The Price Volatility of Bitcoin

A search for the drivers affecting the price volatility of this digital currency

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Spring semester 2014
Master thesis, two-year, 15 hp
Acknowledgements

This thesis marks the end of some interesting and rewarding years at Umeå University and we bring much experience with us. The time at the university has not only put us in contact with big theories, but also with some great people and we would hereby like to acknowledge some of them.

First of all, we would like to thank our supervisor Janne Äijö, for his kind words and for believing in us and our ideas. We would also want to express our gratitude to Jörgen Hellström, for his invaluable support. We appreciate it. Last but not least, we would like to thank friends and family who have consistently supported us throughout this process.

Sincerely,

Nathalie Stråle Johansson & Malin Tjernström

October 28 2014, Umeå
Abstract

Created in 2009, the digital currency of bitcoin is a relatively new phenomenon. During this short period of time, it has however displayed a strong development of both price and trade volume. This has led to increased media attention, but also regulators and researchers have developed an interest. At this moment, the amount of available research is however limited. With a focus on the price volatility of bitcoin and an aim of finding drivers of this volatility, this study is taking a unique position.

The research has its basis in the philosophical position of positivism and objectivism. This has shaped the research question as well as the construction of the study. The result is a describing and explaining research with a deductive research approach, a quantitative research method and an archival research strategy. This has in turn stimulated an extensive literature review and information search. Areas of discussion are microstructure theory, the efficient market hypothesis, behavioural finance and informational structures. Due to the limited amount of previous bitcoin research within the area of price volatility, the study has drawn extensively on research performed on more classical assets such as stocks. Nevertheless, when available, bitcoin research has been used as a foundation/reference and an inspiration.

Reviews of academic literature and economic theories, as well as public news helped to identify the variables for the empirical study. These variables are; information demand, trade volume, world market index, trend and six specified events, occurring during the chosen sample period and included in the study as dummy variables. The variables are all analysed and included in a GARCH (1,1) model, modified following a similar research by Vlastakis & Markellos (2012) on stocks. This GARCH (1,1) model is then fitted to the bitcoin volatility registered for the sample period and is able thereby to generate data of if and how the variables affect the bitcoin volatility.

The test result suggests that five of the ten variables are significant on a 5 % -level. More specifically it suggests that information demand is a significant variable with a positive influence on the bitcoin volatility, something that corresponds to the literature on information demand and price volatility. This also relates to the events found significant, as they generated bitcoin related information. The significant events of the Cypriot crisis and the failure of the bitcoin exchange MtGox are thus specific examples of how information affects price volatility. Another significant variable is trade volume, which also displays a positive influence on the volatility. The last significant variable turned out to be a constructed positive trend, suggesting that increasing acceptance of bitcoin decreases its volatility.

Key words: bitcoin, digital currency, volatility, GARCH(1,1), market microstructure, behavioural finance, information demand, trade volume, asset price, risk, return, exchange
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1. Introduction

Bitcoin is a new and interesting phenomenon on the financial market. In many ways, this digital currency demonstrates unique qualities relative to other financial assets, which ensures that its investors are faced with other concerns and trade-offs than those choosing more traditional investments opportunities. The following exploration of the bitcoin market will lead to the identification of a research gap, a purpose and a research question.

1.1 Bitcoin as a Financial Innovation

Spotify, Skype, Facebook and Swish, are all examples of technological solutions spurred by an “ever-globalizing” world, which is constantly inventing new ways of solving everyday problems. By doing so, they are at the same time challenging the status quo. This development is also seen in the financial industry. Investor acceptance and demand for alternative investments combined with the ability of market actors to create a supply of new instruments determines its success. A case in point is the creation of virtual currencies that recently appeared on the market and are now being traded on exchanges across the world (see e.g. ECB, 2012; Rogojanu & Badea, 2014). Some operate only within virtual communities, while others have a wider reach and a bidirectional flow with traditional currencies (ECB, 2012, p. 5). The theoretical basis for such systems lies with the Austrian School of Economics and Friedrich August von Hayek, a famous Nobel Laureate in Economics (Rogojanu & Badea, 2014, p. 104). Hayek believed that a healthy and efficient currency was best achieved through free competition between private parties.

Within the category of virtual currencies is the subset of digital currencies (Chowdhury & Mendelson, 2013, p. 1). They usually function without the control of a particular counterparty and are used more widely in the general economic system (Bradbury, 2014). As the first of its kind, the digital currency bitcoin maintain its integrity through peer-to-peer networking and cryptography (Grinberg, 2011; Kaplanov, 2012, p. 113; Luco, 2013, p. 6). Its creators introduced the bitcoin in an attempt to move away from the trust-based model of traditional currencies and create a secure system based on cryptographic proof (Nakamoto, 2008, p. 1). See more information about the bitcoin system in Appendix A.

Today, bitcoin is used as payment for not only online services, but also for many physical goods both purchased online and in physical establishments (Bradbury, 2014). Interestingly, last year Virgin Galactic accepted a bitcoin payment for a space flight (Holpuch, 2013). Despite many indications that bitcoin is more widely used as a currency (see Appendix A), researchers such as Yermack (2014, p. 2) have suggested that bitcoin’s properties are more consistent with those of a speculative investment. Its price fluctuates severely and quickly and many uncertainties remain. Regardless if bitcoin manages to emerge as a viable currency, it does have the potential to serve as a platform for future financial innovation (The Economist, 2014).
1.2 A Developing Market

The bitcoin value is not determined by any macroeconomic fundamentals such as interest rates, GDP or inflation (ECB, 2012, p. 21; Kristoufek, 2013, p. 1). Neither is it pegged against any other currency. Instead, the exchange rate is based entirely upon supply and demand. Therefore, it is of utter importance to understand bitcoins market microstructure (Garman, 1976) in order to comprehend its price formation. There are over 40 bitcoin exchanges today, where traditional currencies can be traded for bitcoins [BTC] at varying quotes (Bitcoincharts, 2014c). The number of investors have risen significantly over the last couple of years and have now reached a level of about 68,000 trades per day (Bitcoincharts, 2014a). Some argue that the market is dominated by technology enthusiasts, liberals seeking an alternative to national currencies and criminals taking advantage of the transaction anonymity (Grinberg, 2011, p. 165; Yermack, 2014, p. 7). However, turbulent financial times has led investors to search for innovative investment opportunities and bitcoin’s lack of correlation to other assets makes it an attractive market (Brière et al., 2013; Chowdhury, 2014). Hence, the market is developing and more institutional investors are now opening their eyes to bitcoin, ensuring its development into a mature asset class (Chin, 2014).

The bitcoin market is still in an emerging stage and its unique characteristics have caused debate (Arthur, 2013; Rushe, 2013; The Economist, 2013). Thus, bitcoin has figured extensively in the media (e.g. Bradbury, 2014; Finextra, 2013; Rizza, 2013), been heavily discussed by governments and institutions (e.g. Bloomberg News, 2013; ECB, 2012; Strauss, 2013) and researchers are beginning to investigate the intricacies of this market (e.g. Brière et al., 2013; Chowdhury, 2014; Garcia et al., 2014).

1.3 Bitcoin Price Volatility

The working-papers by Brière et al. (2013) and Chowdhury (2014), argue that bitcoin price volatility is many times larger than that of stocks, bonds, hard currencies and commodities. Further, its lack of fundamental value and lack of regulation suggest different characteristics than many traditional assets. Madhavan (2000, p. 207) argues that the information structure and informational efficiency of a market offers answers for how prices are formed. This is a highly debated issue in finance. The well-known efficient market hypothesis (Fama, 1970) suggests that information is instantaneously incorporated into prices, while behavioural finance argues for the importance of investor psychology and limited attention span (Barber & Odean, 2008, p. 786; Tversky & Kahneman, 1974).

As displayed in Figure 1, bitcoin has exhibited extreme fluctuations in its price during 2013 and early 2014. With a quick glance at news reports around the time of large swings, one discovers some interesting effects. In April 2013, the BTC value dropped 160 USD in a single day (Rushe, 2013). On the other hand, during the two months leading up to this day, the value had increased from 20 USD to an astounding 266 USD/BTC. Some argue that this impressive price surge occurred as a result of the capital controls in Cyprus spurring an interest in denationalized currencies (The Economist, 2013).
Similarly, shortly after the Chinese giant Baidu decided to accept payments with bitcoin in October 2013, the BTC demand on the Chinese market increased, fuelling the global rally (Bloomberg News, 2013). The following month, the BTC price moved more than 200 USD in a single day coinciding with an official comment made by Ben Bernake, chairman of the US Federal Reserve, suggesting that bitcoin might have a positive future ahead (Strauss, 2013). It would not take long until the bitcoin value reached its all-time high of over 1.242 USD/BTC on November 29 (Kitco News, 2013). Alan Greenspan, the former US Federal Reserve Chairman, stated that due to bitcoins lack of intrinsic value this is definitely a bubble (Bloomberg News, 2013). Similarly, last year’s Nobel Prize winner in Economics, Robert Shiller, was quoted saying that ‘it is [...] an amazing example of a bubble” (Balibouse, 2014).

Figure 1: BTC price chart for Bitstamp (USD)
(Bitcoincharts, 2014b)

Perhaps not surprisingly, the high price did not last. In early December, the wind changed as the Chinese government forbade financial institutions to use bitcoins leading also Baidu to follow. These news triggered a sharp BTC price decline of 20% (Bloomberg News, 2013). In February 2014, more problems occurred on the bitcoin market when its largest trading platform MtGox was hacked and subsequently went bankrupt (Hals, 2014). Nearly 6 % of the entire bitcoin supply was lost in the theft, forcing many to question the legitimacy of bitcoin (Thomas, 2014). Others consider this massive blowup as a way to weed out bad actors and hopes this will create an opportunity for serious actors to take the bitcoin market mainstream. However, this would require a better understanding of what affects BTC price formation. Today, managing the extreme risks of a bitcoin investment are complicated and Chowdhury (2014, p. 7) warns investors of investing more than they can bare to lose.

1.4 Research Gap and Problem Identification

The legal grounds for the use of bitcoin as a currency has been discussed by researchers all over the world (e.g. Brito & Castillo, 2013; Grinberg, 2011; Rogojanu & Badea, 2014). However, research concerning bitcoin as an investment is severely limited. At the publication of this thesis, only a few studies have been completed, e.g. Kristoufek (2013), and Moore and Christin (2013). While Kristoufek (2013) studied the effect
information demand has on bitcoin price volatility, Moore and Christin (2013) focused on the risk of bitcoin exchange failure. Recently, working papers by e.g. Chowdhury (2014), Chowdhury and Mendelson (2013), Brière et al. (2013), Garcia et al. (2014) and Yermack (2014a) have also been released. Thus, there is a rising academic interest in the bitcoin market.

Price formation and price volatility have been extensively studied on financial markets (e.g. Barberis et al., 1998; Fama, 1970; Lux, 1995; Schwert, 1990), but due to the emerging nature of the bitcoin market, researchers have only begun to scratch the surface in this area. Thus, the drivers behind the extreme volatility of bitcoin has not yet been sufficiently studied providing for an extensive research gap. This unique market, which have managed to attract so much attention from various directions, offers an interesting setting for a study. With the aid of financial theories and wide information searches, the underlying causes for the high BTC price volatility can best be identified. Inspired by studies such as Vlastakis and Markellos (2012) and Kristoufek (2013) we will use financial modelling to study the variables our theoretical investigation reveal relevant for BTC price volatility.

1.5 Research Question

Research question: What drives bitcoin price volatility?

Sub question 1: Which variables can explain bitcoin price volatility?
Sub question 2: Do the identified variables have a significant effect on bitcoin price volatility?

1.6 Purpose

With this study, we aim to identify the drivers of the high BTC price volatility. As already discussed, its volatility is many times that of other markets (Brière et al., 2013; Chowdhury, 2014). Together with its unique market setting, this makes for an interesting study. Initially, a literature review of theoretical paradigms and previous empirical research will be performed in order to identify which variables appear to be significant for price formation in other markets. By subsequently evaluating them in the light of the bitcoin market, we aim to identify the specific variables affecting the bitcoin volatility. Once identified, these variables will be examined through statistical and econometric methods in order to extrapolate their explanatory power.

We thus seek to contribute to literature on price volatility by offering the perspective of an emerging and highly speculative market. Economic theories are thus studied in a new light, which could potentially lead to new insights. Thus, our purpose is to widen the knowledge of the bitcoin market. By identifying the drivers of BTC volatility, we hope to benefit both the scientific literature and the investor.
1.7 Delimitations

Since only a few years have passed since the introduction of bitcoin and it has only recently become extensively traded, this research is somewhat restricted. To ensure sufficient trading volume and liquidity during the days included, the time period studied has been set to merely 2.5 years, 13.09.2011 – 03.05.2014. For the same reasons, only trades made on two bitcoin exchanges are included in the sample. However, these are among the largest exchanges today and have pertained a significant part of the bitcoin market for the entire period. Both these markets trade in USD, which is also the currency most commonly traded with bitcoin. Perhaps further nuances to the bitcoin market could be discovered through a more inclusive sample. Nevertheless, we argue that this sample ensures a more reliable result and is still representative of the population.

