Bitcoin – a favourable instrument for diversification?

A quantitative study on the relations between Bitcoin and global stock markets

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Abstract

Bitcoin is a peer to peer (p2p) payment cash system and an unregulated digital currency that is primarily designed and developed in 2008 without tender legal status. Bitcoin is so-called cryptocurrency because it uses the cryptographic function in order to secure the creation and transfer of money. During recent years, Bitcoin has been emerging as the well-known electronic currency and gaining popularity worldwide as well as caught the media attention in the area of volume trading. Therefore, Bitcoin will be a potential financial asset for investors due to its extraordinary returns.

The purpose of this research is to find out how Bitcoin returns correlate with stock markets and to assess the risk that the electronic currency bears, to conclude whether Bitcoin is a favourable instrument for investors that want to diversify their portfolios. Therefore, daily data from 2013 to 2017 is used to measure correlations with major global stock markets and analyse in a regression to what extend Bitcoin is integrated into financial systems.

In addition, Bitcoin’s risk has been measured by estimating value at risk, as well as the volatility and a regression analysis with explanatory variables has been performed to identify the driving factors of the unusually high volatility. Finally, the researchers constructed models to forecast expected returns to identify whether Bitcoin is rather a short or long term instrument.

The researchers came to the conclusion that Bitcoin is a favourable instrument to diversify a portfolio as it correlates negatively with most of the analysed stock market indices and the research result showed that Bitcoin is not yet integrated into financial systems. It has however been paid attention to the new types of risk and the questionable image the electronic currency has as it is often used to support criminal activities. The fact that no authority, clearing house or central bank's involvement is present, creates uncertainty for many investors.

Keywords: Bitcoin, virtual currency, Garch model, Value at Risk, portfolio optimization
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Thank you!

Dominik Krause & Nga Pham

Umeå, 2017-05-19
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<th>Description</th>
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<tr>
<td>AIK</td>
<td>Akaike information criterion</td>
</tr>
<tr>
<td>APA</td>
<td>American Psychological Association</td>
</tr>
<tr>
<td>ARCH</td>
<td>Autoregressive conditional heteroskedasticity</td>
</tr>
<tr>
<td>ARIMA</td>
<td>Autoregressive integrated moving average</td>
</tr>
<tr>
<td>BIC</td>
<td>Bayesian information criterion</td>
</tr>
<tr>
<td>Bitcoin IRA</td>
<td>Bitcoin individual retirement account</td>
</tr>
<tr>
<td>BTC</td>
<td>The currency symbol for Bitcoin</td>
</tr>
<tr>
<td>CFTC</td>
<td>Commodity Futures Trading Commission</td>
</tr>
<tr>
<td>CNY</td>
<td>The currency symbol for Chinese Renminbi</td>
</tr>
<tr>
<td>DF</td>
<td>Degree of freedom</td>
</tr>
<tr>
<td>ECB</td>
<td>European Central Bank</td>
</tr>
<tr>
<td>EUR</td>
<td>The currency symbol for Euro</td>
</tr>
<tr>
<td>EWMA</td>
<td>Exponentially weighted moving average</td>
</tr>
<tr>
<td>FinCEN</td>
<td>The Financial Crimes Enforcement Network</td>
</tr>
<tr>
<td>GARCH</td>
<td>General autoregressive conditional heteroskedasticity</td>
</tr>
<tr>
<td>GBTC</td>
<td>Bitcoin Investment Trust</td>
</tr>
<tr>
<td>IMF</td>
<td>International Monetary Fund</td>
</tr>
<tr>
<td>IRS</td>
<td>Internal Revenue Service</td>
</tr>
<tr>
<td>JPY</td>
<td>The currency symbol for Japanese Yen</td>
</tr>
<tr>
<td>KYC</td>
<td>Know Your Customer</td>
</tr>
<tr>
<td>MA</td>
<td>Moving average</td>
</tr>
<tr>
<td>USD</td>
<td>The currency symbol for US Dollar</td>
</tr>
<tr>
<td>RMSFE</td>
<td>Root mean squared forecast error</td>
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<td>VaR</td>
<td>Value at risk</td>
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1 Introduction

In this chapter, the objective is to introduce the study on whether Bitcoin as a decentralized electronic currency is a financial instrument that would be suitable for portfolio diversification that consists of stock from global stock markets.

1.1 Problem statement

“Bitcoin is an experiment. Treat it like you would treat a promising internet start-up company: maybe it will change the world, but realize that investing your money or time in new ideas is always risky”

(European Central Bank, 2012, p. 27)

In 2008, Bitcoin was designed and developed by the programmer working under the Japanese pseudonym that was called Satoshi Nakamoto (Grinberg, 2011, p. 162). The Bitcoin has many various aspects such as having a complicated mechanism system, low or inexistent transaction fees and informational transparency. Therefore, Bitcoin is a potential alternative currency to the standard conventional fiat currencies such as the Euro, US Dollar or Japanese Yen (Satoshi Nakamoto, 2008, p. 1). However, simultaneously with the growing fascination of Bitcoin in recent years, Bitcoin’s system is known as a promising environment for laundering money and illicit activities. It is also the target for hackers who have the intention to attack potential Bitcoin owners (Barber, et al., 2012).

The value of Bitcoin is determined to solely base on demand and supply. The supply of Bitcoin is created by using computer resource in order to tackle the mathematical issues. Bitcoin is not possessing the involvement of any regulatory body such as clearinghouses, financial institutions or responsible central banks in trading. Therefore, many users prefer the decentralized Bitcoin over fiat currencies because the supply of Bitcoin is entirely independent of banking policy (Pandey & Wu, 2014, p. 45). As of May 2017, the Bitcoin market capitalization currently is approximately USD 29 billion even though the price of volatility is still fluctuating (Blockchain, 2017).

The 2012 European Central Bank (ECB) (2012, p. 13) reports that Bitcoin as “a virtual currency is a type of unregulated, digital money, which is issued and usually controlled by its developers, and used and accepted among the members of a specific virtual community”. The virtual currency is not considered as e-money or a foreign currency that does not have a legal tender status (Clinch, 2013). Due to its unique characteristics, Bitcoin can be attractive to hackers (European Central Bank, 2012, p. 26). Furthermore, Bitcoin is built around with a decentralized and unregulated image. To summarize, there is no legal protection to investors or customers. It is estimated that an approximation of 400 million has permanently been lost due to fraudulent activities (Williams, 2014). Consequently, Bitcoin has a tendency to be more volatile than other conventional currencies and there are also more speculative bubbles (Grinberg, 2011, p. 175).

The financial crisis has transformed the global, economic environment. This results in investors seeking for innovative and potential investment opportunities (Gangwal, 2016, p. 3483). Bitcoin has become more and more developed and popular to media and in recent years is being used as a fashionable payment method through internet (European Central Bank, 2012, p. 5). There are many legal or illegal transactions that are performed in bitcoins. Thus, an establishment of a Bitcoin exchange-traded fund, the Winklevoss Bitcoin Trust for example, demonstrates that Bitcoin is a suitable instrument
for investors (Massoudi & Alloway, 2013; Balchunas, 2013). Mostly, all conventional fiat currencies are used as a reliable vehicle for portfolio diversification. However, the academic literature provides a tentative first look on the characteristics of Bitcoin because its value can be diversified into the investment portfolio optimization (Brière, et al., 2015, p. 3).

1.2 Research question

As mentioned above, the virtual currency has recently attracted the investment community and trading volume because of the extraordinary returns, Bitcoin is offering. From a portfolio management’s perspective, it has been researched about the relation between Bitcoin and stock markets. Therefore, the research aimed to concentrate on the following question:

Is Bitcoin a favorable instrument for investors that seek for a diversified portfolio?

1.3 Purpose

The main purpose of the study is to identify whether or not Bitcoin is a suitable instrument for portfolio diversification. This is done by analysing and explaining the causes of the unusually high volatility, identifying the risk types and measuring the behaviour of Bitcoin returns in relation to global stock markets.

1.4 Scope

The research project consists of an extensive academic literature review on Bitcoin, as well as several analytical research phases. The researchers measured the risk by estimating the volatility and used a multiple linear regression with explanatory variables to deliver explanations of the causes of Bitcoin’s high volatility. In addition, a value at risk approach also has been executed. Furthermore, the researchers analysed the relation of Bitcoin returns and stock market returns by measuring respective correlations and performing a regression analysis. Finally, the researchers developed forecast models to be able to estimate expected returns. This allowed to conclude whether Bitcoin is a favourable instrument for portfolio diversification. Furthermore, the results of this thesis deliver a broad orientation on how to invest into the Bitcoin market.

1.5 Time planning

In order to complete the thesis on time, the following deadlines, that are presented in table 1 below, had been used for the time planning.

<table>
<thead>
<tr>
<th>Task</th>
<th>Time completed</th>
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<tbody>
<tr>
<td>Select a research topic / research question</td>
<td>March 24, 2017</td>
</tr>
<tr>
<td>Complete theoretical framework chapter</td>
<td>April 02, 2017</td>
</tr>
<tr>
<td>Complete constructing methodologies</td>
<td>April 09, 2017</td>
</tr>
<tr>
<td>Collect data</td>
<td>April 03, 2017</td>
</tr>
<tr>
<td>Complete data analysis (practical research)</td>
<td>April 28, 2017</td>
</tr>
<tr>
<td>Official submission</td>
<td>May 19, 2017</td>
</tr>
<tr>
<td>Defence seminar</td>
<td>May 26, 2017</td>
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</table>

The first stage was to consult the supervisor and check if the project is going in the right way. As the topic requires a substantial understanding of the Bitcoin system and its structures, the researchers started with an extensive period of desk research and
literature review. The second stage consisted of creating the outline of the main chapters with important points and findings. This also included to decide on methodological structures, before accessing and downloading real data. Beginning of May, an initial draft has been handed in to the supervisor, who gave valuable feedback. In the final stage, minor issues in the thesis have been adjusted and the paper has been checked before submission on May 19. The defence seminar is planned on May 26, 2017.

1.6 Motivation

It has been a long time since the decentralized Bitcoin was born. There is no doubt that the electronic Bitcoin has gone through many ups and downs in its developments. In the recent years, the cryptocurrency became more and more prevalent and developed in many countries in the world. Bitcoin is legally accepted as a traditional payment method for a few reputational websites and certain enterprises such as PayPal, Dell, Amazon or Microsoft. On the other way, the virtual currency is the most dangerous currency because of its unique features like an extraordinary volatility and the anonymity of its users. Many questions are associated with Bitcoins such as how Bitcoin will thrive in the developing world, whether or not merchants invest in cryptocurrencies or Bitcoin will become a new payment method in the future. Reliable answers for these questions can currently not be given and many people, including us, are eager to know more about this complex financial instrument. Therefore, this is a good opportunity for us to perform a study if Bitcoin has potential for professional investors.

As financial students, we embrace the ideas of beginning as investors who would like to experience and invest in this field. Our desire is to find out the risk of the investment and the outstanding advantage of digital currencies. We acknowledge that Bitcoin shows similar characteristics to cash with the very important feature of being available only in a digital form. The exchange rates with other fiat currencies fluctuate up and down and there are many voices in the media on this topic with some contradictory theories. Therefore, we wanted to shed some light by academically investigating this topic.

Hence, it is considered a form of currency and it can be viewed as an investment instrument as well. Yet, Bitcoin now truly is a new, comparatively unelaborated asset and our work will therefore be beneficial for professional investors that seek further portfolio diversification opportunities. Basing on this, we like to know if investors can use Bitcoin in order to diversify their portfolios.
2 Theoretical methodology
This chapter presents the general, broad methodologies for this research. It is started with the philosophy and is scoped down towards the approach and the design. Furthermore, important aspects such as validity, credibility, source criticism and research ethics are addressed.

2.1 Research philosophy
Research is complex and finding solutions to problems of different nature requires different approaches, methods and also beliefs. The research philosophy is usually the starting point for any researcher in social sciences where major decisions have to be made before the practical methodology can be constructed.

2.1.1 Ontology
Ontology is the philosophical study that is relevant to the nature of the social world. It embodies the questions of the assumptions the researchers take about the way the world works (Gray, 2004, p. 19). There are two aspects of ontology that are objectivism and subjectivism (it is also called social constructionism). Objectivism discusses how social entities exist independent of social actors whereas subjectivism discusses the awareness and the action of social actors that will enable to impact on social phenomena (Saunders, et al., 2009, p. 110).

In a study made by Smirch (1983, cited in (Saunders, et al., 2009, p. 111), most of the people based on the objectivist positions always have a tendency to observe the culture of an organization as somewhat that the organization "has". On the other hand, the persons follow the positivist positions that have the tendency to view the culture is something that an organization "is" as the result of the process continuing social enactment. The purpose of philosophical ontology is to recognize if the nature of social entities is positivism or social constructionism (or interpretivism) (Bryman & Bell, 2011, p. 20).

In this paper, philosophical ontology is very difficult to apply since this research is highly based on mathematical principles. However, there is no doubt that financial data will be related and influenced by the social actors on the global financial market. This implies that the perception and the action of actors such as their reaction on the markets, the speed of information or transaction costs are able to have an impact on financial data phenomena. Therefore, it can be stated that the researchers embrace subjectivism as the ontological position to follow. The research purpose is to find out whether Bitcoin is a suitable instrument in portfolio diversification. In order to achieve this objective, the researchers applied statistical models and calculations that forecast and compare the returns and its behaviour against stock market returns. These results have then been interpreted according to financial standards. Thus, the point of view of the reality is that investment in Bitcoin is decided by many actions as social actors.

2.1.2 Epistemology
In social sciences, researchers need to think about whether principles of the natural sciences are transferable to social studies. Epistemology is dealing with this issue and cares about defining requirements for knowledge. It deals with the problem of identifying what constitutes acceptable knowledge in a specific topic area (Saunders, et al., 2009, p. 112). Following this psychological type, researchers can only consider observable and measurable phenomena as knowledge (Collis & Hussey, 2014, p. 47). It can therefore be said that researchers are acting independent and objective. It is however
criticized that a gap between the researcher and his findings may exist. Bryman & Bell (2015, p. 26) explain that a major question that arises in the research planning phase is the question whether principles and practices of natural science research are suitable and useful to apply in a social study.

Epistemology can be classified by four positions. Positivism describes the procedure of copying the natural science principles to social studies (Bryman & Bell, 2015, p. 27). As the practical research part of this thesis builds on the requirement of having suitable, mathematically statistical models, the thesis authors followed a positivism standpoint.

In contrast to this position is interpretivism, which has been formed by researchers who believe that scientific procedures are rather unsuitable to apply in social studies (Bryman & Bell, 2015, p. 28). According to Collis & Hussey (2014, p. 50), interpretivism tends to use rather small samples and produce qualitative, often subjective data. This produces findings with a low reliability. It can clearly be expressed that the researchers are not following the interpretivism paradigm as the study makes use of quantitative research, using a large sample and aims to obtain generalizable data.

Although these two philosophies are the most popular, Saunders, et al. (2009, p. 119) also explains pragmatism and realism. Under pragmatism, researchers are rather flexible as it is believed that both, qualitative and quantitative data, meaning subjective or observable, objective data, can provide sufficient knowledge and the correct approach has to be identified based on the purpose and research question. Realists have a much stricter point and view and state that only observable data is suitable as this is the only method to obtain credible facts. According to this maxim, research can mainly be used to explain and state theories within a context.

The research question requires a quantitative approach and reliable, generalizable data that is processed through various statistical, mathematical models. Therefore, the thesis authors follow a positivism and realism philosophy as they acknowledge that the results will produce generalizable facts whose interpretation must be performed carefully to avoid misinterpretation.

2.2 Research approach

The research approach can be described with two specific types, inductive and deductive. The former type describes the procedure of collecting data first and analysing the research opportunities it provides, followed by carrying out the actual practical research (Bryman, et al., 2011, p. 57). Deductive theory describes the procedure of stating a hypothesis first and proofing or refuting it afterwards (Bryman, et al., 2011, p. 55). The hypothesis may also appear as a research question which is going to be answered. This is the most common research approach and can be performed repeatedly to improve the validity and quality of the findings. A deductive approach is commonly associated with a quantitative approach (Gabriel, 2013).

In this study, the researchers started with a deductive approach as the research question is based on previous knowledge. Factors increasing the Bitcoin volatility have already been proposed in existing theories and they have been tested in this study as far as possible. Furthermore, the selected methods are based on the modern portfolio theory and other financial, as well as statistical standards.

In financial systems, it is often not possible to completely track every transaction or to have a central database for that. The blockchain technology however provides the exact number of transactions and the mining difficulty, which is indicating the average
transaction processing time. These factors have been considered to be important predictors as their impact on the Bitcoin prices and the volatility is widely discussed in the Bitcoin universe, that often consists however of not scientific publications such as websites or blog posts or contributions on social media channels.

