential investors that want to limit their exposure of risk.

5. Conclusion

Cryptocurrencies are an extraordinary financial and technological innovation developed over the last decade. As of today, the first and largest market capped cryptocurrency is the bitcoin. Bitcoin was introduced by its creators in an attempt to step away from the so-called trust-based model of fiat currencies and to create a system that is based on cryptographic proof. Feng, Wang and Zhang (2018) concluded that the market of bitcoin is extremely volatile. In addition, Ciaian, Rajcaniova and Kancs (2016) mentioned that these extreme forms of volatility are unusual within traditional currencies, suggesting that the volatility could be caused by other determinants of factors that influence the returns of bitcoin. Due to the emerging stage of the bitcoin market, researchers have only just started to investigate this financial phenomenon.

This study was proposed in order to classify the factors that influence the volatility of bitcoin returns, by using a quantitative study with a deductive research approach. By providing a thorough literature and information review with regards to the price construction of bitcoin as well as the bitcoin market, the decisions throughout the empirical study have been made clear. Following the ideas of the market microstructure theory (Garman, 1976), details regarding the trading system as well as the characteristics of the investors are thoughtfully being examined. By connecting the concepts of particular traditional financial theories, e.g., efficient market hypothesis (Fama, 1970), with the more recently introduced theory of behavioural finance (Tversky & Kahneman, 1989), an extensive theoretical base was created.

In order to grant a more extensive study with a greater explanatory power, the formulated research question has been defined in a broad approach. By constantly following the theoretical statements with regards to the bitcoin structure, it was possible to identify five explanatory variables that could present understanding of the extreme volatility of bitcoin returns. The explanatory values and the corresponding significance of these variables have been further tested by using a GARCH (1,1) model. The results showed which of the variables within this study have a significant explanatory effect on the volatility of bitcoin returns. In this way, it is possible to answer the main research question as followed:

Which factors influence the volatility of bitcoin returns?

This study has identified that the variable trading volume as well as the variable information demand have a positive significant effect on the volatility of bitcoin returns.

The empirical study indicated that trading volume has a slight positive significant effect on the volatility of bitcoin returns, implying that the returns volatility of bitcoin will slightly increase when the volume of trades increases. The significance of the explanatory variable trading volume is however only identified in the full sample period and the first period of time, whilst exhibiting no significance during the second time period. These results are in contrast with e.g., the study of Li and Wu (2011) who argued that trading volume would have a negative effect on bitcoin volatility, but are however in line with studies of e.g., Balcilar et al. (2017), Alaoui et al. (2019), and Bouri et al. (2019). They mentioned that the returns of bitcoin and trading volume interact mutually, which benefits investors and traders in their decision-making process. This dependency signifies that bitcoin trading volume helps predicting the underlying motion of bitcoin returns, implying that an established assumption with regards to bitcoin returns volatility cannot be accomplished without being accompanied by assumptions with regards to trading volume. However, their findings stated that the predictability of trading volume is only present when returns volatility is low, and trading volume will not be able to predict returns volatility in extremely low or extremely high circumstances. Implementing this knowledge to the empirical results of this particular study, it might be possible that the bitcoin returns volatility either faced minor or major volatility during the second sample period, thus displaying insignificant results.

Similar to the findings of Vlastakis and Markellos (2012), who studied stocks on the NYSE and NASDAQ, and the findings of Kristoufek (2013), who studied bitcoin traded on MtGox, the empirical results of this study also identified a strong positive significant effect of information demand on bitcoin returns volatility. These findings are also in line with the studies of e.g., Ciaian et al. (2016), and Shen et al. (2019). They mentioned that the number of searches on Google Trends positively influences the volatility of bitcoin returns, implying that when the demand for information regarding bitcoin increases, the returns volatility of bitcoin will increase simultaneously. Additionally, their findings argued that the impact of information demand was much larger for the first period of existence, when bitcoin was still fairly unknown, compared to a later stadium, when bitcoin became more established within the financial market. However, the empirical results of this particular study are not able to support these assumptions, as they display no significant differences when testing the impact within both subsamples. This could be due to the fact that this study did not take the early years of bitcoin into account, i.e., 2009-2013, which could have led to different results.