1.8 Disposition

Chapter 1 – Introduction
This chapter offers the reader a glance into the bitcoin market and aims to spur an interest into this new and interesting phenomenon. By describing and discussing the surroundings of this innovative currency, a research gap and a purpose is identified and a research question posed. Finally, the delimitations of this study is explained.

Chapter 2 – Research Methodology
This chapter illuminated the connections between the researchers and the study. This is done through a discussion of the authors’ preconceptions, research perspective, and research philosophy. This forms a base for the research approach and design. Finally, the information collection method is described.

Chapter 3 – Theoretical Framework
This research is based on a number of theoretical concepts and conceptions, which are here described and critically discussed. After each section, the applicability of the theory to the bitcoin market will be directly argued for. In this way, we aim to include a through explanation of the bitcoin market with the support of well-known theories. Further, this provides a solid base for the variable selection performed in chapter 5.

Chapter 4 – Previous Research
The focus of this chapter is previous studies about the bitcoin market. However, due to the lack of acknowledged research in this area some additional material will offer support. The division of the chapter aims to clearly demonstrate the most important issues for the bitcoin market today; it is an emerging and risky market, it exhibits a growing investor acceptance, and it seems to be information sensitive and uncorrelated to other markets.

Chapter 5 – Practical Method
Outlining the various choices made for the practical application of the study, this chapter provides validity to the research. Following a description of the population and sample, the data collection methods are described and the variables to study are selected. The
chapter ends with a critical description of tests and models used, such as the GARCH(1,1).

Chapter 6 - Empirical Results
This chapter presents the results of the empirical study and begins with a review of the characteristics of the variables. This is followed by the result from the tests for correlation and stationarity, before embarking on the main result of the GARCH(1,1). Lastly, this model is evaluated using tests of autocorrelations.

Chapter 7 – Analysis
By analyzing the empirical results together with the theoretical framework, previous research and real market events, this chapter aims to form a base for the upcoming conclusion. The chapter is structured as to provide separate sections for each variable studied.

Chapter 8 – Conclusion
This chapter will bring the variables together to offer a cohesive explanation for the bitcoin price volatility. At this point, the research question will be answered and we will argue for the fulfillment of the research purpose. The chapter also discusses the contributions made to literature and practice as well as offer suggestions for future research in this area.

Chapter 9 – Assessment of Research Quality
This chapter is covering the topics of ethics and social aspects of the research as well as reliability, replicability and validity. These are important issues to discuss as they all concern the quality of the research.
2. Research Methodology

This is the theoretical methodology for the research, which has the purpose of illuminating the connections between the researchers and the subject matter being studied. This is an important chapter since the researchers manage the study. How we view knowledge and the generation of knowledge will have great influence on the study’s execution and result. By disclosing and arguing for the choices made, we hope to generate a good understanding of the research as well as conferring credibility to its end result.

2.1 Preconceptions and Choice of Subject

As will be outlined in this chapter, there are many factors that can and will affect the conduct of research. As explained by Bryman and Bell (2007, p. 30) it is difficult to keep research completely separated from values, but in order to limit their impact as much as possible it is important to declare the researchers’ relationship with the subject of research such as interest, knowledge and experience.

Both authors are master students at Umeå University with finance as major. Previous courses have thus provided a good understanding of financial concepts and theories as well as experience of how to perform academic studies. This knowledge is further supplemented by Swedish and international business news, gathered from sources such as Dagens Industri, the Wall Street Journal and BBC News. It was also through the news streams that the bitcoin phenomenon first was encountered. It did however never develop into any trade. Nor do any of the authors have any close relationship to any bitcoin trader. The interest simply emerged through a fascination of how something that does not have any apparent intrinsic value can be valued several hundreds of USD, which was the case in the beginning of 2014.

Bitcoin was first introduced as an alternative to traditional, national currencies and it was claimed that its supporters consisted mainly of liberals, technology enthusiasts and criminals. It was an unconventional currency and many had difficulties comprehending the reasoning for its existence and its success. However, bitcoins popularity is increasing and investors are seeing potential. Performing this study, we do not bear any feelings for or against neither the traditional monetary system nor alternative systems. We would instead describe our position in the bitcoin matter as curious and open-minded.

2.2 Research Perspective

Bitcoin has created many headlines due to its unique characteristics, one being its exceptionally high volatility. While many people may find it interesting to follow the development of this new phenomenon, some are likely to follow it more closely. These people are the owners of bitcoin. As stated in the introduction, the information and knowledge surrounding bitcoin and its characteristics is limited. Much of what exists today concerns how to classify it, its legal status and whether it is to be considered a true currency. This lack of information of information leads to higher risks for the investors involved. By studying the bitcoin price volatility and what factors affect its ups and downs,
we are not interested in its qualities as a currency, nor are we interested in the legal or political challenges per se. Instead this study is occupied with investigating bitcoin data in the light of well-established economic theories, in order to equip investors with information that can help them use bitcoin in a, for them most appropriated way.

Investors are generally concerned with the price volatility of assets, as the fluctuations result in direct capital gains or losses. Fama (1965), De Bondt and Thaler (1985) and Vlastakis and Markellos (2012) are examples of the numerous studies that have been performed over the years on more classical assets such as stocks. These studies have increased the information about these assets, which in turn has helped investors to a better understanding of their specific asset characteristics. It is also possible that these studies have further fueled financial innovations, which have resulted in a more diversified usage of assets e.g. in terms of financial instruments.

2.3 Research Philosophy

When conducting research it is of great importance to consider which philosophical positions are adopted, as they carry significant assumptions of how the researchers performing the study views the world and thereby lays the foundation upon which the research design will be developed (Saunders et al., 2009, p. 108). It is, thus, important to understand the meaning of the different positions and how they relate to other components of research in order to be able to apply them in a correct manner and later also be able to discuss and defend the position taken (Grix, 2002, p. 176). By evaluating the different philosophical positions, we have been able to define where we stand, something that will be declared in the following sections.

2.3.1 Ontological Considerations

Ontology is the philosophical position concerned with what is viewed as social reality, thus, what kinds of social phenomena is believed to exist, what they look like and how different units interact, and is therefore to be considered the basis for all research (Blaikie, 2009, p. 92; Grix, 2002, p. 177). The view of the researchers is therefore important for the research process, as it will influence how knowledge is believed to be determined, i.e. epistemology, and thereby later also affecting the choice of methods. The central concern within ontology is whether social phenomena exist by their own creation or if they are the results of the interaction between social beings (Bryman & Bell, 2007, p. 22). We believe that social phenomena are independent of social actors and that these phenomena provide patterns, which researchers are to discover and describe. With such an external role as researchers, it is arguable that the study is performed in an objective manner. Our ontological standpoint would thereby be classified as objectivism. The opposite ontological position is the one of constructionism, which views social phenomena as socially constructed and, thus, under a constant state of revision (Bryman & Bell, 2007, p. 23).

Applying this objective ontological position on the chosen research topic allows for investigations of the relationships between different variables and draw conclusions of whether they exist and how strong they are. This type of study would not be possible with the assumptions of constructionism, since we would have to include our own interpretations of the matter, thus, creating bias in our conclusions. The result would further only be valid
from a very narrow and specific perspective, something that is not an issue in a study concerned with why a relationship exists between specific variables, since this question can have many answers. An ontological position of objectivism and the stated research question are thus a suitable combination.

2.3.2 Epistemological Position
While ontology concerns what social reality is, epistemology focuses on what constitutes acceptable knowledge, regardless of how social reality is defined (Grix, 2002, p. 177). The epistemological positions are, however, in many aspects closely connected with the ontological standpoints. Simply expressed, the epistemological positions can be divided according to whether or not they find the methods used within natural science to be applicable also within social science.

Considering our ontological position and that we view data as objective and external to human thoughts, we find that acceptable knowledge has to be supported by empirical findings backed by large samples of data in a law-like way, generalizing the findings. These characteristics suggest that our epistemological position is the one of positivism (Bryman & Bell, 2007, pp. 16-17; Remenyi, 1998, p. 32). This is very different from the opposing position termed interpretivism, which argues that social research demands a different approach due to the difference between people and the objects of natural sciences (Bryman & Bell, 2007, p. 17). The difference resides in that people are believed to interpret the social roles in accordance with a meaning assigned by themselves. This results in a need for the researcher to understand the world from the research subject’s point of view. An assumption like this makes interpretivism more suitable for organizational behavior and management studies where the understanding for complex situations is of key importance (Saunders et al., 2009, p. 116).

Viewing data as objective, it is for us very important to perform our research independent from our own values. This also distinguishes our position from that of realism. Realism, which similar to positivism holds a scientific stance concerning the development of knowledge, recognizes that the process of learning affects objectivism, which ultimately means that the researcher becomes subjective (Fisher, 2007, p. 42). The purpose of this study is to determine if there is a relationship between the identified variables and the price volatility of bitcoins, and not the direction of such relationship, something that would be more of a focus for a research with a realistic standpoint (Fisher, 2007, p. 42). Moreover, considering the lack of preconceived beliefs concerning the topic of bitcoins, it is believed that the objectivity needed for this study is fully achievable. To conclude, it is believed that the declared research philosophy of objectivism and positivism is not only coherent with the posed research question, but that it also supports the study’s ability to answer it.

2.4 Research Approach
Following the philosophical stands stated above there is a natural shift of focus towards the chosen research approach, since they are closely related (Saunders et al., 2012, p. 128). When defining the appropriate research approach it is, however, also important to consider what kind of research that is to be conducted. Theory carries important implications for all types of research, and most studies are concerned with some kind of literature review
It is the reason behind such review that distinguishes the different research approaches. In this study, literature is reviewed in order to identify theories to build a theoretical framework, which is used to test empirical data from the bitcoin market. Hence, it is argued that this study has a deductive approach (Bryman & Bell, 2007, p. 13; Saunders et al., 2009, p. 61). By applying existing theories on the phenomenon of bitcoin, we contribute to the existing knowledge by applying it on a new market. This is a great contrast to the inductive approach, which uses existing literature in order to generate a theoretical overview, from which the own research can start exploring and developing new theories (Bryman & Bell, 2007, p. 13; Saunders et al., 2009, p. 61).

2.5 Research Design

The research design is where the overall plan is laid out for how we attempt to answer the posed research question (Saunders et al., 2009, p. 159). This includes the identification of the techniques of collecting the data needed, the nature of the research as well as its strategy.

2.5.1 Research Method

The research method defines the data collection techniques and the process of analyzing the data (Blaikie, 2009, pp. 200-201). Typically, the different research methods are distinguished by their different emphasis on numerical and non-numerical data (Saunders et al., 2009, p. 161). Even though this is an important aspect, it is a very narrow classification. When considering the choice of research method, the researchers’ philosophical stands continue to be of importance since the selection of method implies a particular view of the topic studied (Barnham, 2012, p. 736; Lee, 1992, p. 88). The ontological and epistemological assumptions shape the posed research question and the roles of the researchers, and will thus also impact how the researchers best go about fulfilling the purpose of the research. The different philosophical standpoints have competing views of what constitutes truth (Barnham, 2012, p. 736). With the mentioned philosophical positions of objectivism and positivism, the researchers are seen as detached from the focus of research and are, thus, able to provide an objective view. It is further believed that the use of neutral scientific techniques makes it possible to uncover new knowledge by statistically testing existing theories. In order to provide a scientific answer to this study, the access to adequate empirical data, such as data with statistical adequacy, representativeness etc., is essential. Considering these points, it is clear that the philosophical assumptions presented for this study require a quantitative research method.

If the study, on the other hand, would be guided by the ontological and epistemological assumptions of constructionism and interpretivism, a qualitative research method would be preferable (Bryman & Bell, 2007, p. 28). By employing methods such as less structured interviews a more thorough understanding of the subject could be achieved. This is due to the possibility for the researchers to intervene and explore certain topics more closely as the work progresses.
2.5.2 Research Characteristics
Not surprisingly there are many ways to perform a study. The nature of the research design is, however, directed by the chosen research question (Saunders et al., 2012, p. 170). The focus of the research question in this case is to study the price volatility of bitcoin and thereby identify factors that affect it. In order to fulfill the objective of the research, an explanatory study needs to be undertaken. By subjecting our data to statistical tests, we will be able to determine, and thereby explain, if there is a relationship between the price volatility of bitcoin and the listed variables. Since bitcoin is a fairly new market and the general knowledge thereby low, more extensive explanations are needed. It is therefore argued that the study also carries elements of a descriptive study.

2.5.3 Research Strategy
The research strategy is the general plan of the process of answering the research question (Saunders et al., 2012, p. 173). The choice of research strategy will, just like the above research aspects, be guided by the underlying research philosophy and objectives, but also by more practical concerns such as the extent of existing knowledge, available resources and access to data. It is thus important that the research strategy is laid out after careful consideration. Grounded theory, survey, experiment and action research are all examples of research strategies, but many more exists.