2.3 Research design

Bitcoin is a relatively new financial instrument. The first detailed plans had been published in 2008 (Chuen, 2015, p. 11). Paired with the problem that the sense and purpose of this cryptocurrency is not clear whether for investors, companies or private individuals, it can be stated that a lot of investigation and research is necessary. Therefore, several research phases in this project are of exploratory nature. Exploratory research helps to identify the nature of a problem, especially if previous studies are rare to find. According to Saunders, et al. (2009, p. 140), the principal methods to answer exploratory questions are literature reviewing and conducting interviews with experts of the field. Although the research purpose is partly of exploratory nature, the primary purpose of this study is explanatory as the aim is to demonstrate relationships between Bitcoin prices and returns and those of global stock markets and exchange rates (Saunders, et al., 2009, p. 140). Saunders advises to collect quantitative data and perform suitable statistical tests and analyses to solve explanatory problems.

Therefore, the research design consists of an extensive phase of literature review with the aim to discover the characteristics and particularities of the digital currency, followed by a practical, quantitative analysis on Bitcoin, stock market and exchange rate data.

2.4 Research strategy

It is crucial to implement a strategy that is suitable to answer the research question. There are two major strategy types, quantitative and qualitative. A qualitative analysis focuses on gaining insight and understanding of complex problems and finding a suitable solution to these (Johnny & Leavy, 2011, p. 4). According to Rynes & Gephart Jr. (2004, p. 455), quantitative research “uncovers important relationships among variables and tests general propositions”.

This fulfils the purpose and will lead to the expected results of providing information about the behaviour of the Bitcoin characteristics and revealing relationships between Bitcoin, stock markets and exchange rates. Due to the research design, a quantitative, practical research strategy has been selected.

2.5 Research credibility & source criticism

Source criticism is very important and it should be paid attention to for both, the literature used and cited, as well as the databases where the numerical data has been collected from. To ensure that sources are credible, researchers can use peer-reviewed publications and articles. These are verified by critical editors who often are active in the same research field as the authors, following several principles and ideas that are described in detail by Spier (2002, pp. 357-358). The majority of sources for this study consists of peer-reviewed material that has been accessed through Umeå University Library and other selected trusted sources. Since Bitcoin is a relatively new financial instrument, there are several knowledge areas that are not yet sufficiently covered by scientific, academic work or peer-reviewed articles. These are mostly news articles or publications on websites that deal with technological topics. In this event, the author of
such not reviewed or not confirmed source has been assessed to ensure that s/he has a sufficient knowledge, for example by being active in the software programming/coding environment. Unconfirmed material has only been used for the literature review about Bitcoin. Any conclusions drawn from it in this study have been confirmed with the practical research which relies on a solid methodology.

2.6 Ethical considerations

Adhering ethical norms and social conventions whenever conducting research is very important out of many reasons. Resnik (2015) mentions reasons such as promoting the aims of research, keeping standards and values that are essential in collaborative works and ensuring that the researcher can be held accountable for his conclusions, which builds up public support. Several research codes have been published to standardize ethical principles.

Smith (2003, p. 56) from The American Psychological Association (APA) warns researchers to be aware of multiple roles and avoid relationships that negatively influence the professional performance. She adds further principles such as following consent rules, respecting confidentiality and informing about ethical codes and principals.

Since the researchers have been working in line with the requirements from Umeå University for Master Theses (Umeå School of Business and Economics, 2017) in addition to being aware of several ethical codes and principles, it can be stated that this study does comply with ethical expectations and standards. The data sources have been verified and the researchers have worked independently without any commission or sponsoring. This ensures that the interpretation of the findings is neutral and objective and not influenced by third party organizations. In addition, general methodological rules are followed to ensure obtaining reliable and valid results and the researchers therefore gladly take the responsibility for their work.
3 Theoretical reference

The digital currency is very unknown to many people including financial experts, therefore the theoretical reference is not only designed to lead to and justify the establishment of the practical methods, but also to provide a collection of reliable sources to deliver valuable information for potential Bitcoin investors and traders.

3.1 Introduction to the Bitcoin technology (Blockchain)

The primary benefit of the bitcoin transaction processing system is its decentralized tracking system called Blockchain that “isn’t stored in any single location (BlockGeeks, n.d.)”, which reports every transaction and the status of it. Vimja describes the Blockchain as a peer-to-peer network, recording all transactions (Einführung zu Blockchains, 2016). Any new transaction is added to other transactions that, together, form a block. The maximum block size currently is 1 Megabyte. Once the size limit is reached, the block will be closed and from this moment on, transactions are considered as being valid. Blocks always build on the preceding blocks and therefore, a status is formed by the longest chain of blocks.

Plassar (2013, p. 386) found that because of the complexity of the blockchain’s structure, it seems to be unlikely to cheat the system as the creation of timestamps and the fact that every single transaction in the Blockchain is recorded helps to protect fraudulent activities against the Bitcoin structure. This timestamp, that is distributed on a peer-to-peer network, in addition with the proof of work, that has to be successfully completed whenever a block shall be finalized will impede manipulations on the chain, for example a double-spend attack (Satoshi Nakamoto, 2008, p. 1).

The difficulty of such proof of work depends on the network usage, so that average processing times remain constant. This proof of work requires mostly computing performance and is called mining. Anyone who is sharing his computing performance is allowed to close a block and will be rewarded with a monetary value paid in bitcoins.

Around each ten minutes, transactions on the network timestamp will be recorded from the previous block in order to create a new block (Lee, 2013). Started at 50 Bitcoins (BTC) per block, the value halves every four years and is now at 12.5 BTC per block. In addition, the miner also is rewarded with the transaction fees. Users initiating a payment can set the value of the transaction fee and can therefore indirectly influence the processing time of their payment as miners are likely to mostly pick transactions with a higher fee.

According to Don & Alex Tapscott (2015), the technology “can be programmed to record not just financial transactions but virtually everything of value”. This means, the system may not only be interesting for financial institutions, but also for any organization that is sharing digital information.
A study of Jurik (2016, p. 26) found that the cryptocurrency Bitcoin has a transaction mechanism that is safe due to complexity of its system. Bitcoin uses cryptography that not only ensures the security of the peer to peer network, but also protects the users. The cryptography, that comes in the form of an alphanumeric key for the users ensures that only the owner can access and use the money. Consequently, it will be able to prevent the re-use the money that has been used before. Therefore, it can be stated that Bitcoin cannot be falsified as other conventional fiat currencies. Bitcoin is like an internet cash as payments do not require the disclosure of informational participants and individual databases. Thus, in this case, it is offered a security level similar to cash.

3.2 Open-source technology for banks

Banks are highly interested in Bitcoins. Although they do not want to invest in the cyber currency, they are highly interested in the open-source Blockchain technology that is recording every transaction (Popper, 2016). The goal for the banks is to track and process transactions more efficiently. Sourcing work out to users is a common practice in the digital world. The most widely-known practice is probably the filling out of captchas which is currently applied by Google, to make users help the company to identify images (Motoyama, et al., 2010, p. 3).

The decentral technology would allow central banks to track every single unit of its currency for all its travels throughout the financial systems – “something that is impossible now (Popper, 2016)”. Jon Southurst (2016) is reporting even further, stating that several banks are about to introduce their own variant of Bitcoin.

According to an interview with Arnold (2016), the Financial Times’s banking editor, banks appreciate not only the increased speed and fewer capital reserve requirements in investment banking, but also the transparency that a shared database provides instead of “each bank having their own records”.

Shen (2016) expects “15% of banks world-wide […] to widely implement blockchain”. The technology will be a useful tool for areas such as consumer lending and retail payments, but may also increase customer trust due to instant, transparent information.

3.3 Bitcoin compared to other security types

3.3.1 Bitcoin, gold and Dollar

Generally, it is known that Bitcoin is designed to work like gold. In fact, Bitcoin and gold have many similarities such as being limited and costly to extract. Gold has two components that are monetary demand and industrial demand, whereas Bitcoin is only demanded out of monetary reasons. Gold is used as a fiat currency or productive factor. Therefore, when the monetary demand is diminished and the industrial demand increases or stays at the same level the supply of gold will be decreased which creates the assumption that the supply is adjusted by the demand. Thus, fluctuation in buying of gold will be less serious than the fluctuation of the purchasing power of Bitcoin. (Faggart, 2015).

Dyhrberg (2016, p. 92) elaborated about Bitcoin, gold and Dollar by using a GARCH model and showed that Bitcoin has a few aspects that are similar to gold because they reacted similarly in the GARCH model. Both have the ability to hedge risk and respond symmetrically to market information. Since both Bitcoin’s transaction and Bitcoin’s reaction to market sentiment simultaneously occur quickly, the frequency of Bitcoin can be higher than gold. The research results suggested that due to decentralization and
limited scale of its characteristics, Bitcoin will be considered something between a fiat currency and a commodity.

This does not mean Bitcoin is less valuable than marketable assets. In another study by Dyhrerg (2016, p. 142), it has been found that in the UK market Bitcoin has similar hedging capabilities than gold. It is therefore possible to use gold (or Bitcoin) to neutralize market risk. The author mentions the fact that, similar to gold, no government is supervising the mining (production process) to justify this correlation. She further concluded that Bitcoin is unsuitable to hedge against market risk of other currencies.

In Whelan’s (2013) perspective, he argued that both Bitcoin and US Dollar are similar. Bitcoin and US Dollar are used as a medium of exchange characteristic. Besides that, both of them have no or limited intrinsic value. However, the fiat currency US Dollar is supported by the U.S. government whereas Bitcoin is a private currency which has been introduced by a private organization. Hence, the supply, governance and control of the two assets are different (Haubo, 2016, p. 90).

3.3.2 Bitcoin mining and gold mining

Unlike other currencies Bitcoin can be mined which is rewarding users who contribute with computational power. Similar to gold mining, Bitcoin mining requires resources, mainly computational power which can cause extensively high energy costs. Bhaskar & Chuen (2015, p. 57) estimated energy costs of 70.7 million USD per year for the entire Bitcoin network. The mining activity increases when the price of Bitcoin is high enough to generate profits.

However, when the Bitcoin’s price becomes too low and the mining does not bring profit to the miner, the mining activity will be decreased. This is partly analogue to the gold mining activity; however, Bitcoin mining will not completely be discontinued when the product’s price is below the production cost since in the Bitcoin protocol, mechanisms are set to ensure the digital currency is always produced. Consequently, regardless of how low the demand decreases, the supply to the market, and consequently the availability of the transaction system is ensured (Faggart, 2015).
3.4 Attempts to regulate virtual currencies

Figure 2 illustrates the regulatory status of Bitcoin in the world. Countries that allow Bitcoin are coloured green, yellow indicates that regulations are debated, red indicates strong limitations or prohibitions and black coloured countries did not provide sufficient data that allowed to evaluate the status of regulation (Coindesk, 2017). It is visible that the majority of Asian governments (including the Asia Pacific area) have a much more hesitative view on electronic currencies compared to Western countries such as Europe and America and Australia.

In Lloyd’s Emerging Risk Report (2015, p. 23) it is stated that over 60 nations all over the world have enforced regulatory frameworks and guidance to decentralized virtual currencies, particularly to Bitcoin. The International Monetary Fund (IMF) bears a high responsibility for coordinating foreign currency exchange (IMF, 1945) in order to guarantee global economic stability by setting up basic criteria of regulation frameworks for all nations.

Since Bitcoin is not officially considered as a legal fiat currency, it is not backed by governmental institutions. Therefore, the prescribes of IMF’s regulatory frameworks will be unable to enforce and implement for Bitcoin and other digital currencies. If the growth of Bitcoin still continues, expanding in popularity and value, the economic stability will be impacted dramatically. Bitcoin could be used as a “speculative attack” in order to attack a conventional fiat currency (Matsui, 1998, pp. 306-307).

However, Plassaras (2013, p. 407) showed in an article that there are at least two ways in order to incorporate Bitcoin into the International Monetary Fund (IMF)’s regulation frameworks. The first way is to attempt to exercise the indirect control over virtual currencies like Bitcoin vis-a-vis member nations by extending the term of IMF’s regulations relating to Article IV, Section 5 of the Articles of Agreement. The second way is to give the IMF a direct control over Bitcoin by granting it and other electronic coins a quasi-membership status.

Extending the section of The Article IV, Section 5 of the Articles of Agreement encompassed three stages. First and foremost, the IMF should be ensured that the organization always has enough supply of Bitcoin against a speculative attack of a few member nations through Bitcoins’ users. Next, by ensuring that he value of Bitcoins...
going in and the value of Bitcoins coming out is equivalent, the IMF will avoid undercapitalization endowment. Finally, to strengthen the legality of the electronic currency Bitcoin, it should be merged into the IMF’s fund and consequently, it is likely to become accepted by the international financial community (Plassaras, 2013, p. 404).

The Financial Crimes Enforcement Network (FinCEN), a bureau of the US Treasury Department, issues the Virtual Currency Guidance for users who engages in virtual currency transactions (Jeffries, 2013). FinCEN wants Bitcoin businesses to have to register to the US government. Particularly, the money transmitters should have to provide data such as tax information, contact information and bank information of all transactions.

3.5 Public criticism about Bitcoin

Bitcoin has often been criticized for indirectly supporting illegal activities like drug or weapon business (Filippi, 2016). Hackers used it to get paid their extortion money in ransomware attacks (Palmer, 2016). The most recent and one of the most intensive attacks ever was the WannaCry ransomware attack that encrypted data of more than 200,000 devices and demanded a payment through Bitcoins to make the files accessible again (Financial Times, 2017). The image of the currency suffers from such criminal usage.

Lee (2013) criticizes that Bitcoin, compared to other currencies, has no protective institution. If credit card details get stolen, it is comparatively easy to reject false payments and get refunded. Such a safety net is not existing for Bitcoins yet.

Another problem is that it is nearly impossible to introduce regulations on Bitcoin on a similar level as for other securities. However, it is possible to force some regulations on the Bitcoin trading platforms. The People’s Bank of China requires platforms to strictly verify the identities of their users (Gautham, 2017). The currency is often compared to gold as it is also mined (Saha, 2017). This mining process is of course performed digitally where miners share their computational power to process the transaction and are rewarded Bitcoins therefore.

In an interview with The Verge, Bill Gates (2015) compared Bitcoin to selected, fiat currencies that have been in trouble and stated that Bitcoin does not offer much improvement for those living on a very low budget. He further adds that many people have difficulties understanding the volatility of Bitcoin and how to ensure that the Bitcoin platform or vendor is safe and will not close down and disappear with the bitcoins stored.

Some Bitcoin users complain that transaction fees can get high if users prefer to have the transaction processed quickly or the transaction is large in bit size. While still being lower than international wire transfers, they are continuously rising as the currency is limited and miners need incentives for providing devices and power (O'Connell, 2016). Miners state that it costs them around 200 US Dollars in electricity not including any equipment, rent or employee costs to mine one Bitcoin (Reuters, 2016). Every four years when the mining reward becomes halved, these costs theoretically double up which is probably a big driver of the increasing BTC rates.

It is also argued that Bitcoin and its Blockchain technology is very complex and difficult to understand, making it even harder to regulate and fully trust this system (Filippi, 2016).
3.6 Money laundering in Bitcoin

As of 1973, the term money laundering was known through the Watergate Scandal. There is no original legal definition for this term but it is described by the process of transforming from illegal assets to legal assets (Ertl, 2004, p. 8). Criminals often use a three-step process in order to launder dirty money. First, criminals place in dirty money into the financial systems, followed by layering which is described by the phenomenon of transferring or convert illegal money to money resulting from a legal source. The third applied step is integration where illicit money finds its way back in financial systems with a now legitimate state (FATF, 2014).

In a study made by Nacholas J. Ajelo (2015, cited in Bååth & Zellhorn, 2016, p. 10) with the unique characteristics as cheap payment and fast transaction in Bitcoin, it therefore will become a potential advantage for dishonest uses who has the purpose to launder dirty money through Bitcoin system.

In the Handbook of Digital Currency, Chuen (2015, p. 302), advises that the risk factors and associated money laundering can be briefed by using the risk categorization by work bank that have been developed for mobile payment.

To combat money laundering, governments have the term of regulation and directives for anti-money laundering (Justice.gov, 2008). It will increase transaction costs of politically unwanted transactions but it will not change any benefit with normal transactions. Know your customer (KYC) is known as a method to combat illicit dirty money. The purpose of KYC is to identify customers of financial institution as well as the third organizations between buyers and sellers (Standard Chartered, 2017).

In Europe, Bitcoin merchants have to enforce the third Anti Money Laundering Directive (AML) that is monitored and regulated by the European Commission. The directive, encompasses three regulatory arrangements that identify and verify customers as well as monitor transactions, report suspicious observations of laundering dirty money, as well as to support funding for government agencies (European Commission, 2013).