The results of the empirical study stated that the world stock market index, using the MSCI ACWI world stock market index returns, has no significant effect on the volatility of bitcoin returns in any time period. Notwithstanding, if a variable does not show any significance, it is not automatically unimportant for understanding the volatility of bitcoin returns. These results are in line with the studies of e.g., Brière et al. (2015) and Chowdhury (2016), whose empirical results also displayed no influence of the overall state of the market on the volatility of bitcoin returns. However, Chowdhury (2016) mentioned that this is a positive outcome, since if it is shown that bitcoin returns has a negative correlation, or no correlation at all, with the world market index, this would offer more protection to potential investors that want to limit their exposure of risk. A more exhaustive research with regards to this specific explanatory variable may offer useful new insights for certain investors who seek to hedge against a financial crisis, since it would be exposed to market contagion.

Both the USD/EURO exchange rate and USD/JPY exchange rate did not show any form of significance in the empirical results throughout all the tested time periods. This implies that changes within these rates do not affect the volatility of bitcoin returns within this particular study, which is in contrast to the study of Ciaian et al. (2016), who argued that it would have a significant effect. However, it could be quite interesting to see whether these variables hold explanatory powers with regards to the volatility of bitcoin returns when for example being tested separately.

One of the advantages of studying a fairly unexplored market such as the market of bitcoin, is the likelihood to creatively create a study by acknowledging for many variables. The chosen variables have consistently been justified based on theories, and were combined with reputable financial methods within the empirical study. This ensured that the bitcoin market was carefully described in an explanatory manner, thus fulfilling the purpose to broaden the general knowledge of the bitcoin market and to identify the factors that influence the volatility of bitcoin returns.

This study provides various contributions to the existing academic literature. From a general point of view, this study presented new observations of various volatility theories by connecting them to the market of bitcoin. Additionally, following the studies of Vlastakis and Markellos (2012), Dyhrberg (2016), and Cermak (2017), and using a Generalized Autoregressive Heteroskedasticity Model (GARCH) in order to test the influence of certain factors, this study complemented their conclusions. This study also contributes to existing literature by providing new insights with regards to the effects of specific variables within a more recent period of time. To this date, research regarding bitcoin, or even cryptocurrency in general, is limited, and many uncertainties remain present. This study complemented the work of e.g., Alaoui et al. (2019), and Bouri et al. (2019), regarding the influence of trading volume on the volatility of bitcoin returns, and provided new insights to the work of e.g., Ciaian et al. (2016), and Shen et al. (2019), with regards to the effect of information demand. In addition, this study complements the findings of Chowdhury (2016), regarding the overall state of a market, thus contributing to the literature.

By completing this study, one more piece of the puzzle has been added towards better insights into the extraordinary field of bitcoin. The majority of investors seek to lower the uncertainties regarding their investments, where this study provides better understanding to those who desire to learn more about bitcoin, and who will establish their investment decisions upon these findings. The market of bitcoin remains relatively risky, and many are unsure about its characteristics and how the price of bitcoin will respond to contrasting forms of information. By utilising the findings of this study, a more extensive understanding of the volatility of bitcoin returns can be achieved. Therefore, this study has presented modest steps towards reducing the uncertainties of the bitcoin market.

5.1 Discussion

5.1.1 Limitations

The most noticeable limitation to this study is the fact that the results show no significance of variables in the variance equation within the second period of time, even though this was to be expected due to the highly volatile periods. Another limitation is the fact that this study used the data of specific variables, i.e., bitcoin price data and trading volume, from the trading platform Bitstamp. Despite this being the largest trading platform for bitcoin, the use of other platforms, e.g., Kraken, could lead to alternative results. Moreover, the information demand variable could only be formed on a weekly basis, due to it being the only available data retrievable from Google Trends when studying a longer period of time. This could cause complications when studying the effects on specific dates. A further limitation is the fact that the data regarding the world market variable is based on the MSCI ACWI world stock market index. However, there are multiple other stock market exchanges, such as the S&P 500 or the

NASDAQ, that may influence the volatility of bitcoin returns. Finally, this study used the GARCH (1,1) model. This particular model assumes that both positive and negative error terms have the same effect on volatility, i.e., bad news has the same size of effect compared to good news, which is in practice not always the case. In addition, the model's explanatory power increases when using larger samples, where the sample of this particular study can be seen as a small sample size.