This study focuses on and is limited to the bitcoin phenomenon and could therefore be said applying a case study strategy. The bitcoin price movement will be studied in relation to specific variables. The main focus is however not to understand the bitcoin behavior in a given situation, which is often the aim when applying a case study strategy (Saunders et al., 2012, p. 179). However, the objective of this research and its philosophical standpoint, suggest that this study is more concerned with generating knowledge about the bitcoin price volatility that has a wider applicability, more generalizable knowledge if you prefer. Since the study further relies on historical data available, an archival research strategy fits better with the research constellation (Saunders et al., 2012, p. 178-179). The process of identifying the variables and the methods of collecting the data will be accounted for in later chapters.

2.5.4 Time Horizon
The focus of this study is the volatility of the bitcoin price. Since volatility is not observable at one point in time (Tsay, 2010, p. 10), a cross-sectional study would therefore not be consistent with the research objective. Rather, in order to study the development of the bitcoin price, it is important to gather information over a period of time. This suggests that this is a longitudinal study (Saunders et al., 2012, p. 190). Due to the short existence of bitcoin, the data gathered covers a period of 2.5 years, beginning September 13th 2011 and finishing May 3rd 2014.

2.6 Information Collection Methods

2.6.1 Literature Review
As mentioned in the research approach section, the review of existing literature possesses an important and central role in the performance of research studies (Bryman & Bell, 2007,
Just like there are different research approaches there are also different methods of conducting literature reviews, and it is important that the choice made reflects the nature of the study performed (Bryman & Bell, 2007, p. 104).

For this study a systematic literature review was chosen. This is a thorough method that aims at generating an exhaustive review of existing literature within a certain area, while at the same time providing a detailed description of the process, thus creating transparency (Bryman & Bell, 2007, pp. 99-100, 102). Such an extensive literature review provides a good understanding of the topic and is also claimed to generate an objective judgment of the quality of the information. This claim has however been frequently discussed between researchers (Bryman & Bell, 2007, p. 104). The systematic literature review’s method of evaluating information sources according to methodological criteria does however correspond well with the philosophical positions of this study. The contrasting approach is the narrative literature review (Bryman & Bell, 2007, pp. 104-105). Here the aim is to enhance human discourse by creating understanding, and quality is rather about finding interesting published research. With a wide-ranging scope and lesser focus, this approach is more unpredictable concerning where it will end up. Such an approach is, therefore, more suitable with an interpretive and subjective philosophical position, as well as with an inductive research strategy.

Literature can further be categorized according to the stage of information flow from the original source (Saunders et al., 2012, p. 69). The idea behind this categorization is that the information, as it comes further away from its primary source, generally becomes less detailed and authoritative, but also more easily accessible. This is an important characteristic to be aware of, in order to choose the appropriate data for the research purpose. In this study, mainly secondary literature has been employed, such as articles from academic journals, accessed through databases provided by the university such as EBSCO, but also Google Scholar and the digital libraries like JStor, to which Umeå University provides access. When searching for literature some of the key words used were: bitcoin, volatility, digital currency, btc and price formation. By consistently following ideas and sources generated by the literature found, we were able to build a comprehensive theoretical framework.

This secondary literature often contains publication from first hand sources, but it is targeted towards a wider audience than the primary literature, and is therefore easier to access (Saunders et al., 2009, p. 69). Using publications from well-renowned journals also makes it possible to ensure a certain quality of the literature, since they first let the work be reviewed and approved by academic peers before publishing it. In this study such peer-reviewed material has been prioritized. However, due to the choice of subject it has not been possible to fulfill this quality for all sources used. The academic information about bitcoins is very limited due to the recent popularity of bitcoin. It has simply not been possible to perform studies on the bitcoin market since data has not been available for more than a few years. The academic literature available for this study has therefore been limited. Through the literature review mainly ‘work in progress’ –papers or graduate/undergraduate papers were found. This is primary literature, as mentioned above, but falls into a grey area due to its lack of recognition. The usage of such more doubtful information goes somewhat against the philosophical position of this study, which provides a rather strict view of what
knowledge is. The thorough examination of literature has however made sure that the study has the best information available and can therefore provide the best result given the existing and available information at the moment. In order to clarify when such “grey” information is utilized in the study, clear reference has been made.

2.6.2 Data Sources

The data collected comes from many different sources. As with the literature, the data necessary to perform this research is secondary and comes from Nasdaq, Google trend and the Bitcoinchart. Performing a longitudinal analysis with primary data would be extremely time-consuming, making secondary data much more attractive (Bryman & Bell, 2007, pp. 326-328). Possible disadvantages of using secondary data are the difficulty of becoming familiar with the data, how to manage it in the best way as well as securing the quality of the data used. These limitations are, however, not something we experienced in this study making the benefits of using secondary data predominating.

2.7 Chapter Summary

Building on the introductory chapter 1, this chapter lays the foundation of the study, from which the practical aspects later spring from. Chapter 2 starts with the researchers and their philosophical position. This is a given point of departure due to their managing role, since every decision made will be influenced by their inherent perception, consciously or unconsciously. This chapter has therefore also the ability to make the researchers reflect over their choices, possibly leading to more objective and coherent choices. It also offers the reader the opportunity to evaluate the suitability of the chosen research strategy in relation to the posed research purpose, and in the end also the reliability of the result. The quality of the research will however be further discoursed in chapter 9. Finally, a so-called research onion is presented to visualize the close connections of the methodological aspects. This picture is further re-worked as to also present an overview of the choices made for this specific study.

*Figure 2: Our application of the research union in Saunders et al. (2012)*
3. Theoretical Framework

The following chapter provides an overview of the theoretical concepts connected to this study. This will form a basis for the understanding of contemporary research and serve as explanatory background for the analysis of the bitcoin market. After a discussion of relevant literature for each theoretical topic, this will be directly connected to how it applies to the bitcoin market. Hence, the theoretical framework is consistently used as a foundation for the description of the bitcoin market.

3.1 Market Microstructure

Understanding price formation is a fundamental aspect of economics and finance (O’Hara, 1995, pp. 1-3). Such knowledge offers valuable insights for market regulation, the establishment of new trading mechanisms and understanding investor behavior. To put it simply, prices are formed as a result of market supply and investor demand. Attempting to understand what lies behind these variables makes the issue more complicated, but also provides a deeper explanatory value.

Within financial markets, Market Microstructure Theory is used as a theoretical foundation for understanding price formation (Madhavan, 2000, pp. 205-206; O’Hara, 1995, p. 3). It aims to understand how the latent demands of investors leads to new transactions and in this way affect prices and volumes. Further, the specific trading mechanisms of a market is considered a vital aspect of the price formation process (O’Hara, 1995, p. 1). The expression market microstructure was introduced in the 1970’s by Mark Garman (1976) and has become an important concept for descriptions of how economic forces affect trades, quotes and prices (Biais et al., 2005, pp. 217-218). Previously, the functioning of financial markets had been a macroeconomic issue, but these conceptions were now abandoned in favor of a more detailed description of markets (O’Hara, 1995, p. 13).

In contrast to many other financial theories, such as the field of investments, market microstructure assumes that asset prices are exposed to a variety of frictions and may not fully reflect available information (Madhavan, 2000 p. 207). As explained by Biais et al. (2005, p. 218), market microstructure instead focuses on how well short-term prices correspond to their long-run equilibrium prices. Thus, by studying markets in the light of market microstructure, microeconomic theories are confronted with the reality of actual markets. In Garman’s (1976) original article on market microstructure, he proposes an alternative to traditional economic theories of exchange markets. Garman argues that in correlation with an increased trading volume on the worlds markets, their market structure has shifted, displaying the importance of investigating the micro issues of markets. His concept of market microstructure suggests a more dynamic and complicated market structure than assumed in traditional economic theories.

As argued by Madhavan (2000, p. 207), informational economics is an important issue for market microstructure studies. He maintains that the information structure and informational efficiency of a market has important implications for agents’ behavior and
therefore market outcomes. Some studies assume that all traders act competitively (O’Hara, 1995, pp. 89-90). Others argue that the existence of private information ensures that some investors will act strategically and seek to take advantage of this. These strategic models are connected to the rational expectations literature in that investors are assumed to make inferences about each other’s information, which will eventually determine the equilibrium price. This category can further be divided into two parts; those with a focus on informed traders and those that include uninformed traders as well. Within the first, the game takes place between market makers and informed traders, while noise traders base their decisions on reasons that are exogenous to the model (O’Hara, 1995, p. 129). Within the second, uninformed traders who base their strategies on the actions of the informed traders are also included in the game. These are all issues that will be discussed further on in this chapter.

Driven by powerful market changes such as technological innovation, regulatory changes and structural shifts, the last few decades has seen an increase in market microstructure research (Biais et al., 2005, pp. 217-218). The bitcoin market is an excellent example of how technological innovations inspire change in financial markets. Its emergent nature implies that research has not yet investigated the variables of the bitcoin market microstructure and their effects on price formation. Within the confines of this study, market microstructure form a basis for understanding the reasons behind bitcoin investors’ decision to invest.

3.1.2 The Bitcoin Trading Mechanism

As explained by O’Hara (1995, pp. 6-7), the rules that govern the trading mechanism will form the basis for an asset’s price development. Bitcoin has reached a circulation of almost 12.6 million bitcoin (Table 1). The supply function of bitcoin is dependent upon the rate of mining as well as the amount of bitcoin owners are willing to sell (Chowdhury, 2014, p. 3; ECB, 2012, p. 24). The fixed final supply of 21 million BTC (Brito & Castillo, 2013, p. 7) implies that more than half of the bitcoins that will ever be produced have already been mined. The total market capitalization of these bitcoins have reached a value of over 5,421 million USD or 4,346 million EUR (Table 1). Thus, the market has grown substantially, considering that bitcoin was created as recently as 2009 (Nakamoto, 2008). The first bitcoin exchange opened in 2010 (History of Bitcoin, 2014), but its use as a tradable investment did not take off substantially until 2013 (Kitco News, 2013). The market is thus still in an emerging stage. Nevertheless, it has reached a total daily trading volume of about 68,000 trades (Table 1). Demonstrating the development of the bitcoin market, the first bitcoin derivative was recently constructed (Miedema, 2014). A company called TeraExchange constructed a bilateral private swap in March 2014.

<table>
<thead>
<tr>
<th>Total BTC in Circulation</th>
<th>12,599,050 BTC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transactions per 24 h</td>
<td>68,397</td>
</tr>
<tr>
<td>Market Cap USD</td>
<td>5,421,457,567 USD</td>
</tr>
<tr>
<td>Market Cap EUR</td>
<td>4,346,680,875 EUR</td>
</tr>
<tr>
<td>Market Cap PLN</td>
<td>17,953,681,875 PLN</td>
</tr>
</tbody>
</table>

Table 1: The bitcoin network economy (Bitcoincharts, 2014a)
Bitcoin is traded continuously throughout the year without interruption for nights or holidays (Bitcoin Project, 2014a). It has low or zero transaction fees depending upon the trade. Through the use of digital wallets, money can quickly be transferred without the involvement of banks or other intermediaries. Through an anonymous network, bitcoin is controlled digitally and cryptographically. Hence, bitcoin can be traded easily, simply and anonymously.

Bitcoin trades on numerous exchanges over the world against many different currencies (Bitcoincharts, 2014c). Many of these exchanges trade only in bitcoin (e.g. Bitstamp, 2014; BTC-e, 2014), while others also exchange other digital currencies such as litecoins (e.g. Bitfinex, 2014; Kraken, 2014). The largest exchanges today are Bitstamp, Bitfinex and BTC-e (see Table 2). On these three exchanges BTC can be traded for USD, which is the principal currency traded for bitcoin, pertaining 85% of the market (Bitcoincharts, 2014d).

As demonstrated by Table 2 below, the bitcoin exchange rates offered for the same currency on different exchanges varies substantially. E.g. while Bitstamp 30 day average price was BTC/USD558, the Bitfinex price was during the same period BTC/USD549.83. In theory, such deviations offer arbitrage opportunities (Shleifer, 2000, p. 3). It has however been proved difficult to take advantage of such arbitrage on the bitcoin market (Wong, 2014). E.g. between August 2013 and February 2014, the price on the former leading bitcoin exchange Mt.Gox consistently displayed a substantial deviation from the prices on other exchanges. On January 28th 2014, the spread between Mt.Gox and BTC-e was as large as 26%. Nevertheless, in practice, bitcoin withdrawal from the Mt.Gox exchange was suspended due to technological difficulties, ensuring that an arbitrage strategy would likely have been unsuccessful.