There is no regulation for Bitcoin in the huge number of America, African and Asian countries, even banning digital currencies. In Oceania, currently, New Zealand has no regulation whereas Australia has regulation governing taxes (CoinDesk, 2014)

3.7 Tax in Bitcoin

In the Handbook of Digital Currency, Bal (2015, p. 272) explained that income in Bitcoin has to be taxable. Yet, taxable income does not mean that it is actually taxed. Bitcoin holders may not pay taxes because either they are not aware that Bitcoin is a taxable asset or they deliberately avoid accumulating taxable income because of the complicated characteristics of virtual currencies.

Marian (2013, p. 39) explained some researchers claim that virtual currencies have traditional characteristics for tax evasion because taxpayers are mostly anonymous and taxable income is therefore actually not taxed. Tax evasion of virtual currencies therefore becomes more and more popular in the future.

Thomas Slattery (2014, p. 856) concluded in a study that since Bitcoin is used as a payment method for various goods and services, it is nearly impossible to differentiate transactions with a legal purpose and those with illegal intentions. Thus, tax evasion will be increased because transactions are difficult to investigate as cash exchanges.
He also showed that in the United States the strong sense of responsibility of *The Bank Secrecy Act* and other power enforcement of *Internal Revenue Service (IRS)* is to cover tax evasion, encompassing many different types of arrangements regarding Bitcoin (Slattery, 2014, p. 873).

### 3.8 Interesting information for investors

According to the Bitcoin risk analysis made by Kiran & Stannett (2014, p. 23), lack of awareness of the Bitcoin topic is the primary reason that creates risk for investors. For example, misconception of how the system works and how secure it is will be an uncertain basis for making investment decisions. In order to decrease risk for users, the mitigation strategy suggests having more information made available to the public.

The *Bitcoin Investment Trust (GBTC)* for example, is gaining exposure to the Bitcoin market price by giving investors an opportunity to access it through traditional investments. Investors will be able to avoid the challenges of buying, storing and safekeeping (Grayscale, 2017).

Investors with long-term intentions need to consider adding a Bitcoin individual retirement account (Bitcoin IRA). The Bitcoin IRA not only provides investors with a potential opportunity to benefit from Bitcoin’s long-term periodical growth, but also ensures Bitcoin’s reputation from risk regarding of conventional capital market (Bajpai, 2016).

Positive information for long term investors is that the volatility of Bitcoin has the tendency to decrease (Stutman, 2016). In Figure 3, Stutman shows that as of 2011, Bitcoin volatility was around 16 % percent whereas in 2016, its volatility was approximately 2.5 percent. The fluctuation in the price Bitcoin is decreasing and the value is also becoming stable.

![Figure 3: Bitcoin volatility time series from 2011 to 2016](http://wealthdaily.com/)

### 3.9 Choosing the right market access

“It’s the underlying platform, […] that holds the real transformative power (Duivestein & Savalle, 2014)”. Choosing the right platform can be crucial which investors learned the hard way when *Mt. Gox* collapsed which, at that time, handled up to 90 percent of the Bitcoin-Dollar trading volume (Bajpai, 2014).

Helms (2016) warns that so-called Bitcoin banks like *Coinbase* are convenient but are not suitable for longer time holdings since users cannot control their private access keys.
The keys, which is a pair of a private and a public key, are the most important tool when trading with Bitcoin in whatever way. Users preferring to stay highly anonymous prefer to have several accounts which is, having several key pairs (Lind, 2015, p. 17). This complicates the consecutive track of payments or other transactions. He further states that wallets actually serve only as a service to store the key information. It may also be possible to store keys on a piece of paper instead of relying on a web service or mobile app, however, losing the key results in an impossible access to the personal Bitcoin volume.

3.10 Obtaining Bitcoin through purchasing or mining
A study of Valfells & Egilsson (2016, p. 1678) came to the conclusion that since the latest mining reward halving event, it has become sincerely difficult and often unprofitable for new miners to enter the market, but the profitability of longer existing miners remained unaffected. They warn that this relationship is critical for the security status of the blockchain making it “vulnerable to attack”.

However, large capital owners may still have entry potentials. As energy costs are the highest cost factor in mining, this expense must be reduced to allow profitability. John McAfee recently joined the mining business (Kannenberg, 2016), aiming to mine 0.7 percent of the entire blockchain mining volume. He stated that the price development, his ability to use low priced water energy and new ASIC chips will turn this investment into profitability.

While mining is usually an option for those that consider a long commitment, buying Bitcoins is recommended for those who like to hold Bitcoin for a shorter period. Bitcoins can be bought through wallet services, Bitcoin ATMs or local exchanges (Shin, 2015).

3.11 The driving factors of the Bitcoin prices
According to a study by Polasik, et. al (2014, pp. 23-24), the increase in the price of Bitcoin is correlated to the amount of transactions and the general interest in the topic Bitcoin (measured through Google searches and number of available articles). Popularity on the media is also a significant price factor. The research group found out that information that was undermining Bitcoin’s reputation caused a decline of the price whereas articles with a praising tone lead to a price increase (Polasik, et al., 2014, p. 25).

Kristoufek (2015) came to the conclusion that the Bitcoin price increases with an increase of the transaction volume (transaction used for “real” purposes like payments). This price increase is followed by an increase in the exchange volume which is likely to create bubbles. The bubbles are going to burst and the unexpected large and rapid price falls are explained with being course corrections, although the price stays higher than the initial value. Garcia, et al. (2014, p. 6) confirms that a growing popularity on the media increases the price. Higher interest leads to more purchases which, according to basic economics, leads to a price increase.

This information is of high value for risk assessment. If one can clearly identify the beginning of such a bubble which means notifying that positive information on media overcalls negative press releases, it can be said that the expected loss of a bubble burst may be less than the initial investment.

Another driving factor which is however difficult to investigate is the acceptance of Bitcoin. Analysts expect a correlation between the number of acceptance as a payment
mean and the price. According to *Time Magazine* (Davidson, 2015), almost all companies and merchants that state to accept Bitcoin are not taking them technically directly. Instead, they have partnered with a middleman taking Bitcoins and directly converting them to another agreed instrument. That complicates it to collect reliable time series data on Bitcoin acceptance and consequently hinders to scientifically test this hypothesis.

### 3.12 Hedging Bitcoin

Some traders identify Bitcoin also as a commodity. During recent years, several Bitcoin derivatives exchanges opened, although the trading offers and volume are by far lower than of other commodities. In 2015, the Commodity Futures Trading Commission (CFTC) decided to consider Bitcoin as a commodity and make it affective to standard commodity trading rules (Sheppard, 2015).

A major problem with Bitcoin derivatives is that such transactions are exposed to counterparty risk (Chan, 2015). Normally, when trading with derivatives, a trustable clearing house is usually involved. Although Bitcoin derivatives are traded on registered platforms, these platforms often have a registration in countries such as the Seychelles and could be difficult to lawsuit in a case of default.

In 2014, *Tera Group* traded on a non-deliverable forward swap to hedge against the risk of fluctuation during the payment period of 25 days (Caruthers, 2014).

### 3.13 The risk types of Bitcoin

Securities usually bear several types of risks. Often these are market risk, credit risk and operational risks. However, Bitcoin as a new financial instrument also bears new forms of risk.

#### 3.13.1 Market risk

Market risk describes potential losses in on- and off-balance sheet position that result from changes in market prices (Committee on Payment and Settlement Systems, 2003, p. 31). It is no secret that Bitcoin is a highly volatile investment, but its volatility has already decreased compared to its beginning period, which could be a sign that the currency is maturing (Osterrieder & Lorenz, 2016, p. 4). Lloyd (2015, p. 20) states that Bitcoin’s value is derived through a function of demand and supply, similar to other freely traded assets. However, there is no central bank that is regulating or guiding exchange rates.

Lloyd further warns (2015, pp. 21-22) not to underestimate liquidity risk that may result from delays in exchanging Bitcoins. This risk mainly exists due to the relatively low number of market participants. Böhme et al. (2015, p. 226) call this a shallow markets problem that is created when users make comparatively large transactions. Unusual large transactions will change the market price immediately and this explains the high intraday swings of Bitcoin exchange rates.

Investors are advised to carefully follow the status of international regulation and tolerance of Bitcoin. According to Möser et al. (2014, p. 19), a catastrophic event, such as a major government prohibits digital currencies entirely, could cause a failure of the entire system. While the general public considers this as unlikely, a few countries like Bolivia (Infante, 2015) and Thailand (Trotman, 2013) have taken this step already.
3.13.2 Credit risk

Counterparty risk can be a crucial factor in Bitcoin’s risk assessment. It is often correlated with cyber security risk. Moore and Christine (2013, p. 3) came to the conclusion that 45 percent of the researched Bitcoin exchanges failed to reimburse their customers after closing down. Böhme et al. adds that exchanges that trade a higher volume are more likely to close down since a higher trading volume makes them more attractive for hackers. However, keeping Bitcoins in a digital wallet instead of an exchange has no effect on risk prevention. Digital wallets are also affected by hackers. For example, 4,100 bitcoins (valued at 1.2 million USD at that time) have been stolen from the Bitcoin wallet service inputs.io in November 2013 (McMillan, 2013). In the following month, 1,295 bitcoins (equal to 1 million USD at that time) have been stolen from BIPS (a bitcoin payment processor) (Southhurst, 2013).

3.13.3 Transaction risk

The non-presence of a central bank, clearing house or similar authority causes several transactions risks. Transactions that have been executed are irreversible and it is not possible to correct or undo any mistakenly or fraudulently performed transaction (Böhme, et al., 2015, p. 227). Due to the blockchain technology, payments are valid once they are added to a block which has been closed by a miner. Due to the structure that the longest chain of blocks indicates the status, it is still possible to manipulate transactions of the latest block with a double spend attack and contradictory transactions (Böhme, et al., 2015, p. 227). Even though the chance that hackers are taking such a step is very low since the proof of work mechanisms increases costs for such activities, it may still be profitable for high value transactions (Einführung zu Blockchains, 2016).

To encounter criminals, it was proposed to mark all Bitcoins that have been stolen or result from fraudulent activities (Bradbury, 2013). In the event a marked Bitcoin is received, the user’s client will alert the marker (the user who marks the bitcoins when s/he noticed illegal activities). If the receiver will be made obligated to return these Bitcoins s/he has a loss since the payment may have been confirmed earlier.

3.13.4 Cybercrime

Bitcoin must deal with a numerous amount of cyber thefts and hackers also performing transactions on the network system. As of 2016, Reuters reported that a third of the cryptocurrency Bitcoin trading platforms have been hacked and around half have closed since Bitcoin is established. Moreover, there was no insurance for depositors when the system is attacked to offset loss to investors. Thus, the risk for investors of losing their bitcoins has increased as traders do not have any other option when exchanging (Coleman, 2016).

The anonymity in the Bitcoin system has made this currency attractive for criminals. Blacklisting Bitcoins with a criminal background is therefore discussed, imposing several risks on users. Möser et. al (2014, p. 22) presented two different implementation methods, poison policy and haircut. In a poison policy system, anyone’s transaction that include a single unit of blacklisted bitcoins are considered to be worth 0 whereas in the haircut system, the transaction becomes only devaluated by the amount of blacklisted bitcoins. Especially through the fact that the blacklisting event may take place significantly after the criminal event, there is a time window for criminal transactions that later become declared invalid. This can extinguish entire bitcoin holdings and therefore exposes the risk to users to accept bitcoins that become worthless in the future. A missing central bank or clearing house makes it nearly impossible to receive a refund.
Avoiding this risk seems to be impossible, however, Bitcoin receivers may charge for an appropriate risk premium. The challenge in this “self-made insurance” is to determine the likelihood of receiving Bitcoins from a yet unknown criminal activity (Möser, et al., 2014, p. 23).

Finding such data is quite difficult. Eling & Schnell (2016, p. 478) however suggest to use the number of claims an insurer is actually facing. Several other sources may also become of interest such as sharing information between merchants or Bitcoin receivers. According to Li, et al. (2015, p. 1851), companies and traders should set up risk-alarming databases that contain scientific categories for the technical risk of mobile finance innovation. The data should be delivered through data mining techniques.

### 3.14 Risk measurement

Risk management is a crucial principle in order to solve prospective threats which can harm existing systems. In a study of Bitcoin risk analysis, Krian & Stannett (2014, p. 1) identified threats and risks of using the decentralized digital currency from computational modelling and engineering perspectives. The potential exposure and level of risk can be considered as a measure of the property that may be affected by threats through the analytical system. There are also many researchers and businesses that have used this method in order to measure and manage the system. They allow that the system security will be brought up to an acceptable level (Hovestadt, et al., 2006). Risk is usually calculated according to the probability and is determined in seven levels from lower to higher in the above-mentioned study. Krian & Stannett (2014, p. 11) mention three basic types that are used to analysis Bitcoin risk.

In order to evaluate the risk assessment of Bitcoin, Kiran & Stannett (2014, p. 26) used the previous method to measure risk by using Cloud computer recourse (Catteddu & Hogben, 2009) to determine the possible effects of the Bitcoin transaction. Kiran & Stannett found risks at all levels from lower to higher of interaction when Bitcoin is traded over a peer to peer network rising across involving for economic system. A detailed list of all identified risk types is available in Appendix A1.

### 3.15 Modern portfolio theory

Based on a study made by Paramitha & Anggono (2013, pp. 30-31), portfolio returns are combined by the expected returns of all securities into the portfolio where the expected returns value is weighted with the percentages of the assets in the portfolio. Portfolio correlation is a statistical measure of how two assets will be relative to each other which is ranged from -1 to 1. A positive correlation means that if the security moves up or down, other securities will follow the same way. A negative correlation defines that if the assets moves up and down, other asset will move to the opposite direction. There is no correlation if the correlation coefficient is 0.

The fundamentals of today’s investment strategies have been formed by Harry Markowitz (1953) with his mean-variance framework, stating that risk averse investors are interested in the mean and the variance of a return distribution. A portfolio is defined by the different assets that are included and its respective weights in the portfolio. The value of diversification is generated as the individual assets compensate returns and losses (Peylo, 2012, p. 35; West, 2004, p. 3).

According to a study made by Witt & Dobbins (1979, p. 7), the Markowitz portfolio theory states that investors ought to choose an efficient portfolio that offers the highest expected return for a given level of risk. To find the efficient portfolio, it can be
considered to apply the optimization problem with $A \ (0 \leq A \leq \infty \ )$ being the risk aversion index. If $A = 0$, the portfolio has the smallest variance. If $A$ increases, it means investors will be willing to deal with substantial risk to get higher expected returns. If $A = \infty$, investors only care more about the highest expected returns regardless of the risk.

The Markowitz model is the principle foundation for the modern portfolio theory but it lacks practical application. The huge weakness of the Markowitz model is that it requires a high amount of data and uses a complex computation using an approximation method (Witt & Dobbins, 1979, p. 17). However, there are many useful models that have been developed from the Markowitz model by the use of approximation. The Sharpe model is the first simplified model that does not require the estimation of the correlation between assets. Yet, it requires the estimation of how the assets will rely on the behaviour of the market (West, 2004, p. 16).

The Markowitz modern portfolio theory demonstrates that risk returns can be controlled by diversifying the securities as a portfolio. Furthermore, it also shows that the optimal portfolio will grant the highest returns at a certain level of risk (Paramitha & Anggono, 2013, p. 29).

Innovissen are keen on the effect of the portfolio variance when adding another asset to their portfolio. Baker & Greg (2013, p. 28) stated that the correlation is the most important factor to determine. Adding another asset to the portfolio will reduce the variance if the correlation is low, and will increase variance if the correlation is high. Further on, it is proved that when increasing the weight of an asset, the beta with the stock of the current portfolio must be smaller than 1 to decrease the portfolio variance.

This step can be graphically summarized by the minimum-variance frontier plotting the lowest possible variance that is achievable for the given portfolio return (Bodie, et al., 2014, p. 220).

According to Francis & Kim (2013, p. 86), portfolio analysis requires certain statistical data such as $n$ expected returns, $n$ variances of returns and $(n^2 - n)/2$ covariances where $n$ is the number of assets. Since many markets often do not compensate risk that is diversifiable (Pfleiderer, 2012), the theory helps investors to receive a higher portfolio return for the same amount of risk by avoiding to include unrewarded risks.

Statman (1987, p. 355) calculated the effect on the standard deviation when further assets are added to the portfolio. He showed that on average, the standard deviation reduced by 24 percent just with adding one more asset while including 10 assets reduced the standard deviation by 51 percent. The function can be described as quickly decaying and approaching a definite limit after several lags.

The diversification benefit is highly dependent on the correlation of the individual securities in the portfolio (Brealey, et al., 2011, p. 200). The highest benefit is realized if the stocks are negatively correlated, which is however unlikely to occur. Diversifying well will result in a portfolio whose risk highly depends on the market risk of the securities that are included in the portfolio (p. 202).