5.1.2 Future research

This research studied the effect of multiple variables on the returns of bitcoin. However, many questions remain present regarding this interesting topic. For example, this study focussed on bitcoin and did not take any other cryptocurrency into account. It could be interesting to see whether the variables have the same effect on for example ethereum or ripple, or if they show dissimilar results. Another aspect that could be interesting is to see which other drivers could influence the bitcoin returns, due to there being various other aspects that influence volatility. Moreover, this study targets the period from January 2014 until December 2020. It could be interesting to see if the results alter when studying a larger sample. As of writing this, the bitcoin returns remain to show strong volatility, and taking this time period into account could lead to interesting new findings. Finally, future research could be conducted using the same data but a different model, e.g., OLS regression analysis, multiple regression analysis, or models such as the VAR, VEC or ARDL model. Additionally, the variables in this particular study could also be studied separately to see if the effects on the volatility of bitcoin returns would differ.

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Appendices

Appendix A: Bitcoin blockchain structure

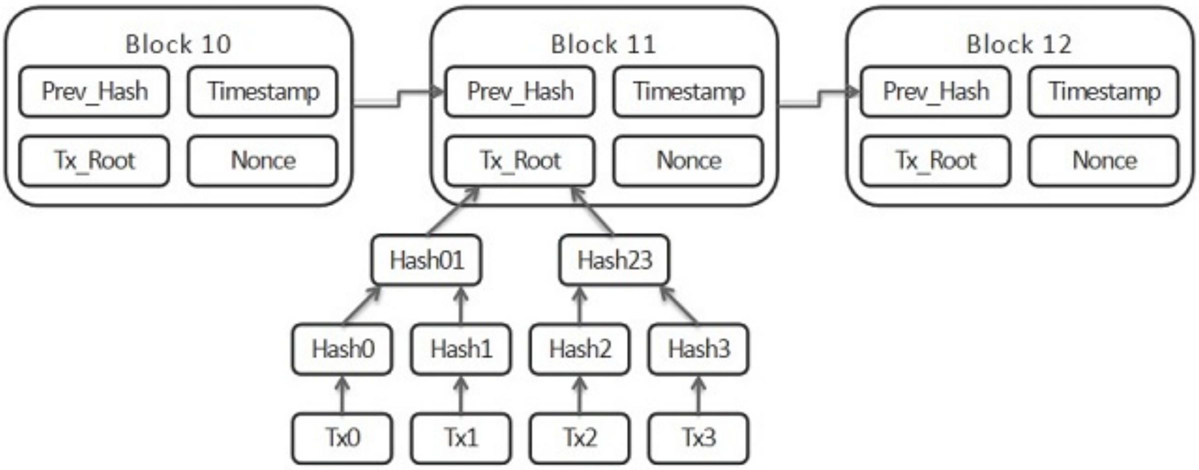

***Figure 3**: Bitcoin blockchain structure (Database answers, 2017)*

Appendix B: Histograms variables

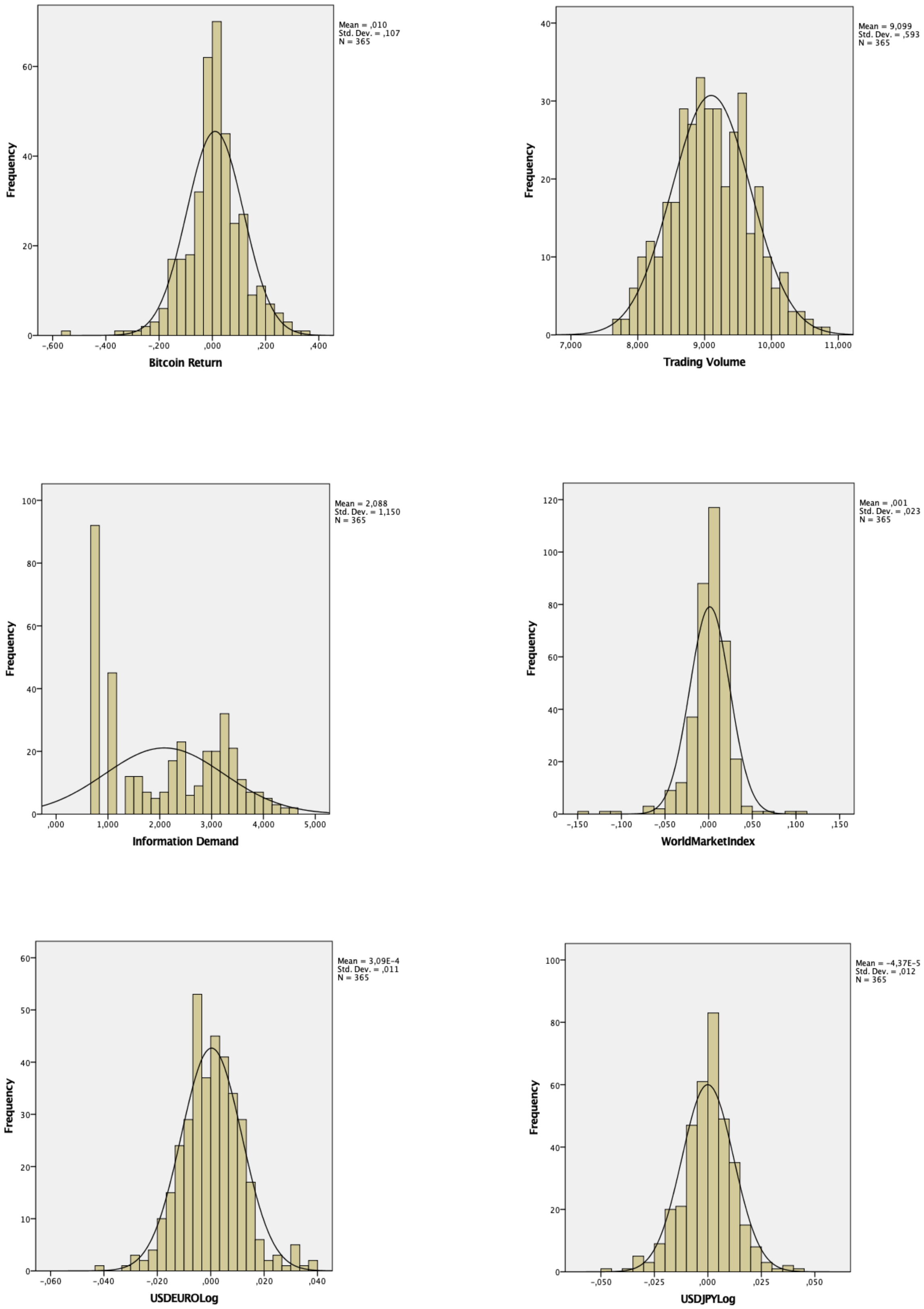

Figure 4: *Histograms variables*

Appendix C: Variance inflation factor (VIF) test

Table 14. *Variance inflation factor (VIF) test*

	Unstandardized Coefficients		Collinearity Statistics	
Variable	B	Std.Error	Tolerance	VIF
(Constant)	-.045	.086		
Trading volume	.004	.009	.989	1.011
Information demand	.007	.005	.985	1.016
MSCI ACWI	-.038	.258	.889	1.124
USD/EURO	-.021	.584	.712	1.404
USD/JPY	.558	.545	.718	1.393

Note. Dependent variable = Bitcoin returns.