<table>
<thead>
<tr>
<th>Market</th>
<th>Currency</th>
<th>30 day Volume BTC</th>
<th>30 day Average Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bitstamp</td>
<td>USD</td>
<td>479,475.82</td>
<td>558.00 USD</td>
</tr>
<tr>
<td>Bitfinex</td>
<td>USD</td>
<td>381,620.96</td>
<td>549.83 USD</td>
</tr>
<tr>
<td>BTC-e</td>
<td>USD</td>
<td>234,231.39</td>
<td>548.94 USD</td>
</tr>
<tr>
<td>BTC China</td>
<td>CNY</td>
<td>152,549.67</td>
<td>3484.60 CNY</td>
</tr>
<tr>
<td>LakeBTC.com</td>
<td>USD</td>
<td>93,337.63</td>
<td>554.86 USD</td>
</tr>
<tr>
<td>Asia Nexgen</td>
<td>HKD</td>
<td>30,359.82</td>
<td>4700.66 HKD</td>
</tr>
<tr>
<td>Kraken</td>
<td>EUR</td>
<td>26,061.76</td>
<td>415.24 EUR</td>
</tr>
<tr>
<td>LocalBitcoin</td>
<td>USD</td>
<td>13,487.58</td>
<td>637.35 USD</td>
</tr>
<tr>
<td>bitcoin.de</td>
<td>EUR</td>
<td>13,330.53</td>
<td>419.81 EUR</td>
</tr>
<tr>
<td>Bitcurex</td>
<td>PLN</td>
<td>10,400.09</td>
<td>2076.44 PLN</td>
</tr>
</tbody>
</table>

Table 2: The largest bitcoin markets (Bitcoincharts, 2014c)

3.1.3 The Bitcoin Investor
The bitcoin market has no central foundation in any one country and its value is not fixed to gold or any other commodity (Grinberg, 2011, p. 160). Consequently, it has no macroeconomic fundamentals determining its value (ECB, 2012, p. 3; Kristoufek, 2013, p. 1). Instead, the bitcoin value is completely based on supply and demand, which is determined on an open market (Brière et al., 2013, p. 3; Brito & Castillo, 2013, p. 4). As
mentioned above, the total supply of bitcoin is fixed, but the daily supply traded varies from day to day in accordance with investors’ willingness to trade. Concerning the demand function of BTC, it varies in connection with investors’ faith in its perpetual growth (ECB, 2012, p. 3; Kristoufek, 2013, p. 1). Thus, bitcoin investors and the drivers of investor demand are highly important for understanding BTC price volatility.

The bitcoin market has been said to be dominated by short-term investors, trend chasers, noise traders and speculators (Kristoufek, 2013, p. 1). Thus, mainly individual, unsophisticated traders participate in the market. However, as the market continues to grow, more and more institutional investors are displaying interest (Bloomberg News, 2013; Matonis, 2013). For this reason, the cognitive and behavioral aspects of bitcoin investors are of great importance for those wanting to understand this market. As stated by Grinberg (2011, p. 165), bitcoin is highly susceptible to bubbles and loss of investor confidence ensuring that demand collapses relative to supply.

3.2 The Efficient Market Hypothesis

The Efficient Market Hypothesis, EMH, is a basic building block for much of modern finance (Malkiel, 2003, p. 430), and its presence poses significant implications regarding the relationship between information and asset prices (Fama, 1970). Therefore, it is an important starting point for our research. The EMH assumes that market equilibrium can be stated in terms of expected returns and that information is fully utilized by the market (Fama, 1970, p. 385). The expected utility theory and the idea of rational investors provide a base for the theory (Ritter, 2003, pp. 429-430). Even though the rationality of all investors is not necessary, it does require markets to be rational and able to make unbiased forecasts of the future. The EMH assumes that the market has properties of a fair game (Fama, 1970, p. 385). The presence of sophisticated arbitrageurs ensures that prices will never divert significantly from its fundamental value (Shleifer, 2000, p. 4). In this way, the EMH operates under the condition of a zero profit competitive equilibrium in a speculative and uncertain market (Jensen, 1978, p. 96).

The EMH is closely related to the random walk theory, which assumes that prices follow a random walk ensuring that tomorrow’s price is unrelated to the price today (Malkiel, 2003, p. 59). Further, new information is generally unpredictable and as prices reflect all known information, it implies that also prices are unpredictable. As explained by Malkiel (2003, pp. 59-60), the fact that new information spreads quickly and is instantaneously incorporated into prices ensures that neither technical nor fundamental analysis can be used to predict future prices. Thus, without accepting above-average risks, investors cannot earn above-average returns. Nevertheless, even though the release of new information is the cause of price changes, the no-arbitrage condition ensures that this new information cannot be used to infer predictable future returns (Shleifer, 2000, p. 5).

3.2.1 Three Forms of Efficient Markets

Fama (1970, pp. 414-415) identifies three forms of efficient markets that have been extensively tested through research. The main difference between them is how they define the information set $\theta_t$, which is used to test the strength of efficiency (Jensen, 1978, p. 97).
The strong-form of market efficiency states that prices reflect all available information and that no one has monopolistic access to information relevant for price formation (Fama, 1970, p. 414). Thus, the information set $\theta_t$ represents all known information at time $t$ (Jensen, 1978, p. 97).

The semi-strong-form asserts that all publically available information, $\theta_t$, that is available at time $t$, is included in prices (Fama, 1970, p. 414; Jensen, 1978, p. 97). Thus, it is less restrictive and empirical evidence have been found in support of such an efficient market. Therefore, it has become an accepted paradigm in literature. The main problem with this form of EMH is the difficulty of defining what pertains ‘all publically available information’.

Finally, in the weak-form of market efficiency, the information that is assumed to be incorporated into prices is the historical sequences of price or return (Fama, 1970, p. 414). Thus, the information set $\theta_t$ is stated by historical prices at time $t$ (Jensen, 1978, p. 97). The most extensive research and support in favor of the EMH can be found through such weak-form tests (Fama, 1970, p. 414).

3.2.2 Anomalies
Throughout the 1980s, the EMH was increasingly questioned as further anomalies were discovered (Shiller, 2003, p. 84). Lux (1995, p. 881) noted that empirical research has shown that stock prices exhibit more volatility than fundamentals or expected returns. This suggests that such excess volatility can give rise to predictability of returns (West, 1988). Malkiel (2003) argue for the existence of momentum in short-term stock prices, mean-return reversals over longer time periods and seasonal or day-of-the-week patterns. Nevertheless, he states that these anomalies are difficult to take advantage of as patterns disappear as they become public and that they are not dependable from period to period.

The most troublesome anomaly has proven to be excess price volatility, as the others could partly be explained by the efficient market hypothesis (Shiller, 2003, p. 84). The consistent failure to prove the EMH implies the presence of noise as a disturbance to fully efficient markets. Therefore, West (1988) argues that other models where the rational investor is not in focus are necessary. Therefore, this theoretical framework will discuss and contrast such theories to the Efficient Market Hypothesis. As the bitcoin price has experienced such extreme volatility, such theories can provide valuable insights into why this has occurred.

3.2.3 The Efficiency of the Bitcoin Market
The EMH states that unless the reason for changes in supply and demand of an asset is accompanied by news about a change of its fundamental value, there should be no effect on price (Shleifer, 2000, p. 5). As the bitcoin price is not based on any fundamentals, it has implications for the applicability of the EMH on the bitcoin market. Nevertheless, the BTC price has experienced a great deal of volatility (see Figure 1), and it is thus interesting to discuss its origin. However, this study does not set out to test the market efficiency of the bitcoin market per se. Regardless, the EMH forms a theoretical basis for understanding how information is incorporated into prices, and is therefore a prerequisite for any analysis of the underlying causes of asset price volatility.
3.3 Behavioral Finance

Trade occurs due to investor’s varying preferences, beliefs or endowments (Grossman & Stiglitz, 1980 p. 402). As discussed in the previous section, economists traditionally assumed that investors are rational in their investment decisions and that markets efficiently display these views (e.g. Fama, 1970). However, persistent diversions from the random walk and the EMH have caused researchers to search for other explanations of price formation (Lux, 1995; Ritter, 2003 p. 429). This has led to the emergence of behavioral finance, which is built upon concepts of cognitive psychology and limits to arbitrage (Ritter, 2003 pp. 429-430). Preferences or mistaken beliefs ensure that not all investors are rational, thus creating informationally inefficient markets. Consequently, behavioral finance highlights the importance of studying the underlying reasons behind investors’ decision to trade. In relation to this study, behavioral finance can complement market microstructure and EMH by offering deeper insights into the origins of investor demand.

The origins of behavioral finance can be traced back to Simon (1955) and Tversky and Kahneman (1974; 1979; 1986). Tversky and Kahneman (1986 p. 273) state that the simplicity, scope and power of the rational choice model is difficult for alternative models to match. However, they argue that the additions of psychological considerations are necessary despite their mathematical and normative complications. Similarly, Ritter (2003, p. 437) argue that behavioral finance will increasingly become part of mainstream financial research and application. He claims that it should not be treated as a separate discipline, but instead be considered an added source of information for interpreting financial markets. Congruently, Wilkinson and Klaes (2012, p. 3) state that behavioral economics merely seek to add to the framework of traditional economic theories. With this in mind, behavioral considerations should be taken into account when analyzing the bitcoin market.

3.3.1 Decision-Making under Risk and Uncertainty

When investors evaluate an investment opportunity, “they know neither the future realization of the asset’s payoff (risk), nor the probability of it occurring (ambiguity)” (Illeditsch, 2011 p. 2213). Under such conditions, investors cannot make logical and rational assessments of chance (Tversky & Kahneman, 1986, p. 251). Therefore, Kahneman and Tversky (1979; 1986 p. 272) developed Prospect Theory where they suggest that the framing of the situation will affect the investors ability to behave rationally and make utility maximizing decisions. Similarly, Illeditsch (2011) show that investors generally wish to avoid ambiguity and by hedging against such situations, they create portfolio inertia and excess volatility. Connecting these conclusions, in nontransparent, ambiguous situations, investors make non-rational decisions. However, when the situation is clear and transparent, by having access to all information, investors are able to make informed and rational choices.

Within prospect theory, the choice process consists of two phases (Kahneman & Tversky, 1979, p. 274). In the first phase, the available prospects are subject to an initial assessment and edited into simplified versions that are more easily analyzed. This procedure of framing the prospects within the boundaries of its acts, contingencies and outcomes varies from investor to investor based upon their norms, habits and expectancies (Tversky & Kahneman, 1986, p. 257). In the second phase, these now framed prospects are evaluated.
and the prospect offering the highest value is chosen. This final choice will stem from the belief that one prospect dominates the other, or through a comparison of their monetary values. Prospect theory states that differences in investor preferences stems from the first phase of decision-making (Kahneman & Tversky, 1979, p. 275). Thus, the final choice will depend upon how the prospects have been framed.

3.3.2 Bounded Rationality and Investor Sentiment
Due to the presence of ambiguity in financial markets it is unlikely that perfect rationality persist in most real life situations (Illeditsch, 2011, p. 2213; Wilkinson & Klaes, 2012, p. 117). The work of Simon (1955) forms a basis for the idea of bounded investor rationality. When faced with uncertainty, the decision-making process is influenced by investors using simple rules of thumb, i.e. heuristics, which create biases in conclusions (Wilkinson & Klaes, 2012, pp. 8, 117). When investor sentiment takes precedence over facts in this way, decision-making is generally merely satisfying and not optimal (Baker & Wurgler, 2007, p. 129; Wilkinson & Klaes, 2012, p. 8).

In the 1970s, Tversky and Kahneman (1974) identified cognitive biases that stem from the reliance on judgmental heuristics. These rules of thumb are often highly useful and can produce successful predictions (Tversky & Kahneman, 1974, p. 1130). Nonetheless, they occasionally lead to errors in judgment, which is problematic, as people generally do not detect their own biases. Representativeness heuristics is a common problem among investors. (Tversky & Kahneman, 1974, p. 1124). This explains how people often place to little weight on long-term averages and instead focus too much on recent experience when analyzing the probability of a prospect (Ritter, 2003, p. 432). This causes biases e.g. due to a failure to consider prior probability of outcomes, a lack of understanding that sample size matters for how representative the sample size is for a population, and a misconception of chance (Tversky & Kahneman, 1974, pp. 1124-1125). Availability heuristics ensures that frequently occurring events are often recalled better and faster (Tversky & Kahneman, 1974 pp. 1127-1128). Consequently, investors place greater weight on many reoccurring small events instead of focusing on fewer large ones. They also tend to imagine correlations between events that do not exist. Anchoring heuristics is a phenomenon describing how people chose an initial value as a starting point for decision-making (Tversky & Kahneman, 1974, p. 1128). This initial value is often insufficiently adjusted to be representative. Subsequently there is a risk of conservatism bias where the investor relies too much on the past (Ritter, 2003, p. 432).

In studies of investor sentiment, it has been shown that the majority of people overreact to unexpected and dramatic news events causing prices to temporarily diverge from their fundamental values (De Bondt & Thaler, 1987, p. 557; De Bondt & Thaler, 1985, p. 804). This further implies a tendency to undervalue base rate data and averages. When a consistent pattern of news occur, e.g. several positive news announcements over a longer period, investors take these events as representative of future price direction. Stambaugh et al. (2012, p. 297) further found that sentiment has an asymmetric effect on prices. High sentiment, i.e. optimism, more often leads to overpricing, than low sentiment, i.e. pessimism, leads to underpricing. Accordingly, he assert that this result provide evidence that mispricing can at least to some extent explain the occurrence of market anomalies.
(Stambaugh et al., 2012, p. 301). In addition, Baker and Wurgler (2007, p. 130) identifies low capitalization, young, high-volatility stocks that are more likely to be subject to financial distress, to be the most affected by sentiment. By taking advantage of this knowledge, sophisticated investors can earn excessive returns and thus beat the market.