It is stated that returns that are not normally distributed require more attention. Investors are recommended to inform about value at risk (VaR) or expected shortfall. Bodie, et al. suggest that value at risk and expected shortfall forecasts that are greater than normal should be followed by more moderate capital allocations to the risky portfolio (2014, p. 229).
According to a study lead by Eisl (2015, p. 3), Bitcoin’s correlation to traditional assets and commodities such as stocks, bonds, real estates, gold and oil has a remarkably low correlation. Therefore, Bitcoin is an interesting asset in order to obtain the optimal portfolio. Based on a research made by Briere (2015, p. 2), a small percentage of Bitcoin in a well-diversified portfolio can also improve the portfolio’s risk-return trade off. Yet, the result should be interpreted with caution because the measured data mainly reflects the short-term periods and may change in the medium and long stage.

3.16 Value at Risk theory

According to a study made by Linsmeier & Pearson (2000, p. 48), Value at risk (VAR) is widely used for derivative market in order to measure the losses of a particular portfolio resulting from market movement.

There are three approaches that is used to calculate Value at risk (VAR). These are historical simulation, variance covariance approach and Monte Carlo simulation (Linsmeier & Pearson, 2000, p. 50). In a research about Value at Risk (VaR), Benninga & Wiener (1998, p. 7) concluded the historical simulation method is useful when the amount of database is very large and both information profitability and loss distribution are not enough. The variance covariance depends on assumption of both distribution of market data and linear approximation of portfolio. The Monte Carlo simulation is flexible enough to incorporate private information with historical simulation. The results of these ways are similar and the purpose is to demonstrate a basic approach to risk measurement through Mathematica.

A study of VAR: Seductive but Dangerous, Value at risk depends on the range of values that analysts assign to the measurement. The VaR is able to have different values if there are different assumptions about return distributions and historical time periods (Beder, 1995, p. 12).

In the research of Value at Risk model at large trading firms in order to measure risk in trading portfolios, Bekowitz &O’Brien (2002, pp. 1110-1111) demonstrated that they often slowly react to changing circumstances; particularly, time series models are simple to compare with sophisticated VaR in forecasting. The study concluded computed Value at Risk is a precautionary value for capital at risk exposure instead of measuring portfolio risk.
4 Practical methodology

This chapter presents the practical methods that have been designed to answer the research question. The creation of the dataset is justified, followed by a reasoning of the calculation and the explanation of the applied statistical models.

4.1 Dataset

The primary data that has been used for the analytical processes has been downloaded from bitcoinity.org, an independent platform recording data from the blockchain and the exchange services that transmit data directly through their APIs (application programming interface) (Cieśla, n.d.). This platform provides data on a daily basis.

4.1.1 Selection of Bitcoin exchange rates

According to bitcoinity.org, the exchange volume per currency within the last two years is presented in figure 4 below.

It is clearly visible that the majority of all transactions is handled in Chinese Renminbi (CNY). However, it is also noticeable that the trading volume of BTC/CNY has cut off in the beginning of 2017. Recent trading volume statistics show that the BTC/USD rate is now the mostly traded Bitcoin exchange since that event.

Table 2: Market shares for the top 5 currencies of the total exchange volume from January 1, 2013 until April 3, 2017, source: data.bitcoinity.org

<table>
<thead>
<tr>
<th>Currency</th>
<th>Volume</th>
<th>Market share</th>
</tr>
</thead>
<tbody>
<tr>
<td>CNY</td>
<td>1,389,503,769</td>
<td>90.27 %</td>
</tr>
<tr>
<td>USD</td>
<td>114,463,331</td>
<td>7.44 %</td>
</tr>
<tr>
<td>EUR</td>
<td>13,987,166</td>
<td>0.91 %</td>
</tr>
<tr>
<td>JPY</td>
<td>9,013,517</td>
<td>0.59 %</td>
</tr>
<tr>
<td>GBP</td>
<td>2,731,529</td>
<td>0.18 %</td>
</tr>
<tr>
<td>PLN</td>
<td>1,751,213</td>
<td>0.11 %</td>
</tr>
<tr>
<td>CAD</td>
<td>1,343,321</td>
<td>0.09 %</td>
</tr>
<tr>
<td>HKD</td>
<td>1,112,622</td>
<td>0.07 %</td>
</tr>
<tr>
<td>Others</td>
<td>4,120,579</td>
<td>0.27 %</td>
</tr>
</tbody>
</table>

Table 2 displays that the market share of the Bitcoin/Chinese Renminbi rate was by far the most used Bitcoin exchange rate worldwide in the period from January 1, 2013 until
April 3, 2017. This period has also been considered the observation period in this research as some of the frequently traded exchange rates did not show consecutive data before January 2013. In addition, the Bitcoin prices, as well as its trading volume showed a straight line around 10 US Dollar for a very long time which might had influenced the statistical calculations and would destroy relationships, as it can be said that Bitcoin started its popularity in the beginning of 2013. Figure 4 shows that there is a strong decline in transactions starting from January 2017. Comparing this data with the price development of BTC, a strict correlation cannot be confirmed. The rate BTC/CNY showed a local peak on January 2, 2017 before declining slightly, followed by another peak around February 27. Since then, prices are falling (analysed on April 2, 2017).

Goh (2017) explains on Business Insider, that the drop of transactions comes from the stricter regulations that have been enforced by the central bank in January 2017. The new regulations caused that several Bitcoin exchanges in the country temporarily discontinued to allow Bitcoin withdrawals (Graham, 2017). This shall grant some time to increase their money-laundering efforts as otherwise, the central bank warned to close down any exchange service violating against the regulations.

As the rate development of Bitcoin and Chinese Renmimbi (BTC/CNY) has been unsure at the time of selection, it was crucial to make the research dependent on more than one rate, or in other words, on more than just the BTC/CNY rate. Table 2 presents the top traded Bitcoin exchange rates. The four major rates cover 99.21% of the trading volume in this period. It has therefore been decided to use these four exchange rates in the quantitative analysis as this will grant a representative result for 99 percent of all Bitcoin traders.

4.1.2 Missing data
The time series of the exchange rate from Bitcoin to Japanese Yen (BTC/JPY) showed 82 missing values due to several closures of exchanges. Many statistical analysis tools and models require consecutive data without gaps (James & Gary, 2008, p. 3). A popular tool is the standard multiple imputation. The problem of imputing the missing values has been solved with the help of the Amelia package in the statistics software R, that is also suggested by James & Gary (Honaker, et al., n.d.). The multiple imputation produced five new time series. The mean for each date of the new values has been calculated and set as the modified BTC/JPY time series.

4.1.3 Stock market indices
The researchers planned to compare Bitcoin data with data from the actual stock markets. As the Bitcoin data is covering the currencies Chinese Renminbi, US Dollar, Euro and Japanese Yen, it has been considered useful to use stock market indices within these represented currencies. The goal was to find market indices that are popular and report reliable data. Based on investing.com, which lists all major world indices, the following market indices have been selected:

The US Dollar has been represented with the Standard & Poor’s 500 (SP500), as it is one of the mostly noticed indices of the world, but differs from more conventional U.S. stock indices due to its complex weighting structures (Investopedia, n.d.). Therefore, DOW30 has been selected to include in the study as a second, more conventional market index. It is the second oldest U.S. market index and therefore enjoys a high popularity. Representing the Euro is rather difficult compared to the U.S. as the European market is very decentralized with local hotspots. The researchers decided
therefore to include two indices as well. Euro Stoxx 50 has been selected as it, according to the owner, “provides a Blue-chip representation of supersector leaders in the Eurozone” and can therefore be seen as a representor of the strong stocks in the Eurozone. In addition, the German equivalent to the Dow Jones Industrial Average, the Deutsche Aktien Index (DAX) has been added to the dataset. The DAX is Germany’s most important index and counts as one of the most important indices worldwide and is the third largest index for derivatives (Deutsche Börse Group, 2017).

To represent the Chinese Renminbi, the index China A50 has been selected. It is operated by the FTSE group and has components from the Shanghai and Shenzhen stock exchanges (FTSE Publications, 2016). The Japanese Yen is represented by the Nikkei 225 index, which is the worldwide most well-known Asian stock index and therefore the most quoted Japanese index (Finanzen.net, 2017).

In addition, three exchange rates have been used, mostly as a control variable since it is known that the Chinese government is manipulating the exchange rates. Several data sources have been used for the stock market indices and the exchange rates as historical data in daily form was not available for all series on a central database. The exact sources for each time series data is given in Appendix A15.

4.2 Volatility estimation

The high volatility, that is also further mentioned with the theoretical references in chapter 4, led to the need to estimate Bitcoin’s daily volatility and compare it to the volatility of the selected market indices. This allowed not only to test whether the volatility still is that high as presented in the media, but it also tried to explain the origin of that high volatility. In risk management, many risk quantifying models rely on the volatility. In this case the volatility is often calculated in a one day unit of time (Hull, 2015, p. 201).

4.2.1 GARCH (1,1) for volatility estimation

The simple calculation of variance or standard deviation, as well as moving average models are often not accurate enough as these models/calculations require an independent and identically distribution of returns (Alexander, 2008, p. 131).

In general, when fitting and applying statistical models, many researchers are interested about the error term. An assumption of the least square method is that the error term, which is denoted by the squared residuals, stays constant (homoscedastic). This is however not useful for financial applications as time series with financial data often have mean and variance volatility values changing over time. Therefore, a homoscedastic approach (assuming a stable variance value over time) is not suitable.

This may be a reason that the generalized autoregressive conditional heteroscedastic (GARCH) model has been introduced by Engle and Bollerslev, (cited in Bollerslev, 2010, p. 148) to capture the volatility clustering of returns. In the GARCH model, the weights applied on the residuals are automatically estimated to the best parameters with the weights getting progressively smaller but never reaching zero. Volatility, measured with GARCH, is often estimated on a series with high frequency, often on daily or even intraday data (Alexander, 2008, p. 137) as the clustering effects on the return of a financial asset will disappear if the returns are measured over longer intervals. Therefore, daily prices have been used. As it is desired to make also assumptions about their trend development, stationary time series with a rather stable mean are preferred.
Usually, the log normal returns of a price series are assumed to fulfill that criteria (Tsay, 2013, p. 91). The log returns have been computed using the following formula:

$$r_t = \ln(P_t) - \ln(P_{t-1})$$

where P is the asset’s price. Consequently, daily log returns have been used as input data for the volatility estimation of Bitcoin, the stock market indices and the currency exchange rates.

According to Bollerslev (1986, p. 311), the basic GARCH model equation is as follows:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

The parameters $\alpha_i > 0 \ (i = 0, 1, ..., q)$ and $\beta_j > 0 \ (j = 1, ..., p)$ ensure that $\sigma_t^2 > 0$. For $p = 0$, the GARCH model simply would become an ARCH model. For all time series, a GARCH (1,1) model has been applied.

In addition, an autoregressive moving average (ARMA) model has been applied with the following formula to fit the conditional mean component of a GARCH model.

$$y_t = c + \epsilon_t + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{j=0}^{q} \beta_j \epsilon_{t-j}$$

The first part of the formula describes the autoregressive component. The signal is composed of a weighted moving average of the $p$ preceding lags with the weights $\alpha_i, \ i = 1, ..., p$. The second part is the moving average component that describes the signal as a weighted moving average of the noise terms $\epsilon_{t-j}, \ j = 0, ..., q$ of the current and $q$ preceding lags. The noise terms are supposed to be independent of each other. This is one reason why this model requires stationary data.

According to Shakya (2015), the parameters $p$ and $q$ can be identified using the statistical software R Studio and the forecast package delivering the $p$, $d$ and $q$ parameters for an Autoregressive Integrated Moving Average, (ARIMA) model. The $p$ and $q$ values are identical for the mean model to include in the GARCH model specification with the condition that $d = 0$. The four time-series have been modelled with these $p$ and $q$ parameters:

- BTC/CNY returns $\ p = 2 \ q = 2$
- BTC/USD returns $\ p = 0 \ q = 1$
- BTC/EUR returns $\ p = 3 \ q = 1$
- BTC/JPY returns $\ p = 3 \ q = 2$

Following the identification of the $p$ and $q$ parameters, a GARCH model with ARMA included has been specified with the statistics software R using the rugarch package (Ghalanos, 2015). The specified and fitted model produces daily sigma estimates.

4.2.2 Other volatility models
To compare the results, other volatility measuring models have been applied. These results yet have been only calculated as a comparison and are not used for any
continuing process. However, it is interesting to see how much the results of the different estimation models differ.

The simplest variance and standard deviation calculation is provided with the functions STDEV.S and VAR.S in Microsoft Excel. According to the developer (Microsoft, n.d.), this function uses the n-1 method, where n is the sample size and x is the sample mean average. A more precise calculation is achieved with the Exponentially weighted moving average (EWMA) method. Before GARCH has become popular, this was the only statistical method in use (Alexander, 2007, p. 14). The following formula describes the model structure:

\[ \sigma_n^2 = \lambda \sigma_{n-1}^2 + (1 - \lambda)u_{n-1}^2 \]

where for the initial \( \lambda \), the standard value from RiskMetrics™ has been used (J.P. Morgan, Reuters, 1996, p. 272).

4.2.3 Multiple linear regression with explanatory variables

As an attempt to explain what factors cause the high volatility of Bitcoin, a multiple linear regression has been executed. As discovered in the theoretical reference (chapter 3.11), factors as the trading volume, the number of transactions, the popularity or the rate of Bitcoin acceptance are affecting the volatility. As all Bitcoin transactions are reported in the blockchain network, statistical data such as the exact trading volume and the number of transactions is available. In addition, the researchers decided to also include the change of the mining difficulty as an explanatory variable into the regression model. The blockchain algorithm regulates the mining difficulty in dependence on the network usage to ensure having a constant transaction processing time. This is a unique feature of the blockchain technology and is unlikely to be found in other, conventional transaction systems. Therefore, it has been considered interesting to see if the market accounts changes in this variable.

According to Granger & Newbold (1974, p. 111), a linear regression analysis needs stationary data as otherwise “spurious” relations may be discovered. Therefore, the explanatory variables have been transformed from actual numbers to the deltas, meaning that the variables are measured as the change from time \( t \) to \( t - 1 \). After this transformation, the data has been checked for stationarity using three popular statistics test. The Box-Ljung test (Box & Pierce, 1970, p. 1521) and Augmented Dickey Fuller test (Zivot & Wang, 2006, p. 120) require p-values lower than 0.05 to confirm the NULL hypothesis that the data is stationary, whereas the KPSS test (Dalla, et al., 2015, p. 3 & Kwiatkowski, et al., 1992, p. 176) rejects the hypothesis of having stationary data for all p-values smaller 0.05. The test results are presented in table 3 below. “Delta …” describes that this variable consists of the change from time \( t \) to \( t - 1 \).
Table 3: Stationary test results in preparation for the regression analysis on volatility and explanatory variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Box-Ljung</th>
<th>ADF</th>
<th>KPSS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Target</td>
<td>&lt; 0.05</td>
<td>&lt; 0.05</td>
<td>&gt; 0.05</td>
</tr>
<tr>
<td>BTC/CNY trading volume</td>
<td>&lt; 2.2e-16</td>
<td>0.0378</td>
<td>0.01</td>
</tr>
<tr>
<td>BTC/USD trading volume</td>
<td>&lt; 2.2e-16</td>
<td>0.0378</td>
<td>0.1</td>
</tr>
<tr>
<td>BTC/EUR trading volume</td>
<td>&lt; 2.2e-16</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>BTC/JPY trading volume</td>
<td>&lt; 2.2e-16</td>
<td>0.01</td>
<td>0.1</td>
</tr>
<tr>
<td>BTC/CNY sigma</td>
<td>&lt; 2.2e-16</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>BTC/USD sigma</td>
<td>&lt; 2.2e-16</td>
<td>0.01</td>
<td>0.1</td>
</tr>
<tr>
<td>BTC/EUR sigma</td>
<td>&lt; 2.2e-16</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>BTC/JPY sigma</td>
<td>&lt; 2.2e-16</td>
<td>0.01</td>
<td>0.1</td>
</tr>
<tr>
<td>delta BTC/CNY trading volume</td>
<td>&lt; 2.2e-16</td>
<td>0.01</td>
<td>0.1</td>
</tr>
<tr>
<td>delta BTC/USD trading volume</td>
<td>&lt; 2.2e-16</td>
<td>0.01</td>
<td>0.1</td>
</tr>
<tr>
<td>delta BTC/EUR trading volume</td>
<td>&lt; 2.2e-16</td>
<td>0.01</td>
<td>0.1</td>
</tr>
<tr>
<td>delta BTC/JPY trading volume</td>
<td>&lt; 2.2e-16</td>
<td>0.01</td>
<td>0.1</td>
</tr>
<tr>
<td>delta Number of transactions</td>
<td>&lt; 2.2e-16</td>
<td>0.01</td>
<td>0.1</td>
</tr>
<tr>
<td>delta Mining difficulty</td>
<td>&lt; 2.2e-16</td>
<td>0.01</td>
<td>0.01</td>
</tr>
</tbody>
</table>

For every predictor variable, at least two of the applied tests confirm stationary data. It has therefore been assumed with a 95 percent confidence level that the data is stationary and a multiple, linear regression can be applied.