Appendix D: Scatterplots variables

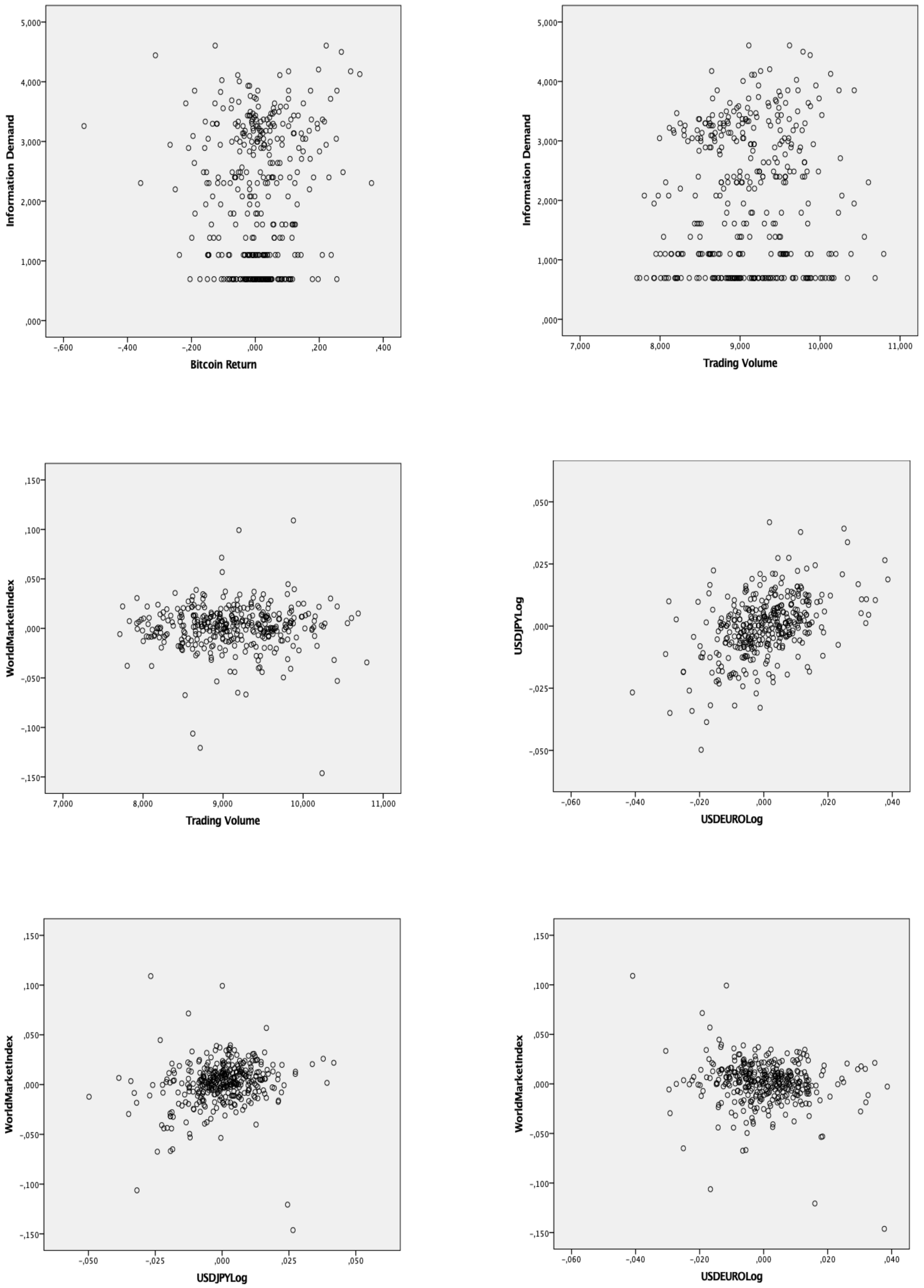

Figure 5: *Scatterplots variables*

Appendix E: GARCH (1,1) models 2 & 3

Table 15. *GARCH (1,1) model 2*

	Mean equation			Variance equation		
Variable	Coef.	Std. Err.	P-value	Coef.	Std. Err.	P-value
Trading volume	-.0045	(.0076)	.553	.5405	(.2325)	.020**
Information demand	.0054	(.0048)	.267	.3609	(.1155)	.002***
MSCI ACWI	.0743	(.2778)	.789	-2.6072	(10.3946)	.802
USD/EURO	-.0363	(.4290)	.933	2.9173	(22.1815)	.895
L. arch α				.1277	(.0561)	.023**
L. garch β				.6382	(.1246)	.000***
Constant	.0408	(.0673)	.544	-11.7860	(2.0199)	.000***
Observations		365			365	

Note. Dependent variable = Bitcoin returns, USD/JPY excluded, $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

Table 16. *GARCH (1,1) model 3*

	Mean equation			Variance equation		
Variable	Coef.	Std. Err.	P-value	Coef.	Std. Err.	P-value
Trading volume	-.0048	(.0076)	.532	.5508	(.2337)	.018**
Information demand	.0055	(.0048)	.251	.3533	(.1096)	.001***
MSCI ACWI	.0498	(.2946)	.866	-3.5473	(11.6102)	.760
USD/JPY	.1533	(.3727)	.681	-2.6316	(19.6459)	.893
L. arch α				.1298	(.0573)	.023**
L. garch β				.6304	(.1265)	.000***
Constant	.0427	(.0673)	.526	-11.8349	(2.0545)	.000***
Observations		365			365	

Note. Dependent variable = Bitcoin returns, USD/EURO excluded, $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

Appendix F: Robustness test first time period (05/01/2014 – 25/12/2016)

Table 17: *Descriptive statistics first time period*

Variables	Min	Max	Mean	SD	Skewness	Kurtosis
Bitcoin returns	-.238	.255	.000	.081	-.024	1.103
Trading volume	7.710	10.796	9.113	.689	.153	-.543
Information demand	.693	2.303	.927	.338	1.627	2.615
MSCI ACWI	-.067	.040	.000	.018	-.671	1.329
USD/EURO	-.031	.039	.002	.013	.173	.427
USD/JPY	-.050	.042	.001	0.15	-.300	1.205

Note. N=156, time period from 05/01/2014 – 25/12/2016.