### 3.3.4 Bubbles, Fads and Herd Behavior

In history, financial markets have experienced several bubbles and volatility bursts such as the stock market crash in October 1989 (Schwert, 1990, p. 23), the internet bubble in the late 1990s (Scheinkman & Xiong, 2003, p. 1206) and the recent financial crisis (Mendel & Shleifer, 2010, p. 303). Fama (1965, p. 38) identifies a bubble as a period where the price level significantly deviates from its intrinsic value. This is a result of overconfident investors with heterogeneous beliefs (Scheinkman & Xiong, 2003, p. 1208). Their speculative trading creates a bubble, which is often accompanied by high prices, high volatility and high trading volume (Scheinkman & Xiong, 2003, p. 1184). The reasons behind these heterogeneous beliefs differ and are often debated (Schwert, 1990, p. 30).

As stated by Lux (1995, p. 882), not every investor is fully informed about market fundamentals. This opens up for the idea that non-sophisticated traders could form expectations based on the behavior and expectations of others. Accordingly, opinions and behavior can be contagious resulting in uniform herding behavior. Schwert (1990, p. 30) argues that when new information suggesting the underpricing or overpricing of an asset is released, this might induce investors to make the same inferences about its future price, and thus buy or sell accordingly. As suggested by Scheinkman and Xiong (2003, p. 1186), the overestimation of the informativeness of this new information is what instigates a trading frenzy and eventually creates a bubble.

In addition, investors often base their trading decisions upon the beliefs of others by watching market price changes (Schwert, 1990, p. 30). In this way, price movements can be socially transmitted creating a bubble or a contagiously volatile price (Topol, 1991, p. 798). Mimetic contagion occur as investors adjust their prices to the average prices of the nearest buyers and sellers. Prices continues to rise until investor behavior become uncorrelated again and the bubble bursts (Topol, 1991, p. 788). Investors believing in persistent market prices will at the indication of a price decline begin to sell off their shares (Schwert, 1990, p. 30). As other investors notice this occurrence, they may believe that these investors hold information they do not and consequently decide to sell as well. Thus, there is a learning component in securities markets. Investors learn from the behavior of others to which they adjust their own behavior.

In the model by Bikhchandani et al. (1992, p. 1016), even small amounts of information can cause cascades in investor behavior. Their term for such behavior is informational cascades. The model suggest that investor behavior can be fragile and idiosyncratic, implying a potential for systematic conformity among investors. They argue that fads, i.e. drastic changes in mass behavior for no apparent reason, can occur as a result of minor changes in the underlying value of alternative decisions (Bikhchandani et al., 1992, p. 995). Thus, even if new information only convinces a few investors to take a certain action, others may imitate this action thus aggregating the information creating an informational
cascade (Bikhchandani et al., 1992, p. 1006). This corresponds to the discussion by West (1988). In a review of studies on excess volatility, he discuss the possibility that fads and behavioral aspects might be necessary to explain the occurrence of bubbles. He suggest that in such a model, naïve and irrational traders are the sources behind excessive volatility as they overreact to news (West, 1988, pp. 652-653).

3.3.5 The Behavior of the Bitcoin Investor
The emergent nature and unique characteristics of the bitcoin market separates it from other more developed financial markets. As few studies have examined these intricacies, the bitcoin market is rather ambiguous. The anonymity, lack of regulation and high risks (Bitcoin Project, 2014a; T. Moore & Christin, 2013; Rogojanu & Badea, 2014, p. 107) further increases the uncertainty for the investor. Therefore, theories that take into account the presence of irrational investors subject to heuristics, biases and investor sentiment (e.g. Barberis et al., 1998; Simon, 1955; Tversky & Kahneman, 1974) are important for an analysis of bitcoin price volatility. Thus, as suggested by prospect theory (Kahneman & Tversky, 1979), the importance of framing bitcoin as a potential investment opportunity becomes vital for the final choice of investors decision to trade. Further, as argued by Baker and Wurgler (2007, p. 130), additional characteristics displayed by the bitcoin market such as its highly volatile price and low market capitalization (see Figure 1 & Table 1), suggest an increased sensitivity to investor sentiment.

The BTC price have been said to exhibit bubble behavior on several occasions. An example of such a period is January 2014, which was highlighted by Robert Shiller (Balibouse, 2014). Researchers have connected such occurrences to informational events (e.g. Brière et al., 2013). In the words of Scheinkman and Xiong (2003, p. 1186), this is likely due to unsophisticated traders overreacting to new information. As Bikhchandani et al. (1992, pp. 1006, 1016) explains, it is only necessary for a few investors to react to the new information for it to trigger an aggregate informational cascade. As the bitcoin market still consists mainly of unsophisticated traders (Kristoufek, 2013, p. 1), it appears likely that they can trigger bubble behavior in the bitcoin price. Further, mimetic contagion (Topol, 1991, p. 798), fads (Bikhchandani et al., 1992, p. 995) and herding behavior (Lux, 1995, p. 882) can be important explanatory reasons for BTC price volatility.

3.4 Sources of Information
Investors gather information from different sources to reduce the uncertainty in their investments (Fama et al., 1969, p. 2). Via news and market data they identify relevant strands of information that are put together to provide a fuller picture of the security they want to trade (Bikhchandani et al., 1992; Fama et al., 1969; Schwert, 1990). This section provides an overview of such information. As already stated, the bitcoin investor appear to be information sensitive. Hence, it is important to consider where this information comes from in order to be able to investigate its potential impact on price.

3.4.1 Individual Asset Information
An individual security and its market offer several sources of information. A basic and often used example, is that of historical prices (Fama, 1965, p. 34; Malkiel, 2003, p. 59).
By observing historical prices investors can hope to gain valuable knowledge and make inferences about future prices. Nevertheless, theoretical models such as the Efficient Market Hypothesis and the Random Walk theory argues that there is no predictive power in historical prices and thus suggest that such analysis is not helpful for investor decision making. Nevertheless, Topol (1991, p. 798) suggest that due to investors incomplete information set, watching price movements is a valuable source of information. In this way, investors can make inferences as to other investors’ beliefs. As explained previously, this can result in socially transmitted mimetic contagion that could potentially lead to a bubble or excessive price volatility.

Trading volume can also act as an additional source of information to investors (O’Hara, 1995, p. 161). However, researchers have struggled to identify exactly what this type of information offers. It has been suggested that the most likely scenario is that volume acts as an informational source in combination with market prices. However, as stated by Miller (1977, p. 1166), merely observing increased volume can increase a security’s visibility and thus investor attention. Whether this will translate into higher prices is dependent upon the behavioral factors of the investors. There is however, a possibility that some investors will purchase the security solely based upon this information. To test the efficient market hypothesis, Gervais et al. (2001, p. 877) set out to test the predictive power of trading volume. They found that unusually high trading volume does correspond to a return premium on prices. As time and volume increases further, this effect grows larger. Thus, their results offer some predictive power to trading volume.

It is often argued that increased trading volume implies an increased liquidity (O’Hara, 1995, p. 223). However, liquidity is not only affected by the actions of the investors, but also by the trading mechanism itself (O’Hara, 1995, pp. 215-216). By offering investors close to costless transaction, trading is stimulated ensuring a minimum price effect from each individual trade. Market microstructure theory suggest that liquidity is negatively correlated to price volatility (Li & Wu, 2011 p. 1511). Thus, it is suggested that an increased trading volume can cause a decreased volatility in securities prices. Nevertheless, it can also simplify flight of investors, thus creating instability and increased volatility in the market (O’Hara, 1995, p. 216). Similarly, Schwert (1990, p. 30) discuss this connection between volatility and liquidity and argues that a sudden increase in trading volume can create increased volatility as herd behavior is instigated. In this way, liquidity and trading volume are important determinants of investor behavior, although not always straightforward.

Apart from market data such as prices and trading volume, information flow in the news are valuable sources of information for investors. News may present itself in the form of company releases such as earnings and progress reports or it may stem from the occurrence of firms-specific news stories or analysts’ forecasts (Drake et al., 2012; Kalev et al., 2004; Vlastakis & Markellos, 2012). This will be discussed more in depth in the upcoming section concerning information acquisition, but a noteworthy comment is how such information can be linked to trading volume and price formation through the use of the Mixture of Distributions Hypothesis [MDH] (Clark, 1973; Li & Wu, 2011 p. 1511). It states that there is a joint dependence of both trading volume and return volatility on the arrival of new information (Kalev et al., 2004 p. 1446; Vlastakis & Markellos, 2012 p.
1809). In this manner, the arrival of new information can create volatility clustering and persistence. Thus, the MDH describes how the firm-specific informational sources described in this section are all interconnected.

3.4.2 Overall Market Information
The price movements of other markets is a potential source of information for investors. Authors such as Lin et al. (1994) and Bekaert et al. (2005) have shown that return and volatility tend to move between markets and across borders. Thus, volatility in one market may affect others as well, which is often attributed to two reasons. First, as many countries are connected through trade and investments, any changes in the fundamentals of one country will most likely affect other countries as well (Bekaert et al., 2005, p. 39; Lin et al., 1994, p. 536). Thus, keeping up with international events could provide valuable information for investors. Second, correlation in prices could stem from market contagion, suggesting a connection that cannot be explained by market fundamentals (Bekaert et al., 2005, p. 39; Lin et al., 1994, p. 536). There is significant disagreement of exactly what contagion entails, nevertheless there is an element of excess correlation seemingly unexplainable by market data.

Ozoguz (2009, p. 4384) suggest that investors’ uncertainty about the underlying state of the economy can explain market returns. This link between economic recessions and increased volatility has been extensively proven by empirical research (Schwert, 1990, p. 30). In such bad economic times, the level of uncertainty is high which causes investors to demand a higher risk premium (Ozoguz, 2009, p. 4418). Additionally, investors are more sensitive to new information, which creates increased asset price volatility. Baker and Wurgler (2007, p. 129) suggest that the occurrence of stock market events such as the Great Crash in 1929 and the Dot.com bubble in the 1990s can be explained by aggregate investor sentiment. Their model is based upon a top-down approach where macroeconomic occurrences and aggregate investor sentiment explain the return on the overall market as well as for individual stocks (Baker & Wurgler, 2007, p. 130). Thus, investors implement their beliefs about individual stocks and markets based on their perception of the overall market. As already explained in the section about investor sentiment, young and highly volatile assets are extra susceptible to such biases and valuation mistakes.

3.4.3 Bitcoin Informational Sources
The bitcoin investor can gather information from many different sources. It has already been argued above that understanding the informational aspect of bitcoin price formation is important due to its lack of fundamental value. Further, the ambiguity of the bitcoin market suggests that the bitcoin investor may be subject to a higher degree of incomplete information than other markets. Therefore, expanding the information set through observing prices (Topol, 1991, p. 798) can be valuable for the bitcoin investor. Further, the argument of Miller (1977, p. 1166) that increased trade volume can increase investor attention and thus trigger additional trading, as well as the argument by Gervais et al. (2001, p. 877) that it creates a return premium appear reasonable to apply to the bitcoin market. Apart from viewing historical prices and trade volume on the disperse websites of individual exchanges (e.g. Bitstamp, 2014; BTC-e, 2014), a centralized website called
Bitcoincharts.com (2014e) has emerged. On this site, an overview of price data, trade volume and bitcoin facts are presented.

The Bitcoin Foundation (2014) is an organization created to develop and support the bitcoin system. They sponsor the website bitcoin.org, which seeks to explain how bitcoin and its markets operate (Bitcoin Project, 2014b). In addition, several online newspapers are dedicated to presenting the latest news about bitcoin, e.g. Bitcoin Magazine (2014) and CoinDesk (2014). Creating more validity to the information pertained, an investor could also seek out more traditional sources of information such as The Economist and The Guardian that have on many occasions published stories about bitcoin (e.g. Arthur, 2013; Rushe, 2013; The Economist, 2013, 2014).

Even though theory suggest that prices are correlated between different markets (Bekaert et al., 2005; Lin et al., 1994), research under way suggest that this might not be the case for bitcoin (Brière et al., 2013; Chowdhury, 2014). However, this will be discussed more in depth in Chapter 4. At this point, it is however noteworthy to comment that general market information can still be valuable in the sense that this lack of correlation can prove to be useful when the rest of the market is experiencing a downturn (Brière et al., 2013; Chowdhury, 2014).

3.5 Identifying and Acquiring Relevant Information

Authors such as Black (1986) argues that one must distinguish real information from that of noise. Noise may inspire trading from uninformed investors and thus increase trading volume and liquidity, but it can also be a source of market inefficiencies. The amount of information and noise in the market is so extensive that investors may find it difficult to pay attention to everything (Barber & Odean, 2008, p. 786). As interest in bitcoin has increased, so has the amount of information presented. Thus, an evaluation of the bitcoin investor’s ability to identify and acquire the relevant information is important for the determination of how information actually affect the demand for bitcoin.