Generally, the multiple linear regression is described with the following formula,

\[ Y = \beta_o + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \varepsilon_n \]

where \( \beta_o \) is the intercept coefficient, \( \beta_n \) the regression coefficient for predictor variable \( n \) and \( \varepsilon_n \) the residuals. The interpretation of the equation with its coefficients and the residual term can be found at chapter 5.2.2.

4.3 Correlations

The modern portfolio theory taught that investors are interested in the change of their portfolio variance when adding another asset to the portfolio. A low correlation, or a negative in best scenario, will decrease the portfolio variance. Therefore, investors are screening financial assets on the criteria of the correlation. (See more in chapter 3.15, Modern portfolio theory.)

It is generally known that financial price series follow a random walk rather than a stationary series. Correlating two time-series investigates their linear relationship, based on past observations. The correlations have been calculated using the following formula, suggested by Microsoft Office Excel (Microsoft, n.d.).

\[ Corr(X, Y) = \frac{\sum(x - \bar{x})(y - \bar{y})}{\sqrt{\sum(x - \bar{x})^2 \sum(y - \bar{y})^2}} \]

where \( \bar{x} \) and \( \bar{y} \) are the sample means of the respective time series.

The correlation of the log returns of the four different Bitcoin exchange rates with the stock market indices, the currency exchange rates and the Bitcoin exchange rates have been measured to identify whether Bitcoin is a favourable instrument in terms of portfolio diversification.
4.4 Regression on log normal returns

A regression analysis identifies the factors, often denoted as independent variables, that are influencing a certain result or event, also known as the dependent variable. It further measures to what extend and with which probability these factors have a significant impact (Gallo, 2015). Multiple linear regression is popularly known as a modelling technique that is used for forecasting and prediction because it measures the relationship between the dependent variable to the independent variables by using straight a line (Ray, 2015).

Normally, the equation of multiple regression, given n observations, is:

\[ Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + [...] + \beta_n X_n + \epsilon_n \]

where: Y is the dependent variable, \(X_n\) are the independent variables, \(\beta_0\) denotes the intercept coefficient and \(\beta_n\) describes the regression coefficient for the variable \(X_n\) and \(\epsilon_n\) represents the residuals.

Similar to the regression analysis on the Bitcoin volatility, it also has been necessary to ensure that the variables consist of stationary data. The same testing procedure has been applied using the Box-Ljung test, the Augmented Dickey Fuller test and the KPSS test. The exact test results are available in Appendix A2.

Nearly for all variables, all the tests confirmed that the variables consist of stationary data, except for the log returns of the series USD/EUR and Nikkei 225, where the Box-Ljung test failed. The distribution and the plotted graph of these return series did not show any unusual finding and it has therefore been assumed that in consistence with the results from the two other tests, all data is stationary and a multiple linear regression can be performed.

An initial regression analysis resulted in not significant intercept values for nearly all predictor variables. According to Paccagnella (2006, p. 83), a model with centred predictors is preferable for studying group effects. This means, the predictor variables have been transformed to the difference from the actual value and the mean of the value.

4.5 Value at Risk

Since Value at Risk (VaR) is widely used to estimate or measure the market risk exposures of a security, a VaR analysis can help investors to classify whether the asset has an acceptable or too high risk level.

A normality test and a histogram of the distribution did show that the log return series of the four Bitcoin exchange rates are non-normally distributed. Therefore, a non-parametric calculation approach, which is based on actual, historical data rather than distribution assumptions, has been preferred in that situation.

Two VaR calculations have been executed, both relying on the actual, historical data. The first calculation estimated the 1-day non-parametric VaR. The second estimation showed the 1 day VaR calculations on a daily interval dating back to the beginning of the time series. These have been estimated using the respective GARCH model from the volatility estimation, performed with the rugarch package in R (Ghalanos, 2015).

4.6 Forecasting returns

One of the largest problems of time series forecasting is to define and construct a suitable model. Autoregressive Integrated Moving Average (ARIMA) models have
become a standardized tool in financial data analysis. An ARIMA model is defined as being nonstationary and having a unit root, because its Autoregressive (AR) component has a unit root (Tsay, 2013, p. 91). It is further said that ARIMA models respect events dating back long in time. As the coefficients in its Moving Average (MA) component do not decay over time, a past extreme event will have a permanent effect on the series. Financial data is often considered to be nonstationary and therefore need to be converted into a stationary time series. A common way to perform this conversion is called differencing. Depending on the number of unit roots, the order of differencing is defined although it is warned to be more “hesitative” as a too high order leads to overfitting a model and will destroy results (Duke University, 2014).

The forecast package in R (Hyndman, et al., 2017) can suggest the best ARIMA model according to either the Akaike Information Criterion (AIC), using a penalized likelihood, the AIC with a correction (AICc, used for finite samples) or the Bayesian Information Criterion (BIC). According to Hyndman & Khandakar (2008, p. 8), both the AIC or the BIC can be an appropriate model selection criterion. The smallest value of the selected criteria will deliver the best model according to the R function (Adebiyi, et al., 2014, p. 106).

Based on this approach, two models for each time series have been constructed that allow conducting estimate point forecasts as well as prediction intervals at an 80 percent and 95 percent confidence level (Hyndman & Khandakar, 2008, p. 16).

Models are further compared by a Box-Ljung test on the squared residuals and a Jarque-Bera test on the residuals of the corresponding ARIMA model. For a p value of lower than 0.05, the tests confirm that the model residuals are normally distributed (Gavrilov & Pusev, 2014). Furthermore, the value of the root mean squared forecast error (RMSFE) has been compared as it is a preferable model comparison method when the errors follow a normal distribution (Chai & Draxler, 2017, pp. 1248-1249).

The exact model selection and the lead to the model equations are described with the presentation of results in chapter 5.5.
5 Results and analysis

This chapter presents the analytical results that are obtained through the methods described in the previous chapter. The results are also directly analysed as a split of the raw results and an analysis has been considered inconvenient for the reader, as the numerical data or graphs are often necessary to understand the relations and effects that are discovered.

5.1 Volatility

5.1.1 Volatility of log returns

As expected from the literature research, it has been found that the daily volatility for the log returns of the four Bitcoin rates is by far larger than those for the market indices returns or the exchange rate returns. The estimated volatility values for all studied time series are visible in Appendix A3. The volatility of the Bitcoin exchange returns is more than three times larger than those for the U.S market indices returns, and more than twice as high as for European and Chinese indices returns. The highest volatility has been measured for the returns from the BTC/JPY rate with 0.0175, the lowest volatility has been achieved by the BTC/CNY log returns. It can therefore be confirmed that Bitcoin still has a very high volatility.

Against many expectations, it cannot be confirmed that the volatility has significantly reduced over time. Generally, the volatility can be described as being at a level around 0.01 and 0.02 with extreme events occurring once or twice per year and several smaller local peaks. Figure 5 plots the volatility of the returns from the BTC/USD series over the entire observation period. It showed that the intensity of the extreme events has decreased over time. For all four observed time series, the highest volatility measured occurred in the end of 2014 or for the BTC/JPY rate in the beginning of 2015. It can therefore be assumed that even though the average of the volatility is not getting significantly lower, the intensity of unpredictable extreme events highly reduces which makes Bitcoin a nowadays already safer investment as two or three years ago. The volatility development of the other studied Bitcoin rates is available under Appendix A4.

Figure 5: Daily volatility estimates for BTC/USD returns
5.1.2 Volatility in regression with explanatory variables

Table 4: Regression coefficients for Bitcoin’s volatility based on log returns

<table>
<thead>
<tr>
<th>BTC/CNY sigma (F-statistic: 10.05 on 6 and 1426 DF, p-value: 6.689e-11)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>2.998e-02</td>
</tr>
<tr>
<td>delta BTC/USD trading volume</td>
<td>-5.889e-08</td>
</tr>
<tr>
<td>delta BTC/EUR trading volume</td>
<td>-3.715e-07</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>BTC/USD sigma (F-statistic: 8.805 on 6 and 1426 DF, p-value: 1.912e-09)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>2.998e-02</td>
</tr>
<tr>
<td>delta BTC/USD trading volume</td>
<td>-5.809e-08</td>
</tr>
<tr>
<td>delta Mining difficulty</td>
<td>-4.450e-13</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>BTC/EUR sigma (F-statistic: 10.13 on 6 and 1426 DF, p-value: 5.393e-11)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>2.701e-02</td>
</tr>
<tr>
<td>delta BTC/USD trading volume</td>
<td>-5.184e-08</td>
</tr>
<tr>
<td>delta BTC/EUR trading volume</td>
<td>-2.980-07</td>
</tr>
<tr>
<td>delta Mining difficulty</td>
<td>-3.410e-07</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>BTC/JPY sigma (F-statistic: 0.7173 on 6 and 1426 DF, p-value: 0.6357)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>5.061e-02</td>
</tr>
</tbody>
</table>

Table 4 shows the significant (p-value < 0.1) regression coefficients for the volatility estimated through GARCH (1,1) and explanatory variables. The first column shows the dependent variable at the top with the predictor variables below it. The second column lists the values of the regression coefficient, which indicates the extent of influence on the dependent variable.

A significance test, that assesses the significance of the entire regression calculation instead of individual predictors, has been performed before continuing to interpret results. As this analysis follows a multiple linear regression, the F statistics test is preferred over the t test as coefficients are accompanied by more than one degree of freedom (Steel & Torrie, 1960, p. 287). The test of significance is denoted by:

$$F = \frac{\text{additional reduction mean square}}{\text{residual mean square}}$$

The F statistic is used to confirm or reject the Null hypothesis that the variance between the variables is not due to random chance, meaning that the measured relation is true and could be explained with logical reasons (Draper & Smith, 1998, pp. 38-40). According to the F statistic table, the critical value of 2.802 (for DF1 = 6 and DF2 = ∞) for an alpha of 0.01 is undoubtedly exceeded for three of the four models. The Null hypothesis can therefore be rejected for these three series, or in other words, the measured regression coefficients are not of a random nature. For these series, it can be continued analysing the p-values of the predictor variables.

The regression on the volatility of BTC/JPY returns did not pass the F statistics test as the result is smaller than the critical value (see 0.7173 < 2.802). The F-statistics p-value however also is not significant, the F statistic is in this case not useful to make any assumptions on the significance of the measured relations. It is therefore also not possible to make any interpretations of the results as measured regression coefficients may be of a spurious origin.

The third column presents the p-value that is used in testing the null hypothesis. It indicates whether the measured impact is significant or not. For conclusions from this
regression analysis, all results that have a p-value lower than 0.1 are considered to be significant. However, in social sciences, a reliable confidence usually starts from 95 percent although researchers are free to choose a confidence level based on the nature of their researching field (Nuzzo, 2014, p. 152). Therefore, a confidence level of 95 percent has been taken as the border and therefore p values ranging between 0.05 and 0.1 (95 percent to 90 percent) had been included, but are marked with (*).

It has been tested whether the volatility of the Bitcoin exchange rates is affected by changes in the trading volume and changes in the number of transactions and the mining difficulty.

Against the expectation of finding a dependency between the volatility and the trading volume of the corresponding exchange rate, it can only be confirmed that the volatility of the log returns of three Bitcoin exchange rates (BTC with CNY, USD and EUR) is dependent on the trading volume of the BTC/USD rate. The regression coefficient for this dependency for all three rates is similar, ranging between -5.184e-08 and -5.889e-08. It can therefore be stated that a change in the trading volume will contribute to a reverse change of 0.000005% in the volatility, which will be barely noticeable.

A second factor that has been tested on its influence was the mining difference. The volatility of BTC/CNY and BTC/JPY log returns do not seem to be affected by this variable, however a small significant dependency has been discovered for the BTC/USD and BTC/EUR log returns. With regression coefficients of -4.450e-13 or -3.410e-07, this dependency is again very little in addition to its questionable significance. It can therefore also not be confirmed that a change in the mining difficulty of the Blockchain will noticeably affect Bitcoin’s volatility.

A third factor, the number of transactions in the Blockchain has been included in the regression analysis as an explanatory variable, it has however not been significant for any of the studied rates.

5.2 Correlations

Table 5: Measured correlations between log returns from Bitcoin exchange rates and log returns from stock market indices and currency exchange rates

<table>
<thead>
<tr>
<th>Variable</th>
<th>BTC/CNY</th>
<th>BTC/USD</th>
<th>BTC/EUR</th>
<th>BTC/JPY</th>
</tr>
</thead>
<tbody>
<tr>
<td>DOW 30</td>
<td>-0.009167</td>
<td>0.008686</td>
<td>-0.012695</td>
<td>0.040466</td>
</tr>
<tr>
<td>S&amp;P 500</td>
<td>-0.011758</td>
<td>0.010700</td>
<td>-0.013241</td>
<td>0.033051</td>
</tr>
<tr>
<td>DAX</td>
<td>-0.004956</td>
<td>0.006720</td>
<td>-0.003431</td>
<td>0.042553</td>
</tr>
<tr>
<td>Euro Stoxx50</td>
<td>-0.005382</td>
<td>0.010614</td>
<td>-0.005399</td>
<td>0.022887</td>
</tr>
<tr>
<td>China A50</td>
<td>0.024292</td>
<td>0.038295</td>
<td>0.035372</td>
<td>0.028230</td>
</tr>
<tr>
<td>Nikkei 225</td>
<td>0.006125</td>
<td>-0.011783</td>
<td>0.006820</td>
<td>0.003298</td>
</tr>
<tr>
<td>CNY/USD</td>
<td>-0.013206</td>
<td>-0.014923</td>
<td>-0.015601</td>
<td>-0.037940</td>
</tr>
<tr>
<td>CNY/EUR</td>
<td>0.004455</td>
<td>0.020756</td>
<td>0.051877</td>
<td>-0.011970</td>
</tr>
<tr>
<td>USD/EUR</td>
<td>0.002481</td>
<td>-0.006176</td>
<td>-0.055346</td>
<td>-0.012135</td>
</tr>
<tr>
<td>BTC/CNY</td>
<td>-</td>
<td>0.865115</td>
<td>0.877399</td>
<td>0.324715</td>
</tr>
<tr>
<td>BTC/USD</td>
<td>0.865115</td>
<td>-</td>
<td>0.928581</td>
<td>0.359125</td>
</tr>
<tr>
<td>BTC/EUR</td>
<td>0.877399</td>
<td>0.928581</td>
<td>-</td>
<td>0.363664</td>
</tr>
<tr>
<td>BTC/JPY</td>
<td>0.324715</td>
<td>0.359125</td>
<td>0.363664</td>
<td>-</td>
</tr>
</tbody>
</table>

Low correlations are coloured blue and negative correlations are coloured green for a faster visibility.
According to the theory from Brealey, et. al, (2011, p.200) expanded in chapter 3.15, negative correlations are highly desired but unlikely to find on the financial markets. Table 5 shows that with the log returns from BTC/CNY, BTC/USD and BTC/EUR rates, negative correlations can be achieved for many stock market indices and the currency exchange rates. The log returns of BTC/CNY show negative correlations with the market indices Dow 30, SP 500, DAX, EuroStoxx 50 and a low correlation for Nikkei 225.

There is however a favourable correlation with the Chinese market index China A50. Indeed, none of the observed Bitcoin rates showed a favourable correlation with the Chinese index. For all other market indices however, all BTC rates showed a negative correlation except for the Japanese, where only the log returns of the BTC/USD rate correlated negatively. The returns from all other rates are only at a very low level. The log returns of BTC/JPY only offer favourable low correlations to the Japanese market index Nikkei 225 and negative correlations to the currency exchange rates.

### 5.3 Regression with stock market indices

The regression coefficients are presented in Appendix A5. The analysis showed that the Bitcoin exchange rates are highly interrelated as the log returns of the BTC/USD and BTC/EUR rates showed significant relations with all other Bitcoin exchange rates and the others showed relationships with two other Bitcoin rates. In addition, there were also significant relations between BTC/USD and USD/EUR as well as BTC/EUR with CNY/EUR and USD/EUR log returns.

However, significant relationships with stock market indices could not be confirmed. According to the results, only the log returns of the Japanese market index Nikkei 225 have an impact on the return series BTC/USD and log returns of the DAX (Germany) are influencing returns from BTC/JPY.