Table 18: *Pearson's correlation matrix first time period*

	Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1)	Bitcoin returns	1					
(2)	Trading volume	-.021	1				
(3)	Information demand	.192*	.219**	1			
(4)	MSCI ACWI	.028	.054	-.059	1		
(5)	USD/EURO	-.072	.064	-.043	.141	1	
(6)	USD/JPY	.011	-.015	-.099	.384**	.495**	1

Note. Time period from 05/01/2014 – 25/12/2016, **p<0.01, Correlation is significant at the 0.01 level (2-tailed), *p<0.05, Correlation is significant at the 0.05 level (2-tailed).

Table 19. *Variance inflation factor (VIF) test first time period*

	Unstandardized Coefficients		Collinearity Statistics	
Variable	B	Std.Error	Tolerance	VIF
(Constant)	.014	.087		
Trading volume	.003	.010	.940	1.064
Information demand	-.048	.020	.941	1.062
MSCI ACWI	-.064	.384	.844	1.185
USD/EURO	-.643	.574	.746	1.340
USD/JPY	.209	.553	.648	1.543

Note. Dependent variable = Bitcoin returns, Time period from 05/01/2014 – 25/12/2016.

Table 20: *Durbin-Watson test first time period*

	D-statistic
Durbin-Watson	2.011

Note. Time period from 05/01/2014 – 25/12/2016.

Table 21: *Ljung-Box test first time period*

	No lag Portmanteau (Q) statistic	1 lag Portmanteau (Q) statistic	2 lags Portmanteau (Q) statistic	3 lags Portmanteau (Q) statistic
Ljung-Box test	36.1034 (*p*=.646)	.0548 (*p*=.815)	1.2117 (*p*=.546)	1.3785 (*p*=.711)

Note. Time period from 05/01/2014 – 25/12/2016.

Appendix G: Robustness test second time period (01/01/2017 – 27/12/2020)

Table 22: *Descriptive statistics second time period*

Variables	Min	Max	Mean	SD	Skewness	Kurtosis
Bitcoin returns	-.536	.363	.018	.122	-.430	2.137
Trading volume	7.803	10.427	9.088	.511	-.025	-.449
Information demand	1.386	4.605	2.954	.681	-.215	-.217
MSCI ACWI	-.146	.109	.002	.026	-1.276	9.962
USD/EURO	-.041	.038	-.001	.010	-.020	1.748
USD/JPY	-.032	.027	-.001	0.10	-.250	.529

Note. N=209, time period from 01/01/2017 – 27/12/2020.

Table 23: *Pearson's correlation matrix second time period*

	Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1)	Bitcoin returns	1					
(2)	Trading volume	.068	1				
(3)	Information demand	.053	.200**	1			
(4)	MSCI ACWI	-.007	-.033	-.005	1		
(5)	USD/EURO	.103	.016	-.006	-.404**	1	
(6)	USD/JPY	.105	-.036	.012	.029	.413**	1

Note. Time period from 01/01/2017 – 27/12/2020, **p<0.01, correlation is significant at the 0.01 level (2-tailed).

Table 24. *Variance inflation factor (VIF) test second time period*

	Unstandardized Coefficients		Collinearity Statistics	
Variable	B	Std.Error	Tolerance	VIF
(Constant)	-.137	.151		
Trading volume	.015	.017	.957	1.045
Information demand	.007	.013	.959	1.042
MSCI ACWI	.124	.366	.790	1.266
USD/EURO	1.034	1.064	.655	1.526
USD/JPY	.883	.963	.781	1.280

Note. Dependent variable = Bitcoin returns, time period from 01/01/2017 – 27/12/2020.

Table 25: *Durbin-Watson test second time period*

	D-statistic
Durbin-Watson	2.049

Note. Time period from 01/01/2017 – 27/12/2020

Table 26: *Ljung-Box test second time period*

	No lag Portmanteau (Q) statistic	1 lag Portmanteau (Q) statistic	2 lags Portmanteau (Q) statistic	3 lags Portmanteau (Q) statistic
Ljung-Box test	35.4560 (*p*=.675)	.2338 (*p*=.629)	1.9881 (*p*=.370)	3.3303 (*p*=.344)

Note. Time period from 01/01/2017 – 27/12/2020