3.5.1 Noise vs. Information

Fischer Black (1986) refers to information as the source of profitable investment decisions, while he accredits noise to be all those small events that can cause investors to make incorrect decisions. De Bondt and Thaler (1989, p. 190) defines noise as incorrect conditional probability assessments. Black states that noise is what keeps markets somewhat inefficient, while it at the same time keeps investors from taking advantage of those inefficiencies (Black, 1986, p. 529). In other words, noise makes investor observations imperfect and prevents a full understanding of the market. A result of this is excessively volatile market prices, which may divert from their fundamental values (De Long et al., 1990, p. 706). Nevertheless, noise trading is what makes financial markets possible since it allows for trading in individual assets (Black, 1986, pp. 530-532). If investors all had the same information, no one would be willing to take the losing side. Noise traders would generally be better off not trading and will often lose money as a group. Nevertheless, their existence create the incentives for other investors to seek out costly information in order to earn positive returns. In a study of the Mixture of Distributions Hypothesis [MDH], Li and Wu (2011, p. 1511) asserts that uninformed
trading, i.e. noise trading, increases trading volume and thus creates market liquidity, which reduce volatility.

Black (1986, p. 530-532) argues that even though noise trading incorporates the noise into market prices, they will eventually move back toward their fundamental value. Similarly, Fama (1965, p. 38) asserts that even when prices temporarily display bubble behavior, sophisticated traders will ensure that they have no significant long-term impact on price. He takes this as evidence in favor of stock prices following a random walk (Fama, 1965, p. 98). However, De Bondt and Thaler (1989, p. 190), argues that this implies that prices do not follow a random walk and can to some extent be predicted. Further, De Long et al. (1990, p. 735) suggest that some efficient market anomalies such as excess volatility and mean reversion in stock prices, can be explained by noise trader risk. Since noise trader actions are unpredictable, it is risky for rational investors to take advantage of these anomalies, which reduces the attractiveness of arbitrage. Thus, even if prices diverge from the random walk and the market is not entirely informationally efficient, the benefits for the informed trader are low. Nevertheless, recent studies such as Barber et al. (2009), and Mendel and Shleifer (2010) seem to argue in favor of considering the characteristics of, and actions taken by, noise traders.

Black (1986) did not offer an identity of noise traders, while Barber et al. (2009) identifies noise traders as individual investors. They argue that individual investors trading behavior is systematic and highly affected by noise. As the individuals’ buying and selling decisions are correlated to other individuals’ decisions and they cumulate over time, individual investors can, as a group, have significant effects on asset prices. Thus, the study emphasizes the importance of the representativeness heuristic, the disposition effect and limited attention for noise trading.

### 3.5.2 Investment Visibility and Investor Attention

As stated by Miller (1977, p. 1164), the decision of an investor to purchase a security initially stems from the likelihood that he will investigate it in the first place. Since investor attention is a scarce resource (Barber & Odean, 2008, p. 786), the factors creating visibility of individual investment opportunities are of great interest. Miller’s (1977, pp. 1165-1166) discussion of stock visibility recognized that some securities are naturally prone to high visibility. This is due to the advertisement and usage of the output produced by the company in question. He further argues that instances of high publicity and increased trading volume can also increase investor attention and possibly instigate additional trading. Miller does however state that this does not necessarily have to be the case. The information presented must also be interpreted by the investor and is thus dependent upon many factors in itself. Thus, the mere observance of increased trading volume or the publicity attained does not instigate increased trading and prices by themselves.

Barber and Odean (2008, pp. 788-789) argues that professional investors are the least affected by attention. Their study found that individual, non-professional investors are often net buyers on high-attention days, and professional investors thus often take the selling position on such days. When investors wish to purchase new stocks, the computer is often their source of information (Barber & Odean, 2008, p. 813). Stocks that are displayed in the
news, exhibits excessive trading volume or have experienced extreme positive or negative results the previous day, seem to be the ones grabbing the attention of these individual investors. Of course, not all such stocks are purchased, but the likelihood increases. As explained by Da et al. (2011, p. 1471), investor attention is a necessary condition for strong investor sentiment. Thus, increased investor attention is a potential source of higher investor sentiment, especially when the information is in fact noise. However, investor attention can also lead to quicker and more appropriate incorporation of actual information.

### 3.5.3 Information Demand

As discussed above, there is a strong theoretical link between information and financial markets. Nevertheless, information flow is a difficult variable to observe and thus identify (Vlastakis & Markellos, 2012, p. 1809). Therefore, a proxy is required for studies into the informational effect on prices. As Barber and Odean (2008, p. 813) suggests, the computer is often the source of information for investors. In the past, studies have often been built on investors’ ability to pay attention to all information provided for them. Thus, they have focused on indirect proxies for investor attention such as turnover, extreme returns, news and advertising expense (Da et al., 2011, p. 1462). In this way, they have largely focused on information supply (Vlastakis & Markellos, 2012, p. 1809).

Drake et al. (2012, p. 1002) argues that the mere fact that information is available does not translate into an ability to absorb all this information. In addition, Grossman and Stiglitz (1980, p. 405) states that obtaining all available information is too costly for investors. Thus, prices cannot fully reflect the supply of information. The conflict between incentives to acquire information, i.e. information demand, and the information provided, i.e. information supply, ensures that some investors can benefit from knowledge. Therefore, they propose a model with what they call ‘an equilibrium degree of disequilibrium’ (Grossman & Stiglitz, 1980, p. 393). Thus, by suggesting that the market under certain conditions reflect the information known to the informed trader, they attempt to redefine the idea of efficient markets (Grossman & Stiglitz, 1980, pp. 404-405). The model posits that when a large degree of noise is present in the market, the demand for information and thus the amount of informed traders will increase. This will eventually cause the price to better reflect the available information.

The cost of acquiring information has reduced since the Grossman and Stiglitz (1980) model was created. Moscarini and Smith (2002, pp. 2351-2352) states that the rise of internet ensures that there also exists inexpensive information units. They suggest that when the cost of additional information is small relative to the payoff stakes, more information is demanded. Thus, since searches on the internet is a relatively inexpensive way to gather information, it is a useful tool displaying information demand (Da et al., 2011, p. 1462; Drake et al., 2012, p. 1003; Vlastakis & Markellos, 2012, p. 1810). The research by Moscarini and Smith (2002) further states that information demand reflects how investors value the information supply. As described by Vlastakis and Markellos (2012, p. 1810), when a significant event occurs, investors will demand more information in an attempt to reduce the ambiguity caused by the event. Similarly, once they have understood the effects of this event, information demand will reduce again.
3.5.4 Information Relevant for the Bitcoin Investment

The large presence of uninformed noise traders in the bitcoin market (Kristoufek, 2013, p. 1) implies that their incorrect probability assessments (De Bondt & Thaler, 1989, p. 190) could explain the excessive bitcoin price volatility (De Long et al., 1990, p. 706). The presence of noise traders further increase market liquidity (Black, 1986, p. 530), which could offer an explanation for the rapid rise in bitcoin trading volume (Table 1) since its introduction on the market in 2010 (History of Bitcoin, 2014). As stated by Li and Wu (2011, p. 1511), the Mixture of Distribution Hypothesis suggest that a large presence of noise traders should increase liquidity and thus reduce volatility. This would suggest that as the bitcoin market continues to grow; its price should become less volatile and susceptible to the effects of noise traders.

Barber et al. (2009) identified noise traders as individual investors, which today pertains the larger share of bitcoin investors (Bloomberg News, 2013; Kristoufek, 2013; Matonis, 2013). Nevertheless, institutional investors are rising in presence. Theory suggest that they could reduce the impact of noise traders as more sophisticated traders would take advantage of any arbitrage opportunities and effectively reducing volatility (Fama, 1965, p. 38). In relation to the research by Barber and Odean (2008, pp. 788-789), this further suggest that the limits of investor attention are especially important to consider for a market like bitcoin. Therefore, it might be even more important to focus on information demand instead of information supply for the bitcoin market than what is suggested by Vlastakis and Markellos (2012, p. 1810) and Da et al. (2011, p. 1462). However, as suggested by Grossman and Stiglitz (1980, p. 405), this will reduce in importance as the bitcoin market continues to develop.

3.6 Chapter Summary

As market microstructure theory forms a basis for price formation, we have used its insights to describe the bitcoin trading mechanism and the bitcoin investor. To provide a more thorough understanding, we have further built the chapter upon various forms of information and explained how this information could affect the demand for bitcoin. Some economists argue that the assimilation and interpretation of information is an individual and independent process (Hirshleifer, 2001, p. 1540). Thus, any investor biases and limits of attention should cancel each other out resulting in a market where information is automatically incorporated into prices (e.g. Fama, 1970). Others argue that the cognitive and behavioural aspects of individual investors are similar for all investors and creates systematic biases (Hirshleifer, 2001, p. 1540) that must be understood for the market to be understood (e.g. Kahneman & Tversky, 1979). We argue that the unique characteristics of the bitcoin market ensures that considering information flow, market characteristics and investor behaviour is of extra importance. This line of argument is followed throughout the chapter, offering a foundation for the identification of the variables to study in this research.
4. Previous Research

To bring the extensive theoretical framework presented above into a narrower and contemporary perspective, recent empirical research will be presented in this chapter. As research concerning bitcoin from a financial perspective, and in particular with a focus on its price volatility, is severely limited, the research discussed in this chapter will include work in progress papers. However, when doing so, it will be explicitly stated. Bitcoin is a new phenomenon and research has not yet had time to investigate the intricacies of this market. However, all knowledge must begin somewhere and by examining both published and ongoing studies with a critical mindset, this chapter can offer a fuller picture of the bitcoin market and its potential for continued research.

4.1 An Emerging and Risky Market

The bitcoin market is still in an emerging stage and traded on many different exchanges (T. Moore, 2013, p. 148; T. Moore & Christin, 2013, p. 7). This ensures a low trading volume on each exchange, which posits a high risk for investors. Moore and Christin (2013, p. 7) found that maintaining a high trading volume increases the potential of an individual bitcoin exchange to survive. Nevertheless, increased size also makes them more susceptible to hacks and other criminal actions. As many as 45% of bitcoin exchanges fail due to thefts and hacks, pertaining a real risk of investors not being reimbursed for their lost funds (Moore & Christin, 2013, p. 3). Thus, the exchange risk is substantial for all bitcoin investors. As will be discussed further below, evidence suggests that the BTC price has experienced additional volatility when an exchange experience problems with criminal activities. Thus, there is a link between lack of liquidity, exchange risk, and eventually price volatility. Consequently, through the route of exchange risk, this corresponds to the theoretical argument of market microstructure that suggest that low liquidity creates increased price volatility (Li & Wu, 2011 p. 1511).

4.2 Growing Investor Acceptance

Moore, (2013, p. 148) argues that the greatest risk bitcoin investors face is the exchange rate risk due to excessive volatility. However, they may have other than the traditional reasons for investing, possibly indicating a willingness to accept higher risks. Moore and Christin (2013, p. 7) suggest that non-economic aspects may play a significant role in the investor’s selection of exchange and they suggest that studying the unique characteristics of bitcoin users and investors is an avenue worth exploring for future work.

Further, the working paper by Garcia et al. (2014, p. 1) maintains that social interaction between market actors are strong potential drivers for the dynamics of the bitcoin economy. They base their work on the ideas of Fama et al. (1969) and Grossman and Stiglitz (1976) concerning the ability of economic agents to quickly integrate common sources of information to determine the price of a good, including the information pertained by the price itself. Another source of inspiration for Garcia et al. (2014, p. 2) was the work of Bikhchandani et al. (1992) about how purely social information can, e.g. through investor imitation, influence the price formation process. Garcia et al. (2014) found that increased
popularity of bitcoin leads to higher internet search volumes, which further creates additional social media attention. In turn, this leads to an increased user base where more people purchase bitcoin, which will raise the price. This social feedback loop is complete when the increased price circle back to raise additional popularity. Hence, corresponding with increased public acceptance and new users, the bitcoin economy grows and price surges take place (Garcia et al., 2014, p. 11). As argued by Schwert (1990, p. 30) increased liquidity generally results in reduced volatility. Nevertheless, when new information arrives that implies that the price is either too low or too high, it can trigger bubble behavior as many investors seek to take the same side of the transaction. In other words, the information spurring increased liquidity and/or the mere fact that there is an increased liquidity seem to correlate with bitcoin price surges.

Chowdhury & Mendelson (2013, p. 10) argue that a lack of wide acceptance among investors is the reason for bitcoin’s lack of liquidity. Their working paper on bitcoins monetary and financial potential does however predict an increased acceptance within a not so far future. Nevertheless, together with Moore (2013), they suggest that this will only occur if the exchange risk is mitigated by governmental and institutional recognition. However, the continuously increasing trading volume (Bitcoincharts, 2014c) and the increasing user base (Garcia et al., 2014, p. 4) implies an already increasing acceptance.