This lead to the assumption that the Bitcoin trading market still seems to be very isolated and not connected to the global financial systems and economies. This may also explain the origin of the negative correlations discovered earlier. It seems that most Bitcoin traders are not trading on the investigated stock exchanges and the majority of stock traders does not perform any transactions with Bitcoin. However, the slight influence of Nikkei 225 on BTC/USD log returns shows that Japanese stock traders may have started to discover Bitcoin as an instrument for their portfolios.

The F statistics analysis rejects the Null hypothesis for all time series. The critical value of 2.185 (for DF1 = 12 and DF2 = ∞, with a 99 percent confidence level) has been exceeded by all regression models. This means that the measured regression coefficients are not due to a random chance and it can be supposed that the relations have a true and logically explainable origin.

### 5.4 Value at risk

The histograms (figure 6) plot the distribution of the log returns from the four BTC rates subtracted by the lag 1 of it. The red line demonstrates the desired 99% confidence level. As visible also in table 6 below, the quantile is different for all four rates. The quantile closest to 0 is provided by the BTC/USD rate, followed by BTC/EUR and BTC/CNY. A very big difference is visible for the BTC/JPY rate. One reason for these tremendous differences could be explained with the high volatile log returns. Especially in 2014, log returns experienced huge drops and several exchanges closed resulting in high losses for traders.
Figure 6: Histograms showing the return distribution of Bitcoin return rates. The red line indicates the 99 percent quantile.

Table 6: Value at risk (VaR) results for Bitcoin returns

<table>
<thead>
<tr>
<th></th>
<th>BTC/CNY</th>
<th>BTC/USD</th>
<th>BTC/EUR</th>
<th>BTC/JPY</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quantile</td>
<td>-0.1862496</td>
<td>-0.1441503</td>
<td>-0.1505482</td>
<td>-0.6431707</td>
</tr>
<tr>
<td>VaR</td>
<td>0.1699336</td>
<td>0.1342424</td>
<td>0.1397638</td>
<td>0.4743768</td>
</tr>
</tbody>
</table>

Considering the non-parametric VaR for all four Bitcoin rates, it is visible that the returns from the BTC/CNY rate, that was used for nearly all worldwide transactions before 2017, do not provide the lowest VaR. Buying Bitcoin with USD or EUR will result in a lower VaR rate. Regarding the VaR results, it can be recommended, to not purchase any Bitcoins currently with Japanese Yen.

When the VaR results from Bitcoin returns are compared to those of the market indices (see Appendix A6), that have been calculated with the same parameters to be comparable, it can without further doubt be stated that VaR values are much higher than those of the market indices. This is an important information especially for those investors who have to comply with specific capital requirement regulations (for example organizations that have to apply Basel or Solvency regulations). For those investors, adding Bitcoin to a portfolio may result in a strong increase of capital reserves.
Figure 7: VaR limits for a 99 percent confidence (red) plotted with actual log returns (blue) for the series BTC/CNY. The green line can be ignored since it shows the profit limit for a 99 percent confidence.

Figure 7 shows the VaR limits for a 99% confidence for the entire observation period (2013/01 – 2017/04) for BTC/CNY. There is a pattern visible where comparatively high losses (but also high returns) are occurring approximately every 9 months. According to the graph, the intensity of the losses is declining over time. This could be an indicator that the volatility is declining and the Bitcoin rate is becoming slowly more stable (it is maturing). It is however also visible that the returns and losses in between the extreme events are declining as well. This behaviour is similar to the observed rates BTC/USD and BTC/EUR, as visible under Appendix A7.

The Value at Risk rate for BTC/JPY is however not following the patterns of the other investigated rates. From early to mid-2014, the log return was highly fluctuating and is now following the pattern of extreme events than the other observed currencies showed. However, the intensity of the extreme events was not gradually declining, but cut off in late 2014.

5.5 Forecasts

Forecasting Bitcoin prices is difficult as the currency is still in its “finding phase” and no structure is not clearly visible. Forecasts have been estimated based on Arima models with different parameters on a 180-day period, starting from the last value of the time series, April 03, 2017.

5.5.1 BTC/CNY series

To forecast the Bitcoin – Chinese Renminbi (BTC/CNY) rate time series, three models have been set up. The first model CM1 was based on an Arima (3,1,2) model.

\[ \hat{y}_t = \mu + \phi_1(Y_t - Y_{t-1}) + \phi_2(Y_t - Y_{t-2}) + \phi_3(Y_t - Y_{t-3}) + \theta_1e_{t-1} + \theta_2e_{t-2} \]
In Figure 8, it is clearly visible that high auto correlation is existing and decaying slowly. Therefore, the series (called $G_t$) must have been differenced with $x_t = (1 - B) \cdot G_t$. The auto correlation for the differenced series is plotted in Figure 8 (right). The intensity of the autocorrelations highly decreased, however there are still a lot significant autocorrelations remaining. Differencing by a second order did not change much, but as the danger of overfitting increases, it has been decided to keep the differencing order at $d = 1$. This matched with the R tool, which suggested the Arima (3,1,2) model (CM1) with the following equation:

$$
\hat{y}_t = 0.8530 \cdot (Y_t - Y_{t-1}) - 1.0251 \cdot (Y_t - Y_{t-2}) + 0.0984 \cdot (Y_t - Y_{t-3}) - 0.7272 \\
\quad \times e_{t-1} + 0.8554 \cdot e_{t-2}
$$

In Appendix A8, the predicted forecast which shows the time series starting from 2016, can be found.

The forecasted line (blue) slightly wiggles initially before becoming a straight line at the value of the last observation in the data set. The blue shaded area shows the upper and lower 85 percent confidence interval, the grey coloured area shows the upper and lower 95 percent confidence interval. As a continuous growth in the time series of the BTC/CNY prices is visible, this model may not be very suitable, therefore, a second model has been created.

To tackle the problem with stationarity, a second model, CM2 has been constructed. Since preceding theories speak of an ongoing upwards trend of Bitcoin, this model includes the concept of a drift.

CM2 follows an Arima (2,1,2) as base. The model equation is as follows:

$$
\hat{y}_t = 4.482 + 0.7335 \cdot (Y_t - Y_{t-1}) - 0.9512 \cdot (Y_t - Y_{t-2}) - 0.6793 \cdot e_{t-1} + 0.8581 \\
\quad \times e_{t-2}
$$

The plotted forecast is available in Appendix A9. The drift degree is lower than the average of the recent two years which may probably be the result of the very stable and even decreasing periods around 2014 and 2015.

To compare the models, visual and analytical back testing has been used. The visualized back testing uses a data set that has been cut on December 31, 2016 resulting in a data set from January 1, 2013 until this date and another set starting from this date ranging to the end of the time series. The forecast model has then been applied from January 1,
2017 (one lag after the cut day) to plot it against the actual values. Figure 9 shows the graphical back test for the three models.

![Graphical back test for the three models](image)

*Figure 9: Models CM1 and CM2 backtested graphically*

For an exact fit, five percent of the values should remain outside the grey confidence area. As this is difficult to observe, a more analytical method for back testing has been applied. In particular, a root mean squared forecast error (RSME) test, Ljung-Box test and Jarque Bera test have been performed. The results are presented in table 7 below.

**Table 7: Backtest results**

<table>
<thead>
<tr>
<th></th>
<th>CM1</th>
<th>CM2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ljung-Box p-value</td>
<td>3.03e-09</td>
<td>1.845e-12</td>
</tr>
<tr>
<td>Jarque Bera p-value</td>
<td>&lt; 2.2-16</td>
<td>&lt; 2.2e-16</td>
</tr>
<tr>
<td>RMSFE</td>
<td>736.2253</td>
<td>651.3607</td>
</tr>
</tbody>
</table>

The RMSFE has been calculated using R. According to the result, model CM2 is preferred as the RMSFE value is smaller. Therefore, model CM2 can be seen as the most accurate model among the two and this model has been used to calculate the expected log return.

**Table 8: Predicted returns from the BTC/CNY price series**

<table>
<thead>
<tr>
<th>Per period</th>
<th>Point Forecast</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Daily average</td>
</tr>
<tr>
<td>30 days</td>
<td>0.027167</td>
<td>0.000906</td>
</tr>
<tr>
<td>60 days</td>
<td>0.042913</td>
<td>0.000715</td>
</tr>
<tr>
<td>90 days</td>
<td>0.060974</td>
<td>0.000677</td>
</tr>
<tr>
<td>180 days</td>
<td>0.113982</td>
<td>0.000633</td>
</tr>
</tbody>
</table>

Table 8 shows the expected log return range for the BTC/CNY prices. It has been calculated by using the forecasted prices, computing the sum of log returns from the point forecast output, as well as the lowest and highest value on the 95 percent confidence range. This example confirms statements from financial experts, presented in chapter 3 of this paper, that Bitcoin is an instrument with a more short-term holding period. The expected return per day is declining with an increasing holding period.

**5.5.2 BTC/USD series**

To forecast the Bitcoin – US Dollar (BTC/USD) rate time series, two models have been set up. The first model UM1 was based on an Arima (2,1,0) model and the second model UM2 was based on an Arima (5,1,5) model with drift. The procedure in setting up the models was similar to the BTC/CNY modelling. The model equations are as follows:
UM1: Arima (2,1,0)

\[ \hat{y}_t = 0.2501 \times (Y_t - Y_{t-1}) - 0.1596 \times (Y_t - Y_{t-2}) \]

UM2: Arima (5,1,5) with drift

\[ \hat{y}_t = 0.7370 + 0.1211 \times (Y_t - Y_{t-1}) - 0.0278 \times (Y_t - Y_{t-2}) - 0.2625 \times (Y_t - Y_{t-3}) \\
- 0.0658 \times (Y_t - Y_{t-4}) + 0.6352 \times (Y_t - Y_{t-5}) + 0.1054 \times e_{t-1} \\
- 0.0309 \times e_{t-2} + 0.2218 \times e_{t-3} + 0.1714 \times e_{t-4} - 0.6206 \times e_{t-5} \]

Model UM1 has been created by finding the best fit model using the Bayesian Information Criterion as deciding tool. Model UM2 has been derived by starting with the same approach, with the difference of applying the Akaike Information Criterion (AIK). To be consistent in the set-up structure, it was preferred to include one model with a drift and one model without. The second smallest AIK value included a drift and led to the Arima (5,1,5) model.

A graph for each model is available under Appendix A10. Considering only the recent months (starting from 2015), an upward drift seems to be a more suitable model. Considering the price series, a sharp decline in prices is visible during the entire year 2014. Such extreme events and course changes are however, difficult to include in a model.

The graphical back tests are plotted in Appendix A11. According to the graphs, model UM2 is to be preferred. For both models, the 95 percent confidence range is exceeded by the actual values in the beginning. Actual values do also exceed another time the confidence range in model UM1, but remain within the 80 percent confidence in model UM2.

The results from the Ljung-Box and Jarque Bera test are not beneficial towards model decision as the values are very similar. The RMSFE value however confirms what has been visible already in the graphical back testing, therefore, model UM2 has been chosen to compute expected returns. These returns are calculated with the identical calculation process of the previous forecast series and are presented in table 9.

Table 9: Predicted returns from the BTC/USD price series

<table>
<thead>
<tr>
<th>Per period</th>
<th>Daily average</th>
<th>Low 95% conf.</th>
<th>High 95% conf.</th>
</tr>
</thead>
<tbody>
<tr>
<td>30 days</td>
<td>0.042980</td>
<td>-0.176424</td>
<td>0.212857</td>
</tr>
<tr>
<td>60 days</td>
<td>0.058439</td>
<td>-0.287588</td>
<td>0.301323</td>
</tr>
<tr>
<td>90 days</td>
<td>0.077317</td>
<td>-0.369269</td>
<td>0.368893</td>
</tr>
<tr>
<td>180 days</td>
<td>0.129882</td>
<td>-0.554864</td>
<td>0.512402</td>
</tr>
</tbody>
</table>

Similar to the results from the BTC/CNY series, it confirms that investors are advised to hold Bitcoins rather for a shorter period of time.

5.5.3 BTC/EUR series

To forecast the Bitcoin – Euro (BTC/EUR) rate time series, two models have been set up following a similar procedure to the previous series. The suggested model has been directly accepted which resulted in an Arima (4,1,4) model and has been denoted EM1. The second model EM2 was based on an Arima (5,1,5) model including a drift, which has been found by the same command (with Aike information criterion) but including
the drift requirement in the criteria of model selection. The model equations are as follows:

EM1:
\[
\hat{y}_t = -0.7201 \times (Y_t - Y_{t-1}) - 0.5862 \times (Y_t - Y_{t-2}) - 0.8484 \times (Y_t - Y_{t-3}) - 0.6311 \\
\times (Y_t - Y_{t-4}) + 0.9421 \times e_{t-1} + 0.7168 \times e_{t-2} + 8526 \times e_{t-3} + 7176 \\
\times e_{t-4}
\]

EM2:
\[
\hat{y}_t = 0.6869 + 0.0824 \times (Y_t - Y_{t-1}) + 0.0678 \times (Y_t - Y_{t-2}) - 0.3779 \times (Y_t - Y_{t-3}) \\
+ 0.0451 \times (Y_t - Y_{t-4}) + 0.5671 \times (Y_t - Y_{t-5}) + 0.1564 \times e_{t-1} \\
- 0.0817 \times e_{t-2} + 0.2876 \times e_{t-3} + 0.0761 \times e_{t-4} - 0.5721 \times e_{t-5}
\]

Under Appendix A12, the two forecast models are plotted. The two models have been back tested graphically and analytically using the split version of the data set that cuts off on December 31, 2016 and plots the forecast against the remaining actual values. Under Appendix A13, the graphical back testing results as well as the results from the Box-Ljung test, Jarque Bera test and the values for RSMFE are available.

Both the Box-Ljung and the Jarque Bera test show that both models can be accepted since the p-value is smaller than 0.05. Graphically, the two models show only slight differences which is reflected also with the RMSFE values. The EM2 obtained a slightly smaller RMSFE value and is therefore the preferred model. Consequently, the calculated expected returns are presented in table 10.

**Table 10: Predicted returns from the BTC/EUR price series**

<table>
<thead>
<tr>
<th>Point Forecast</th>
<th>Range</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Per period</td>
<td>Daily average</td>
<td>Low 95% conf.</td>
<td>High 95% conf.</td>
</tr>
<tr>
<td>30 days</td>
<td>0.040717</td>
<td>0.001357</td>
<td>-0.143190</td>
<td>0.188571</td>
</tr>
<tr>
<td>60 days</td>
<td>0.057672</td>
<td>0.000961</td>
<td>-0.227456</td>
<td>0.269000</td>
</tr>
<tr>
<td>90 days</td>
<td>0.076083</td>
<td>0.000845</td>
<td>-0.288246</td>
<td>0.330435</td>
</tr>
<tr>
<td>180 days</td>
<td>0.128570</td>
<td>0.000718</td>
<td>-0.415940</td>
<td>0.463807</td>
</tr>
</tbody>
</table>

5.5.4 BTC/JPY series

The forecast for the series of the Bitcoin – Japanese Yen (BTC/JPY) rate has been processed similar to all preceding forecast models. Two models have been constructed using R to find the best fit model, applying the Bayesian Information Criterion for the first model approach and the Akaike Information Criterion with the requirement for a drift for the second approach. This resulted in the two models JM1, which is an Arima (0,1,1) model that simply follows exponential smoothing and JM2, which is an Arima (1,1,1) with drift.

It needs to be reminded that the data set available for Bitcoin prices in JPY contained about 5 percent of missing data with nearly all missing values at one period. This was the case due to several closures of exchange platforms in Japan. As described in chapter 4.1.2, the missing values have been imputed using the Amelia II package in R, which results in five imputed data set. The average of the imputed time series created the time series JPYmod. The model equations are as follows:
JM1:

\[ \hat{y}_t = Y_{t-1} - 0.2938 \cdot e_{t-1} \]

JM2:

\[ \hat{y}_t = 79.9369 + 0.1704 \cdot (Y_t - Y_{t-1}) - 0.4452 \cdot e_{t-1} \]

Under Appendix A14, the two plotted models and its back testing results are available.

Similar to the BTC/EUR series, the differences are very small. In both models, the actual values exceed the 95 percent confidence interval in the beginning. A larger drop in prices around March 2017 is very likely affecting the forecast calculations. The last few observations are showing a sharp incline, which could be an argument in favour of the drift model. According to the statistical tests, which are presented in Appendix A14, model JM2 is to be preferred.

Consequently, the expected returns have been calculated using model JM2. These are presented in table 11 below.

### Table 11: Predicted returns from the BTC/JPY price series

<table>
<thead>
<tr>
<th>Period</th>
<th>Point Forecast</th>
<th>Daily average</th>
<th>Low 95% conf.</th>
<th>High 95% conf.</th>
</tr>
</thead>
<tbody>
<tr>
<td>30 days</td>
<td>0.016540</td>
<td>0.000551</td>
<td>-0.177441</td>
<td>0.161736</td>
</tr>
<tr>
<td>60 days</td>
<td>0.035163</td>
<td>0.000586</td>
<td>-0.270443</td>
<td>0.244908</td>
</tr>
<tr>
<td>90 days</td>
<td>0.053445</td>
<td>0.000594</td>
<td>-0.342688</td>
<td>0.307986</td>
</tr>
<tr>
<td>180 days</td>
<td>0.105795</td>
<td>0.000591</td>
<td>-0.503037</td>
<td>0.445214</td>
</tr>
</tbody>
</table>

Very conspicuous is the fact that the daily average of the forecasted returns in the BTC/JPY price series is not declining with a longer holding period, instead it remains stable or rather is very slightly increasing. This could be a first indicator whether investments into Bitcoin paid in Japanese Yen may be worth holding for a longer period.

However, comparing the returns reveals that the price series BTC/JPY grants the lowest return rates among the studied exchange rates. Combined with the fact that in this research analysis, the BTC/JPY log returns had the highest volatility, a BTC/JPY investment could be unfavourable since higher returns with a lower risk are possible.

### 5.6 Returns and risk

As investors are generally free to choose with which currency and through which exchange service they like to invest in and trade with Bitcoin, it is of crucial interest to compare the returns with the estimated risk.

Table 11 shows the realized returns of the four Bitcoin rates, converted to USD with the closing rates on April 03, 2017 and the volatility (risk), expressed in sigma, that has been converted to a 30, 60, 90 and 180 day period using a complex conversion scheme. As Diebold, et al. (1997, p. 6) published a warning that a simple multiplication of the daily volatility with the square root of the desired time horizon is not effective, the time horizon sigma has been converted using the following formula:

\[ \sigma_h = \frac{1}{\sqrt{2}} \left( \frac{\sigma_h}{2} + \frac{\sigma_{h+1}}{2+1} \right) \cdot \sqrt{h} \]
Instead of multiplying the sigma, calculated for April 3, 2017, the median of h-days dating back sigma values has been calculated and multiplied with the square root of the desired time horizon. This calculation has been repeated daily dating back in the time series until April 04, 2013. The average of all the calculation results are presented as the sigma values. The returns are calculated by simply summing up h-day daily difference of the price at time t and t-1. In addition, a sigma/return quotient has been computed which allows to compare the balance between risk and return. A smaller value indicates a better compensation of risk for the investor.

Table 12: Realized Bitcoin returns in relation to volatility

<table>
<thead>
<tr>
<th></th>
<th>BTC/CNY</th>
<th>BTC/USD</th>
<th>BTC/EUR</th>
<th>BTC/JPY</th>
</tr>
</thead>
<tbody>
<tr>
<td>30 day sigma</td>
<td>0.116772</td>
<td>0.115032</td>
<td>0.106727</td>
<td>0.190276</td>
</tr>
<tr>
<td>30 day return</td>
<td>15.26</td>
<td>14.60</td>
<td>18.00</td>
<td>23.38</td>
</tr>
<tr>
<td>Sigma/return</td>
<td>0.007654</td>
<td>0.007877</td>
<td>0.005928</td>
<td>0.008137</td>
</tr>
<tr>
<td>60 day sigma</td>
<td>0.162977</td>
<td>0.158686</td>
<td>0.148651</td>
<td>0.292810</td>
</tr>
<tr>
<td>60 day return</td>
<td>29.56</td>
<td>26.88</td>
<td>34.10</td>
<td>43.43</td>
</tr>
<tr>
<td>Sigma/return</td>
<td>0.005514</td>
<td>0.005903</td>
<td>0.004359</td>
<td>0.006742</td>
</tr>
<tr>
<td>90 day sigma</td>
<td>0.163352</td>
<td>0.158391</td>
<td>0.148984</td>
<td>0.286132</td>
</tr>
<tr>
<td>90 day return</td>
<td>33.83</td>
<td>29.00</td>
<td>41.17</td>
<td>45.67</td>
</tr>
<tr>
<td>Sigma/return</td>
<td>0.004828</td>
<td>0.005462</td>
<td>0.003619</td>
<td>0.006265</td>
</tr>
<tr>
<td>180 day sigma</td>
<td>0.299550</td>
<td>0.288038</td>
<td>0.269019</td>
<td>0.469405</td>
</tr>
<tr>
<td>180 day return</td>
<td>56.34</td>
<td>47.38</td>
<td>68.18</td>
<td>66.21</td>
</tr>
<tr>
<td>Sigma/return</td>
<td>0.005317</td>
<td>0.006079</td>
<td>0.003946</td>
<td>0.007089</td>
</tr>
</tbody>
</table>

As presented in table 12, the highest average 30-day return has been achieved with the BTC/JPY rate, which goes in line with the predicted returns that have been estimated earlier. However, this series also comprises the highest volatility on average. The lowest average volatility has been achieved with the BTC/EUR series on a holding period for 30 days. The optimal relation between return and risk is achieved with the same Bitcoin exchange rate for a holding period of 90 days.

It can therefore be concluded that among the four investigated Bitcoin exchange rates, the BTC/EUR rate is the least risky and also provides the optimal balance between risk and return. The highest returns are however, achieved with the BTC/JPY series, for a holding period of less than 180 days. Holding Bitcoins for a period of 180 days, the highest return has been achieved with BTC/EUR.
Discussion

In this chapter, the results are discussed with respect to preceding literature and scientific works. In addition, the quality of the research is assessed and limitations are mentioned and explained. Furthermore, suggestions for further research are provided by the authors.

6.1 Integration with existing work

In the Bitcoin universe, that consists more of blogposts, news and website articles rather than scientific work, there are many, and often controversial opinions out on whether Bitcoin is risky or safe, volatile or stable, and might be considered as a financial instrument or an experiment. Despite this, a lack of awareness, as identified by Kiran & Stannett (Kiran & Stannett, 2014, p. 23) is a major reason for risk averse investors to hesitate. The statistical findings that show that Bitcoin can actually reduce risk or increase portfolio returns without changing the portfolio volatility. Furthermore, the theoretical framework is not only useful to understand and justify the constructed methods, but also to deliver more information in a broader context to potential Bitcoin traders.

Bitcoin is often compared to gold as it can be mined (digitally) and it is recommended in the media to use Bitcoin as the new, long-term investment and a good hedge. The results of this study definitively confirm the opinions on the media that Bitcoin can be used to diversify a stock portfolio. However, considering returns, this thesis concludes that a shorter holding period is to be preferred since the returns will decline over time. Bitcoin therefore is a good instrument to reduce risk but returns become smaller over time. On the other hand, prices often have recovered and it is therefore very difficult to predict the future performance.

Several theories and reports warn about the comparatively high level of market and credit risk that exists when obtaining or trading with Bitcoin. This study could show that value at risk estimations are of course on a much higher level than for the stock market indices which is however no surprise since Bitcoin is a single instrument and stock market indices can be seen as a well-diversified portfolio. The researchers also demonstrated that the risk created through the volatility is not constantly at a very high level. The general volatility is in contrast to Stutman (2016), or several media articles (such as news or publications on social media platforms about Bitcoin) not significantly declining. Though, the extreme events, the so-called bubble bursts are becoming less intensive. This explains that the extraordinary returns are decreasing, but also the risk decreases as losses are not that high any more than a few years ago.

6.2 Suggestions for further research

This research can be considered as a basement for future, specializing academic works. It would be feasible and logical to build up on these results for analysing whether a relation between volatility and the image of Bitcoin exist as well as the acceptance of Bitcoin. The largest difficulties in this research would be to obtain sufficient data. In addition, it would be of interest to analyse the consequences of adding Bitcoin to a portfolio. This could be done by testing the effect of adding the instrument to various, simulated portfolios, that may, in addition to stocks, also contain other commodities like gold, oil or bonds.

As Bitcoin is relatively new and its structure, processes and opportunities are unknown to many people including many financial experts, this research studied a high amount of
theories and research results from preceding studies that are summarized in the theoretical reference chapter. However, detailed technical specifications are not mentioned to a further extent than necessary for this research purpose. Therefore, qualitative studies could use this work as a basis and investigate opportunities for applications of the Bitcoin technologies or investigating the image of Bitcoin on financial markets on a qualitative approach.

It is also worth to point out that Bitcoin is not the only digital currency available on markets. In May 2016, traders could choose out of 100 alternatives (Manager Magazin, 2016). It may therefore be a very interesting study to compare the performances of these alternatives to Bitcoin and identify to what extent these have an impact on the Bitcoin price.

6.3 Limitations

Since the topic is, from a scientific point of view, a relatively new and undiscovered area, the researchers faced several limitations during the study. A major difficulty was that Bitcoin trading does not follow financial standards which means that rates are changing 24 hours on 7 days in a week, whereas stock exchanges have specific trading times. This resulted in having data of two different scales. As statistical software usually allows to define time series with a specified frequency, the volatility estimation had been performed with two different sets of time series. The regression analysis with Bitcoin and stock data lead to the necessity to delete rows in the Bitcoin data and convert it to a time series with only 252 trading days.

The researchers also faced some technical issues. Initially, it had been planned to use a GARCH model with explanatory variables to estimate and explain Bitcoin’s volatility. The researchers however struggled with technical issues and out of timing issues decided to apply the method with estimating the volatility with GARCH first and performing a multiple linear regression with explanatory variables after.

The results of this report may primarily be of a high value for investors that are constantly seeking for new opportunities to diversify their portfolio and are not fully risk averse. The thesis paper not only presents results from several analytical researches, but also comprises with a collection of knowledge and theories that are mostly of highly academic quality. This paper will be of excellent value for anyone seeking for reliable information on the trending, electronic currency Bitcoin.

6.4 Research quality

Ensuring sufficient quality of research is crucial. Formulating and following quality criteria has become more popular and important. Bryman, et al. (2008, pp. 264-265) discovered that validity seems to be the most important aspect in ensuring quality.

6.4.1 Validity

The validity can be distinguished into internal and external validity. Internal validity indicates the confidence of a cause and effect relationship (Morgan, et al., 2000, p. 529). It has to be ensured that the research methods are fully suitable to identify the cause (reasons) of the measured effects. The study fulfils this criterion as several statistical models are applied before conclusions were drawn. When the correlations had been computed, the researchers used a multiple linear regression as a follow-up method to check whether this leads to the same conclusions. Furthermore, a regression analysis allows several significance tests to ensure that the relationship is not a result out of coincidence. In addition, the data has been tested on stationarity and transformed when
necessary to ensure it is suitable for the regression model. The same caution has been applied for all other models and calculations have been performed twice by both researchers to avoid processing errors. It can therefore be undoubtedly stated that the researchers provide a high internal validity.

External validity is necessary to ensure that the results are generalizable. It was a crucial demand from the researchers that the findings are valid for 99 percent of all Bitcoin traders. Therefore, a dataset that represents 99 percent of the Bitcoin trading volume has been constructed. As the trading volume of stock market indices was often not available, this metric could not have been used to select the indices. These have therefore been selected rather on qualitative criteria. First, it was decided to have stock market indices of a major stock exchange in the currency of the Bitcoin exchange rates to allow a comparison within the same currency (market). Second, the researchers assessed the stock indices on its reputation, popularity and history. This has been done by reading respective literature about these indices.

6.4.2 Reliability

Reliability is crucial as it ensures that the research can be repeated. According to Collis & Hussey (2014, p. 217), results are reliable if it has been ensured that they have been measured accurately and precise. Bryman & Bell (2015, p. 49) mention that reliability is very important for quantitative studies to identify whether a measurement is stable or not. A major problem for example can be the measurement in time. In this case, measuring the volatility at a specific time point is rather unstable, especially when it is known that the volatility is frequently changing. Therefore, a model has been constructed to measure the volatility on each time point throughout the entire time series to draw conclusions about the volatility. The dataset, that carries daily data for a time period of more than four years (in total 1554 price observations for Bitcoin) provides a solid basis and allows to obtain authentic and trustable results. Furthermore, the models, are all justified by peer-reviewed, scientific and academic literature and are widely in use in financial analyses. The raw results are analysed carefully based on scientific and academic literature and knowledge through the study program. Furthermore, raw findings are presented in the result section or the appendices of this thesis which increases the transparency of the researchers’ work.
7 Conclusion

The aim of this research was to find out how beneficial Bitcoin can be for investors that seek for a diversified portfolio. The correlations with the stock market indices Dow Jones 30, Standard & Poor 500, DAX and Euro Stoxx 50 were negative for three of the four Bitcoin rates. The multiple linear regression analysis on the Bitcoin returns with stock market returns confirmed the results. From the result, it can be stated that stock markets and Bitcoin markets do not correlate much yet. This means that the majority of stock investors has not acknowledged the opportunities of Bitcoin yet and do therefore not perform any trading with the electronic currency. It can also be interpreted that Bitcoin traders are generally not active on the stock markets.

It was also shown that the volatility of Bitcoin is still very high and there is, against the conception of the public, no declining trend visible. However, the researchers could show that the intensity of extreme events, that are often called a bubble burst in the media, is declining. This means the loss resulting from sharp price falls that occurred on a regular basis is therefore becoming smaller. This already decreases the risk significantly and recently, Bitcoin is again in an upwards trend and retired after most of the shocking events. However, the danger of another busting bubble is still present. The volatility seems to be dependent on the trading volume of Bitcoin and US Dollar exchanges, as well as the mining difficulty. In contrast to what is believed in the media, the number of transactions had no influence on the volatility.

The Value at Risk calculation showed that Bitcoin may not yet be suitable for investors that have to comply with capital requirement regulations. The Value at Risk level for Bitcoin was significantly higher than for the stock market indices which means that investing into Bitcoin may increase the amount of capital required.

Regarding returns and holding period, it can be stated that the BTC/JPY rate provided the highest returns among the four studied Bitcoin exchange rates, but also comprised the highest volatility. The optimal relation of volatility and return has been achieved with the BTC/EUR rate in a time period of 90 days. The predicted returns show that Bitcoin is highly profitable as a short term investment but returns gradually decline with a longer holding period. In addition, the risk that unexpected events may occur is of course becoming stronger with a longer holding period.

The literature study pointed out that Bitcoin traders must be aware of the consequences for a currency that does not feature any central bank or supervising authority. Bankruptcies of popular Bitcoin exchange and wallet services proved that traders’ investments were completely lost. A high level of IT security is very important as hackers could steel Bitcoins from wallets already.

To summarize, stock market investors have not fully realized the opportunities that Bitcoin provides which causes negative asset correlations and makes Bitcoin therefore a very good instrument to diversify a portfolio consisting of stocks from the major stock exchanges. Investors can also profit from high returns in a short period but need to pay attention to the risk types the new, electronic currency bears.
References


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Massoudi, A. & Alloway, T., 2013. Bitcoin ETF plan struggles to find support. [Online] Available at: https://www.ft.com/content/1e187c88-eda2-11e2-8d7c-00144feabd0 [Retrieved 9 May 2017].


[Retrieved 5 April 2017].

[Retrieved 23 March 2017].

[Retrieved 28 March 2017].


[Retrieved 27 March 2017].

[Retrieved 10 May 2017].