4.3 The Informational Effect

With a solid base in theory about limited investor attention (Barber & Odean, 2008) and the idea that obtaining all information is too costly for investors (Grossman & Stiglitz, 1980, p. 405), investor demand reflects investors evaluation of the information they are exposed to (Moscarini & Smith, 2002, p. 1810). In their study Da et al. (2011) moves away from the indirect proxies for investor attention, i.e. information supply, to the more direct measure of search frequency on Google though the Search Volume Index (SVI), i.e. investor demand. In their study of the stocks included in the Russell 3000 index, they show that SVI captures the attention of retail investors (noise traders) and that an increase in SVI can predict an increase in stock prices over the next two weeks. Building on this work, Vlastakis and Markellos (2012) also use Google Trends among other variables to explain and model stock price volatility (e.g. by using GARCH(1,1)). In their study they find that information demand on the market level has a significant positive association with market activity. Their results support the Mixture of Distributions Hypothesis (MDH), mentioned in chapter 3, as they conclude that the observed volatility persistence in their stock return data appears to be related to the demand and supply of information.

In order to investigate the informational effect on BTC price volatility, Kristoufek (2013) used search queries on Google and Wikipedia. The study identified a strong correlation between the price of bitcoin and the search queries on both search engines. He found a bidirectional relationship between prices and search queries (Kristoufek, 2013, p. 5). Thus, search queries affect the bitcoin price, but prices also affect search queries of bitcoin. Further, when prices are above trend, increasing interest will continue to raise the price, and when prices are below the trend, a growing interest will ensure a continued price decline. This indicates that investors searching for information about bitcoin after a positive event
incite further price increases. Bitcoins lack of fundamental value suggests that such bubble behavior is expected as the market is dominated by speculation and trend chasing investors.

This fits with the connection made by Brière et al. (2013, p. 4) between events such as the Cyprus crisis and a major theft of BTC to periods of excessive volatility. In addition, Garcia et al. (2014, p. 10) found that when negative events occur, e.g. a security breach, the negative attention ensures a faster reaction on bitcoin information demand and on BTC price. More specifically, their results thus suggest that spikes in information demand are possible early indicators of upcoming price drops.

4.4 The BTC Investment in a Wider Perspective

Ongoing studies by Brière et al. (2013) and Chowdhury (2014) indicate that there is an extremely low correlation between the bitcoin price and that of other assets. Brière et al. (2013) assert that including BTCs in a well-diversified portfolio can significantly improve portfolio performance. Although not suggested for the most risk averse investor, BTC offers diversification benefits for those willing to accept a moderate level of risk. In spite of their short time span of three years, July 2010 – July 2013, their study included two major speculative BTC crises, the first major BTC theft in July 2011 and the Cyprus crisis in April 2013 (Brière et al., 2013, p. 4). They found the average annual return of a BTC investment to be 371% and its annual volatility to be 175% (Brière et al., 2013, p. 5). In addition, a kurtosis of 10.05, approaching that of emerging government bonds, suggests that bitcoin is an extremely risky investment.

By extending the testing period in Brière et al. (2013) until January 2014 to include another extremely volatile period for bitcoin, Chowdhury (2014) confirm their results. The author suggest that the nearly fivefold price increase between early November 2013 and the end of January 2014 is due to investor expectation of bitcoin gaining acceptance as an alternative method of payment. This extreme price increase could explain that this study found even greater average annual return and volatility than Brière et al. (2013), 476% and 258% respectively (Chowdhury, 2014, p. 6). In addition, the kurtosis value is higher at 16.10. Consequently, Chowdhury’s (2014) research documented lower gains from holding BTC than Brière et al. (2013) did. Nevertheless, the results are still positive. With caution, Brière et al. (2013, p. 5) further suggest that BTC has the potential to serve as a partial hedge against financial crisis. This is based on BTCs particularly high skewedness of 1.99, a number usually only found among volatility investments. Chowdhury (2014, pp. 6-7) make the same conclusion based on an even higher skewness of 2.30.

Thus, the lack of correlation to other asset and its high skewedness offer interesting insights into how BTC is connected to a wider market perspective. Even though the high kurtosis and extreme volatility imply that bitcoin is an extremely risky investment, those investors willing to accept this risk have the potential for financial gain by including BTC in their diversified portfolio. However, as suggested by Chowdhury (2014, p. 8), bitcoin should be considered a long-term speculative asset and investors should not invest more than they are willing to loose.
5. Practical Method

This chapter presents the data chosen for this study and the methods employed to collect and process it. This is an important aspect of the research, as it is crucial that correct data and methods have been used for the stated purpose. This study about bitcoin, is in many ways unconventional. Bitcoin is a rather new phenomenon and it is worth mentioning that studying it from a financial aspect in this way demands a certain amount of “innovativeness”. The practical method has therefore been constructed by drawing on similar research made on more conventional assets, as well as bitcoin research underway.

5.1 Population and Sample Data

A population is a complete group with all its members (UWE, 2006; Saunders et al., 2009, 259-260). Research is often undertaken in order to say something about the chosen population. It is therefore important to define the population that will be of focus for the research. Due to the high costs of studying the whole population, a representative sample is taken. A sample is thus a subset to the population. For this thesis, the purpose is to study the volatility of bitcoin and it is therefore natural that the bitcoin market becomes the population. As explained in section 3.1.2, the bitcoin market is made up of many different market places, which offer bitcoin in exchange for different currencies. Table 2 displays a list of the largest bitcoin markets at the time of the data collection and how much that was currently traded.

5.1.1 Sample Size

For this study, two of the largest bitcoin exchanges, Bitstamp and BTC-e, were chosen as they together represent 50% of the current bitcoin market (see figure 4). Bitstamp and BTC-e both trade bitcoins against USD, which also represent the most common exchange medium. At the time of the data collection 85% of the bitcoin exchanges were made with dollars. Bitfinex, another large exchange, is also trading in dollars, but since this exchange only opened last year the limited amount of trading data led us to exclude it from our sample (Bitcoincharts, 2014b).

Figure 3: Exchange volume distribution of bitcoin (Bitcoincharts, 2014d)
5.1.2 Time Period
Due to the relatively short existence of the bitcoin market, it was desired to include as much data for these two exchanges as possible. The data collected reaches from September 13th 2011, which was when Bitstamp first started trading bitcoin, until May 3rd 2014, which was the day the data was extracted (Bitcoincharts, 2014b; Boase, 2013). 2.5 years is a limited time period, but since this study uses daily data and the bitcoin market is open for trade every day of the year, over 900 trading observations are generated for the analysis. This would correspond to a period of almost 4 years of ordinary stock market trading, which is argued to be a reasonable amount of data.

5.2 Data Collection Method and Classification of Variables
This research is built upon secondary data, collected through numerous sources, such as journals, web pages and public records. Common for these sources is however that they all have documentary characteristics and have primarily been collected by someone else, for some other purpose. This kind of data is incorporated in almost any research but can, combined with an archival research strategy, also be the main source of data (Saunders et al., 2012, p. 308).

All studies examine some kind of variables (Laerd, 2013b). Variables have different characteristics related to the measurement scale and are therefore organized into nominal, ordinal, interval or rational categories. While the nominal variables do not display any intrinsic order, the ordinal variables can be ranked. Interval variables are measured along a continuum and thereby offer comparison opportunities. The ratio variables have the same characteristic as the interval variables, but with the added feature of zero as a reference value.

5.2.1 Bitcoin Price Data
The price data of bitcoin is a ratio variable and is retrieved from the online source Bitcoincharts.com, which provides financial and technical data related to the bitcoin network. It is currently the only site offering a complete overview of the bitcoin markets with a register of all their historical prices, as well as current market prices.

5.2.2 Information Demand
As explained in chapter 4, several studies such as the ones of Da et al. (2011), Vlastakis and Markellos (2012) and Drake et al. (2012) have displayed the usefulness of information demand in explaining movements in stock prices by utilizing search frequencies on Google for certain key words. Even within the generally unexplored area of bitcoin, information demand in terms of search queries has been a topic of interest and studied by Kristoufek (2013). The fact that many scientific studies have been performed using search queries, suggests an academic acceptance for this specific method. Applying information demand as a variable in this way can therefore be considered acceptable. In addition, Google accounted for 67.5% of all search queries in the US, as of March 2014 (comScore, 2014). The search volume reported by Google is thus likely to be representative of the Internet search behavior of the general population. Google Trend reports the amount of search queries relative to the total amount of Google searches over time (Google, 2014). This method generates values
that are normalized and presented on a scale from zero to 100. This is thus an index without an exact number of search queries. Considering its usefulness in similar research and the difficulty of generating such information, Google Trend is still believed to be the most useful tool currently available for this purpose.

For this study, the interest concerns the frequency of queries for the word ‘bitcoin’. The search frequency for this key word is downloaded from Google Trend and covers the whole period of interest, from September 13th 2011 until May 3rd 2014. For this study, daily data is desired but due to the construction of Google Trend, it is only possible to extract daily data for the three most recent months, and earlier search queries are only displayed on a weekly basis. In order to have daily data for the whole period of this study, a reconstruction similar to the one in the work-in-progress paper by Garcia et al. (2014) is required. For a description of the reconstruction method see appendix C. The information demand variable is like the bitcoin price data also a ratio variable with a reference value of zero for the periods with very small amounts of search queries.

5.2.3 Event Effects
Without any fundamental value and a suggested sensitivity to investor sentiment (Baker & Wurgler, 2006, p. 130; Kristoufek, 2013, p. 1), it is likely that the information of certain events may lead to swings in the bitcoin price. As was displayed in figure 1 in section 1.3, the bitcoin price exhibits extremely high volatility and a glance at historical prices does not reveal any specific pattern. It is thus possible that particular events have contributed to the volatility of the bitcoin price. By scanning the information on the Internet, as well as academic databases for information concerning bitcoin, several events have been identified as important for the development of the bitcoin market. With a thorough information review, scanning the available information for reoccurring news, the basis of this selection is considered robust. It is nevertheless subjective, as the human mind has been entrusted with this task. By performing an extensive literature review with the stated philosophical position in mind, it is however argued that it is possible to perform an objective identification of important events for the bitcoin. The chosen events are displayed below. They are used as dummy variable in the volatility model and are nominal variables.

**Cyprus:** The capital controls imposed in connection to the financial crisis on Cyprus in the middle of March 2013, is claimed to have sparked increased interest for bitcoin as an alternative to the standard monetary system (Kitco News, 2013).

**Silk Road:** This American website was a known market place for illegal products such as drugs (Greenberg, 2013). In the beginning of October 2013 it was however shut down by the FBI.

**Baidu:** This Chinese competitor to Google announced in the middle of October 2013 that it would accept payments in Bitcoin (Clinch, 2013a; Chang, 2013).

**USA:** The chairman of Federal Reserve, Ben Bernanke, said in an open letter to the Homeland Security in the middle of November 2013 that bitcoin “may hold long-term promise” (Strauss, 2013).
China: The Chinese government declared in the beginning of December 2013 that banks and payment companies are forbidden to deal with bitcoin (Bloomberg News, 2013; Hill, 2013).

MtGox: The largest bitcoin exchange, MtGox, declares bankruptcy in the end of February 2014, after being hacked and losing a great deal of investors’ money (Hals, 2014; Thomas, 2014).

5.2.4 Trade Volume
As mentioned in section 3.4.1, it is often argued that increased trading volume implies increased liquidity (O’Hara, 1995, p. 223). Adding to this, the market microstructure theory suggests a negative relationship between liquidity and price volatility. It is therefore reasonable to include trade volume as an explanatory variable for the bitcoin price volatility. This choice is further supported by the findings of Moore and Christin (2013), mentioned in section 4.1. Their finding, that increased trading volume on a bitcoin exchange reduce the risk of it failing, suggests that trade volume, incorporated as an explanatory variable, will likely provide knowledge about its ability to explain the price volatility of bitcoin. The information about the bitcoin trade volume, on the chosen market places, is available on Bitcoincharts.com.

5.2.5 Trend
It has already been made clear that bitcoin has displayed an extraordinary development from its creation in 2009 to a market value of 558 USD and a daily trade volume of over 68,000 trades as of April 3rd this year (see Table 1 and 2). Despite this, the bitcoin market is still regarded as in an emerging phase with large risks for investors (Moore, 2013, p. 148; Moore & Christin, 2013, p. 7). Since there is no fundamental value connected to bitcoin to talk about (Kristoufek, 2013, p. 1), investors are dependent on information they can get elsewhere in order to evaluate its value. The information available about bitcoin can be assumed to have increased over time, something that the literatures review for this study supports. Today information about bitcoin is no longer limited to technological magazines and forums, but can be found in articles in business papers such as the Economist and the Guardian. The fact that governments have started to discuss bitcoin openly and financial instruments are being built using it as an underlying asset, can be seen as further indications of a greater and increasing acceptance. The work in progress paper by Garcia et al. (2014) further supports this. Their research suggests that the increase of new bitcoin users from public circles is a sign of increased openness and that this increase has driven the seen growth of the bitcoin economy.