### Appendix

#### A1: Risk analysis of Bitcoin at all levels

*Taken from Kiran & Stannett (2014, p. 26)*

<table>
<thead>
<tr>
<th>Category</th>
<th>Risk Identified</th>
<th>Level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social</td>
<td>Bubble formation</td>
<td>High</td>
</tr>
<tr>
<td>Social</td>
<td>Cool factor</td>
<td>Medium</td>
</tr>
<tr>
<td>Social</td>
<td>Trust transaction chain</td>
<td>High</td>
</tr>
<tr>
<td>Social</td>
<td>Generation of new Bitcoin</td>
<td>High</td>
</tr>
<tr>
<td>Legal</td>
<td>Regulation</td>
<td>High</td>
</tr>
<tr>
<td>Legal</td>
<td>Complicity</td>
<td>High</td>
</tr>
<tr>
<td>Legal</td>
<td>Government Issued Warning</td>
<td>High – Medium</td>
</tr>
<tr>
<td>Economic</td>
<td>Deflation and Finite Supply</td>
<td>High</td>
</tr>
<tr>
<td>Economic</td>
<td>Volatility</td>
<td>High</td>
</tr>
<tr>
<td>Economic</td>
<td>Timing issue</td>
<td>High</td>
</tr>
<tr>
<td>Economic</td>
<td>Lock in Transaction</td>
<td>High</td>
</tr>
<tr>
<td>Technological</td>
<td>Equipment</td>
<td>High</td>
</tr>
<tr>
<td>Technological</td>
<td>Lock in device</td>
<td>High</td>
</tr>
<tr>
<td>Technological</td>
<td>Loss of Equipment</td>
<td>High</td>
</tr>
<tr>
<td>Technological</td>
<td>Denial of service attacks</td>
<td>Low</td>
</tr>
<tr>
<td>Technological</td>
<td>Peer to peer network</td>
<td>High</td>
</tr>
<tr>
<td>Technological</td>
<td>Hash function for mining</td>
<td>Low</td>
</tr>
<tr>
<td>Technological</td>
<td>Software risk</td>
<td>High</td>
</tr>
<tr>
<td>Security</td>
<td>General security risks</td>
<td>High</td>
</tr>
<tr>
<td>Security</td>
<td>Deanonymisation</td>
<td>Low</td>
</tr>
<tr>
<td>Security</td>
<td>Subversive miner strategy</td>
<td>High</td>
</tr>
<tr>
<td>Security</td>
<td>Loss of key</td>
<td>High</td>
</tr>
<tr>
<td>Security</td>
<td>Man in the middle</td>
<td>High</td>
</tr>
<tr>
<td>Economic landscape</td>
<td>Double spending</td>
<td>High</td>
</tr>
<tr>
<td>Economic landscape</td>
<td>Lack of Bitcoin awareness</td>
<td>High</td>
</tr>
<tr>
<td>Economic landscape</td>
<td>New currencies</td>
<td>High</td>
</tr>
<tr>
<td>Economic landscape</td>
<td>Bitcoin mining companies rising</td>
<td>High</td>
</tr>
<tr>
<td>Economic landscape</td>
<td>Malicious transactions</td>
<td>High</td>
</tr>
<tr>
<td>Economic landscape</td>
<td>Natural disasters</td>
<td>High</td>
</tr>
</tbody>
</table>

Lower risk: 1 - 2  
Medium risk: 3 - 5  
High risk: 6 - 7
A2: Results of stationarity tests in preparation for the multiple linear regression on Bitcoin, stock market and exchange rate returns

<table>
<thead>
<tr>
<th>Target</th>
<th>Box-Ljung</th>
<th>ADF p &lt; 0.05</th>
<th>KPSS p &gt; 0.05</th>
</tr>
</thead>
<tbody>
<tr>
<td>BTC/CNY log returns</td>
<td>6.362e-14</td>
<td>0.01</td>
<td>0.08414</td>
</tr>
<tr>
<td>BTC/USD log returns</td>
<td>&lt; 2.2e-16</td>
<td>0.01</td>
<td>0.08981</td>
</tr>
<tr>
<td>BTC/EUR log returns</td>
<td>&lt; 2.2e-16</td>
<td>0.01</td>
<td>0.1</td>
</tr>
<tr>
<td>BTC/JPY log returns</td>
<td>&lt; 2.2e-16</td>
<td>0.01</td>
<td>0.1</td>
</tr>
<tr>
<td>DOW log returns</td>
<td>0.04674</td>
<td>0.01</td>
<td>0.1</td>
</tr>
<tr>
<td>SP500 log returns</td>
<td>0.03901</td>
<td>0.01</td>
<td>0.1</td>
</tr>
<tr>
<td>DAX log returns</td>
<td>0.0007454</td>
<td>0.01</td>
<td>0.1</td>
</tr>
<tr>
<td>Euro Stoxx 50 log returns</td>
<td>0.0006436</td>
<td>0.01</td>
<td>0.1</td>
</tr>
<tr>
<td>China A50 log returns</td>
<td>4.033e-07</td>
<td>0.01</td>
<td>0.1</td>
</tr>
<tr>
<td>Nikkei 225 log returns</td>
<td>0.4685</td>
<td>0.01</td>
<td>0.1</td>
</tr>
<tr>
<td>CNY/USD log returns</td>
<td>0.00521</td>
<td>0.01</td>
<td>0.06755</td>
</tr>
<tr>
<td>CNY/EUR log returns</td>
<td>0.0162</td>
<td>0.01</td>
<td>0.1</td>
</tr>
<tr>
<td>USD/EUR log returns</td>
<td>0.4702</td>
<td>0.01</td>
<td>0.1</td>
</tr>
</tbody>
</table>

A3: Daily volatilities for all time series computed through an Exponentially Weighted Moving Average approach, a GARCH(1,1) model and the simple standard deviation.

The table shows the daily volatility estimates on April 3, 2017. It can be used to compare the results of the different estimation models. All variables are measured as the log return of the price at time $t$ and $t-1$.

<table>
<thead>
<tr>
<th>T</th>
<th>EWMA variance in %</th>
<th>EWMA sigma</th>
<th>Garch(1,1) sigma</th>
<th>STDEV.S</th>
<th>VAR.S</th>
</tr>
</thead>
<tbody>
<tr>
<td>2017/04/03</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BTC/CNY</td>
<td>0.07287</td>
<td>0.02700</td>
<td>0.0142</td>
<td>0.04783</td>
<td>0.22877</td>
</tr>
<tr>
<td>BTC/USD</td>
<td>0.07262</td>
<td>0.02695</td>
<td>0.0148</td>
<td>0.04295</td>
<td>0.18449</td>
</tr>
<tr>
<td>BTC/EUR</td>
<td>0.06731</td>
<td>0.02594</td>
<td>0.0157</td>
<td>0.04104</td>
<td>0.16845</td>
</tr>
<tr>
<td>BTC/JPY</td>
<td>0.07158</td>
<td>0.02675</td>
<td>0.0175</td>
<td>0.11573</td>
<td>1.33945</td>
</tr>
<tr>
<td>DOW 30</td>
<td>0.00209</td>
<td>0.00046</td>
<td>0.0043</td>
<td>0.00765</td>
<td>0.00585</td>
</tr>
<tr>
<td>SP 500</td>
<td>0.00237</td>
<td>0.00049</td>
<td>0.0042</td>
<td>0.00791</td>
<td>0.00625</td>
</tr>
<tr>
<td>DAX</td>
<td>0.00489</td>
<td>0.00070</td>
<td>0.0064</td>
<td>0.01185</td>
<td>0.01403</td>
</tr>
<tr>
<td>Euro Stoxx 50</td>
<td>0.00637</td>
<td>0.00080</td>
<td>0.0059</td>
<td>0.01258</td>
<td>0.01582</td>
</tr>
<tr>
<td>China A50</td>
<td>0.02085</td>
<td>0.01444</td>
<td>0.0049</td>
<td>0.01673</td>
<td>0.02800</td>
</tr>
<tr>
<td>Nikkei 225</td>
<td>0.02042</td>
<td>0.01429</td>
<td>0.0101</td>
<td>0.01544</td>
<td>0.02385</td>
</tr>
<tr>
<td>CNY/USD</td>
<td>0.00004</td>
<td>0.00006</td>
<td>0.0016</td>
<td>0.00158</td>
<td>0.00025</td>
</tr>
<tr>
<td>CNY/EUR</td>
<td>0.00317</td>
<td>0.00056</td>
<td>0.0045</td>
<td>0.00549</td>
<td>0.00301</td>
</tr>
<tr>
<td>USD/EUR</td>
<td>0.00374</td>
<td>0.00061</td>
<td>0.0053</td>
<td>0.00548</td>
<td>0.00300</td>
</tr>
</tbody>
</table>
A4: Volatility for Bitcoin returns over the entire observation period

BTC/CNY rate

BTC/EUR rate

BTC/JPY rate
A5: Regression coefficients for Bitcoin returns with returns from stock market indices and currency exchange rates

All variables are measured as the log return of the prices at time $t$ and $t - 1$. Please note that Bitcoin data is reported disregarding holidays and weekends, whereas stock data follows the trading hours of the respective exchange. The table shows only variables and coefficients that were significant with a p value equal to or larger as 0.01. P values ranging from 0.01 to 0.005 are marked by (*).

<table>
<thead>
<tr>
<th>BTC/CNY (F-statistic: 320.5 on 12 and 1008 DF, p-value: &lt; 2.2e-16), centred</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>intercept</td>
<td>0.0038868</td>
</tr>
<tr>
<td>BTC/USD</td>
<td>0.4413345</td>
</tr>
<tr>
<td>BTC/EUR</td>
<td>0.5964634</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>BTC/USD (F-statistic: 745.2 on 12 and 1008 DF, p-value: &lt; 2.2e-16), centred</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>intercept</td>
<td>0.0039392</td>
</tr>
<tr>
<td>BTC/CNY</td>
<td>0.1691417</td>
</tr>
<tr>
<td>BTC/EUR</td>
<td>0.8029412</td>
</tr>
<tr>
<td>BTC/JPY</td>
<td>0.0074722</td>
</tr>
<tr>
<td>Nikkei 225</td>
<td>-0.0756118</td>
</tr>
<tr>
<td>USD/EUR</td>
<td>0.2961620</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>BTC/EUR (F-statistic: 792.3 on 12 and 1008 DF, p-value: &lt; 2.2e-16)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>intercept</td>
<td>0.0008954</td>
</tr>
<tr>
<td>BTC/CNY</td>
<td>0.1986525</td>
</tr>
<tr>
<td>BTC/USD</td>
<td>0.6977684</td>
</tr>
<tr>
<td>BTC/JPY</td>
<td>0.0087094</td>
</tr>
<tr>
<td>CNY/EUR</td>
<td>0.2074398</td>
</tr>
<tr>
<td>USD/EUR</td>
<td>-0.3775465</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>BTC/JPY (F-statistic: 16.76 on 12 and 1008 DF, p-value: &lt; 2.2e-16), attempt to center, however no significant intercept. Therefore not centred results are displayed</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>intercept</td>
<td>-0.002306</td>
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<tr>
<td>BTC/USD</td>
<td>0.374641</td>
</tr>
<tr>
<td>BTC/EUR</td>
<td>0.502492</td>
</tr>
<tr>
<td>DAX</td>
<td>1.201457</td>
</tr>
<tr>
<td>logDAX (F-statistic: 369.6 on 12 and 1008 DF, p-value: &lt; 2.2e-16), centred</td>
<td></td>
</tr>
<tr>
<td>intercept</td>
<td>0.0001586</td>
</tr>
<tr>
<td>BTC/JPY</td>
<td>0.0026549</td>
</tr>
<tr>
<td>logNIK (F-statistic: 10.55 on 12 and 1008 DF, p-value: &lt; 2.2e-16), centred</td>
<td></td>
</tr>
<tr>
<td>intercept</td>
<td>0.0006849</td>
</tr>
<tr>
<td>BTC/USD</td>
<td>-0.0600064</td>
</tr>
<tr>
<td>logCXE (F-statistic: 26.2 on 12 and 1008 DF, p-value: &lt; 2.2e-16), centred</td>
<td></td>
</tr>
<tr>
<td>intercept</td>
<td>0.0001659</td>
</tr>
<tr>
<td>BTC/EUR</td>
<td>0.0237226</td>
</tr>
<tr>
<td>logUXE (F-statistic: 25.54 on 12 and 1008 DF, p-value: &lt; 2.2e-16)</td>
<td></td>
</tr>
<tr>
<td>intercept</td>
<td>-0.0001826</td>
</tr>
<tr>
<td>BTC/USD</td>
<td>0.0287966</td>
</tr>
<tr>
<td>BTC/EUR</td>
<td>-0.0422429</td>
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</table>
A6: Value at Risk results for stock market indices

<table>
<thead>
<tr>
<th>Index</th>
<th>DOW</th>
<th>SP500</th>
<th>DAX</th>
<th>EURO50</th>
<th>CHINA50</th>
<th>NIK225</th>
</tr>
</thead>
<tbody>
<tr>
<td>VaR</td>
<td>0.0256</td>
<td>0.0263</td>
<td>0.0381</td>
<td>0.0391</td>
<td>0.0548</td>
<td>0.0502</td>
</tr>
</tbody>
</table>

A7: Var limits for a 99 percent confidence level plotted with log returns of the time series

BTC/USD

BTC/EUR

BTC/JPY
A8 Forecast model CM1
The first three years of the data have been faded out for better visibility of the forecast period.

A9 Forecast model CM2

A10 Forecast models UM1 and UM2
The figure shows the zoomed in forecast starting from April 4, 2017 and the actual prices from January 1, 2016 for model UM1 on the left and model UM2 on the right.
A11 Model backtesting for UM1 and UM2

The graphs show the graphical backtest for model UM1 on the left and UM2 on the right. The table below presents the analytical tests. As UM2 obtained a lower RMSFE error value, this model is preferred for forecasting prices and returns.

<table>
<thead>
<tr>
<th></th>
<th>UM1</th>
<th>UM2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ljung-Box p-value</td>
<td>&lt; 2.2-16</td>
<td>1.224e-07</td>
</tr>
<tr>
<td>Jarque Bera p-value</td>
<td>&lt; 2.2-16</td>
<td>&lt; 2.2e-16</td>
</tr>
<tr>
<td>RMSFE</td>
<td>149.9526</td>
<td>114.6065</td>
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</tbody>
</table>

A12 Forecast models EM1 and EM2

Consistent with the previous time series, the years 2013 to 2015 of the original time series have been faded for better visibility. The data was of course included in the calculation.

A13 Backtesting for forecast models EM1 and EM2

<table>
<thead>
<tr>
<th></th>
<th>EM1</th>
<th>EM2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ljung-Box p-value</td>
<td>3.209e-09</td>
<td>9.73e-08</td>
</tr>
<tr>
<td>Jarque Bera p-value</td>
<td>&lt; 2.2-16</td>
<td>&lt; 2.2e-16</td>
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<tr>
<td>RMSFE</td>
<td>122.3334</td>
<td>107.2753</td>
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</table>
A14 Forecast models JM1 and JM2 including backtesting results

<table>
<thead>
<tr>
<th></th>
<th>JM1</th>
<th>JM2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ljung-Box p-value</td>
<td>&lt; 2.2-16</td>
<td>&lt; 2.2-16</td>
</tr>
<tr>
<td>Jarque Bera p-value</td>
<td>&lt; 2.2-16</td>
<td>&lt; 2.2-16</td>
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<tr>
<td>RMSFE</td>
<td>15096.66</td>
<td>13402.63</td>
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A15 Data sources

<table>
<thead>
<tr>
<th>Data</th>
<th>Label</th>
<th>Frequency</th>
<th>Date</th>
<th>Source</th>
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<tbody>
<tr>
<td>Standard &amp; Poor 500</td>
<td>SP500</td>
<td>Daily data (252)</td>
<td>2017-04-03</td>
<td>1</td>
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<tr>
<td>Dow Jones 30</td>
<td>DOW30</td>
<td>Daily data (252)</td>
<td>2017-04-03</td>
<td>1</td>
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<tr>
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<td>DAX</td>
<td>Daily data (252)</td>
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<td>Chinese Renminbi/US Dollar</td>
<td>CNY/USD</td>
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<td>2017-04-03</td>
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<td>CNY/EUR</td>
<td>Daily data (252)</td>
<td>2017-04-03</td>
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<tr>
<td>US Dollar/Euro</td>
<td>USD/EUR</td>
<td>Daily data (252)</td>
<td>2017-04-03</td>
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<tr>
<td>Bitcoin/Chinese Renminbi</td>
<td>BTC/CNY</td>
<td>Daily data (365)</td>
<td>2017-04-03</td>
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<tr>
<td>Bitcoin/US Dollar</td>
<td>BTC/USD</td>
<td>Daily data (365)</td>
<td>2017-04-03</td>
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<td>Bitcoin/Euro</td>
<td>BTC/EUR</td>
<td>Daily data (365)</td>
<td>2017-04-03</td>
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<td>Bitcoin/Japanese Yen</td>
<td>BTC/JPY</td>
<td>Daily data (365)</td>
<td>2017-04-03</td>
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<tr>
<td>BTC Trading Volume</td>
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<td>Daily data (365)</td>
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<tr>
<td>Number of transactions</td>
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<td>2017-04-25</td>
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</tr>
<tr>
<td>Mining Difficulty</td>
<td></td>
<td>Daily data (365)</td>
<td>2017-04-25</td>
<td>11</td>
</tr>
</tbody>
</table>

1 http://finance.yahoo.com
2 http://investing.com/indices/fsse-china-a50-historical-data
4 https://de.investing.com/realtimequotes/
5 https://data.bitcoiinity.org/markets/price/5y/CNY?r=day&t=1
6 https://data.bitcoiinity.org/markets/price/5y/USD?r=day&t=1
7 https://data.bitcoiinity.org/markets/price/5y/EUR?r=day&t=1
8 https://data.bitcoiinity.org/markets/price/5y/JPY?r=day&t=1
9 https://data.bitcoinity.org/markets/volume/5y?c=c&r=day&t=b
10 https://data.bitcoinity.org/bitcoin/tx_count/5y?r=day&t=l
11 https://data.bitcoinity.org/bitcoin/difficulty/5y?r=day&t=l