To test whether there is an increasing acceptance of bitcoin, a variable symbolizing a positively increasing trend is included in our attempt to model the price volatility of bitcoin. If the trend variable is significant, it is evidence supporting the belief of an increasing acceptance of bitcoin. The trend variable is a ratio variable, as there is a starting value of zero, which later values relates to.
5.2.6 World Market Index
As stated in section 3.4.2, Lin et al. (1994) and Bekaert et al. (2005) found evidence that return and volatility moves between markets and countries, suggesting close ties between markets. The extremely low correlation of bitcoin with other assets, pointed out by the work-in-progress by Brière et al. (2013) and Chowdhury (2014), indicate that bitcoin has a unique resistance against factors that affect the more traditional assets. This indicates that the bitcoin price is not affected by market events and possibly also the state of the market. Thus, this is an interesting issue to examine closer and we will therefore let a world market index represent the overall state of the market. If bitcoin is shown to have no or negative correlation with the world market, it would offer protection to investors who want to limit their risk exposure, as suggested by Brière et al. (2013) and Chowdhury (2014).

With a coverage of more than 13,000 securities across large, medium and small cap, and across styles and segments of 44 developed and emerging markets, the MSCI ACWI is an equity index that can be called a world market index (NASDAQ, 2014). In this study, the MSCI ACWI index return is used as a proxy for the world market state. This is also a ratio variable.

5.3 Logarithmic Return
There are many reasons why the usage of asset returns is popular within financial studies (Tsay, 2010, p. 2). One of the main reasons is the more favorable statistical properties of asset return compared to the ones of asset prices. Asset returns also make it possible to observe asset volatility, as volatility is defined as the standard deviation of the return (Hull, 2012, p. 205; Tsay, 2010, pp. 110-111).

There are many ways of calculating return (Tsay, 2010, p. 2). One of the most popular ways when analyzing financial data is through continuous compounding (Ruppert, 2004, p. 77; Wooldridge, 2003, p. 337). This is due to its simplicity when dealing with time series, which is often the case within finance. The continuously compounded return, also known as the logarithmic return, is calculated using equation 1 below (Ruppert, 2004, p. 76).

\[
\text{Equation 1: Logarithmic return}
\]

\[
r = \ln(S_{t+1}) - \ln(S_t) = \ln\left(\frac{S_{t+1}}{S_t}\right)
\]

Where:
\[
r = \text{logarithmic return}
\]
\[
\ln(S_{t+1}) = \text{natural logarithm of stock price at } t+1
\]
\[
\ln(S_t) = \text{natural logarithm of stock price at } t
\]

If the general assumption of independent and identically distributed [i.i.d] and log-normally distributed returns is followed, the log-returns are i.i.d. normally distributed, which result in much statistical freedom (Ruppert, 2004, p. 77). Hence, it is not surprising that the assumption of normal distribution is standard within financial analysis, even though the data is known to display both kurtosis and non-stationarity (Aas, 2004, p. 2). The difference
between the normal distribution and the lognormal distribution is however claimed to be insignificant when analyzing returns for fairly short periods. For analysis of longer periods the lognormal distribution has further proved to be more accurate (Brealey & Myers, 2003, p. 187).

5.4 Pearson’s Product Moment Correlation Coefficient

In order to study the relationship between the variables, the collected data is exposed to a correlation test (Saunders et al., 2009, p. 521; UWE, 2006). This makes it possible to explore the strength of association between the variables from a statistical point of view. The performance of such test is further important since correlation between independent variables, known as collinearity, can cause problems when performing regression analysis (Saunders et al., 2012, p. 524). Since this study aims at investigating whether the specified variables have an effect on bitcoin price volatility, it is important to know that there is no collinearity affecting the estimation of the individual regression parameters. Since the variables to be tested are numerical and have interval character the choice of correlation test has fallen on the Pearson’s Product Moment Correlation Coefficient [PMCC]. To see if this is the case descriptive statistics, distribution tables, normality tests and scatterplots are generated and will be presented in the following chapter. The correlation between two variables, X and Y, is calculated using equation 2 below (Wright, 1921, p. 557):

\[ r_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y} \]

Where:
- \( r_{X,Y} \) = correlation coefficient of variable X and Y
- \( \sigma_Y \) = standard deviation of dependent variable Y
- \( \sigma_X \) = standard deviation of independent variable X
- \( cov(X,Y) \) = covariance between variable X and Y

The correlation coefficient always reaches between -1 and 1 (Bryman & Bell, 2007, pp. 362-363; Wright, 1921, pp. 157-158). With a correlation equal to 1, the two variables have a perfectly positive correlation, denoting identical movements. If the correlation coefficient is -1, the variables have a perfectly negative correlation and they always move with the same amplitude, but in opposite direction. If the correlation test shows a value of 0, the variables display no relationship at all.

5.4.1 Limitation of Correlation Analysis

As explained above, the information provided by a correlation test can be helpful when investigating the relationship between variables. It is however important to remember limitations inherent in this information (Moore, 2009, p. 140). This concerns the inferences that can be made from the result. One should e.g. be careful interpreting the result as true for other than the data studied. The data may e.g. be a linear part of a non-linear relationship. The relationship between two variables displayed in a correlation test can also be influenced by other, peripheral, variables that are not included in the study, so called lurking variables.
(Moore, 2009, pp. 141-142). Such lurking variables may explain a relationship and inference from a correlation test should therefore be done carefully. Another reason for carefulness is the potential influence from outliers, which can result in a significant difference in the resulting correlation coefficient (Laerd, 2013a). In this case, it is useful to generate scatterplots to visualize the data.

5.5 Significance test

In order to evaluate the coefficients of this study, a significance test is performed (Bryman & Bell, 2007, pp. 370; Saunders et al., 2012, p. 522). This test provides the probability that the coefficient of the sample will be found in the population and thereby help to determine whether the result occurred by chance. The test is performed using the software SPSS and it generates a p-value. If the p-value for a coefficient is less than 0.05, the coefficient is statistically significant and it is therefore a low likelihood that the given correlation occurred by chance (Saunders et al., 2012, p. 522).

5.5.1 Type I and II errors

The alpha of 0.05 is however not a given limit, since such a limit does not exist (2009, pp. 398-399). Where it is drawn depends on the researcher and his or her reasons. That is why significance often is presented together with the chosen alpha, such as “significant on a 0.05-level”. This alpha represents the limit when enough evidence against the null hypothesis is presented by a test. With an alpha of 0.05, the risk of rejecting the null hypothesis when it is actually true is 5%. This risk can be made smaller by using an alpha of 0.01, decreasing the risk to 1%. The downside is however that with such strong evidence needed to reject $H_0$, the risk of failing to reject the null hypothesis, when it is false, is higher. These risks are called the type I and type II errors respectively and the choice of alpha is thus a balancing act. As stated in the text above, this study is using an alpha of 0.05 when concluding the result, a level used by many researchers. This study is further not investigating a common truth, which would argue for strong evidence and thus a low p-value. It is rather one of the first studies of its kind and an alpha of 0.05 is therefore argued to be enough.

5.6 Time Series

As previously described, the collected data are variables of varying forms and origin. Some of the data, such as the prices of bitcoin and the frequency of search queries display change over time. This type of data is often referred to as time series data (Pindyck & Rubinfeld, 1981, p. 3). The relation to time is what differs time-series data from cross-sectional data where the data is collected at one specific point in time.

5.6.1 Unit Root Test

Stationarity refers to the time invariant properties of time series (Ruppert, 2004, p. 102). This is an important characteristic of the data in order to be able to draw conclusions about how change in one time series variable affects another (Wooldridge, 2003, p. 362). With stationarity it is possible to model a process through an equation with fixed coefficients that can be estimated using historical data (Pindyck, 1981, p. 497). Since this research is
concerned with modeling the volatility of the bitcoin price using time series data, the condition of stationarity is of utmost importance.

To be stationary the data does not have to have fixed values over time, but rather exhibit constant statistical properties (Wooldridge, 2003, p. 361). The time series is then said to exhibit strict stationarity, which is a very strong assumption (Ruppert, 2004, p. 102). Within finance, it is common to assume that asset returns exhibit weak stationarity, meaning that only the first and second moments are constant (Tsay, 2010, p. 30). Stationarity can be verified empirically by applying a unit root test (Alexander, 2008, p. 215). There are different versions of this test, but the Augmented Dicker-Fuller [ADF] test is one of the most popular (Wooldridge, 2003, p. 638) and also the one applied in this study. According to Dickey and Fuller (1979, p. 427) the time series moves towards stationarity as time passes ($t$ increases) if $\alpha < 1$, in the autoregression model in equation 3 below. If $\alpha = 1$, the time series exhibits a random walk and if $\alpha > 1$, it increases exponentially, suggesting cases of non-stationary time series.

*Equation 3: First order autoregressive model*

$$Y_t = \theta + \alpha Y_{t-1} + \varepsilon_t$$

Where:
- $Y_t$ = current value of time series
- $\theta$ = constant
- $\alpha$ = real number (parameter)
- $\varepsilon_t$ = independent random variable

With the ADF test, we test the null hypothesis, $H_0$: $\alpha = 1$ against the alternative hypothesis, $H_1$: $\alpha < 1$ (Tsay, 2010, p. 77). Initially, an ordinary least square [OLS] regression is run, which gives the estimated standard error, $\bar{\alpha}$. This is then used to generate the ADF t-statistic through the formula in equation 4 below:

*Equation 4: ADF t-statistic*

$$ADF = \frac{\bar{\alpha} - 1}{se(\bar{\alpha})}$$

Where:
- $\bar{\alpha}$ = least-square estimate
- $se(\bar{\alpha})$ = standard error of least-square estimate

For evaluation of the test, the result is compared to the critical values (Tsay, 2010, pp. 76-78). If the test value is greater than the critical value, the null hypothesis of a unit root is rejected, which suggests that the time series is stationary. If the time series on the other hand is non-stationary, which is often the case for level data within finance, it is possible to perform a so-called differencing in order to transform the time series into a stationary one. The logarithmic returns, calculated for the bitcoin and the world market index prices, are the first differenced series, thus not level data, and is therefore likely to be stationary. However, if that would not be the case, multiple unit roots are likely present and a second differencing is preferable.
5.7 GARCH Model

One of the properties of the volatility of financial assets is clustering (Alexander, 2008, p. 131). This means that the volatility is not constant over time, a property that is easy to spot in daily data, but which tends to disappear in monthly and yearly data. These irregularities, often termed heteroscedasticity, are captured by the Autoregressive Conditional Heteroscedasticity [ARCH] model, introduced by Engle in 1982 (Engle, 2001, pp. 159-167). In this model, volatility is modeled by including and weighting past observations (in favor of the more recent observations). This model is however somewhat complicated due to the inclusion of numerous lags, creating difficulties in estimating the various parameters (Tsay, 2010, p. 131). That is why Bollerslev (1986) developed it into the General Autoregressive Conditional Heteroscedasticity [GARCH] model, which also utilizes declining weights, but in contrast to the ARCH model, never lets the weights to go completely to zero (Engle, 2001, p 159). This gives a model that is easy to use and that has proven especially successful predicting conditional variances within finance.

The GARCH model consists of two equations: a conditional mean equation (see equation 5) and a conditional variance equation (see equation 6) (Alexander, 2008, p. 136). The conditional mean equation specifies the behavior of the returns and its error term, \( \varepsilon_t \), represents the unexpected return. Equation 5 below displays a first order regressive model (Alexander, 2008, p. 203).

**Equation 5: Conditional mean equation**

\[
 r_t = c + Q r_{t-1} + \varepsilon_t \quad \text{with} \quad \varepsilon_t \sim \text{i.i.d.} \ (0, \sigma^2) \quad \text{and} \quad |\varrho| < 1,
\]

Where:
- \( r_t \) = return
- \( c \) = constant
- \( Q \) = parameter
- \( r_{t-1} \) = last period’s return
- \( \varepsilon_t \) = error term

This conditional mean equation generates an estimation of the error terms from information provided by previous period’s return (Alexander, 2008, p. 136). The error term is then applied in the conditional variance equation. Together with the variance of previous period, it is then possible to estimate also the variance of the next period.

**Equation 6: Conditional variance equation**

\[
 \sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 .
\]

Where:
- \( \sigma_t^2 \) = conditional variance of \( \varepsilon_t \)
- \( \varepsilon_{t-i}^2 \) = residuals from previous period
- \( \sigma_{t-j}^2 \) = the variance from previous periods
- \( \omega \) = constant
- \( p \) = number of autoregressive lags
- \( q \) = number of moving average lags
- \( \alpha, \beta \) = GARCH parameters

Since its introduction, the GARCH model has been both extended and modified, but the GARCH(1,1), which is the simplest model, is claimed to be the most robust (Engel, 2001, p. 159).
This is strengthened by Hansen & Lunde (2005), which compare different volatility models and found no evidence that the GARCH(1,1) is outperformed when compared with other volatility models using exchange rate data. The ‘(1,1)’ indicates that the variance is calculated from the most recent observation of the squared residual and the most recent estimate of the variance, which can be demonstrated in equation 7 below (Hull, 2012, p. 218). Due to the strength and simplicity of the GARCH (1,1), the model was considered suitable for this first of a kind study on the bitcoin.

\[ \sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad 0 \leq \alpha_1 , \beta_1 \leq 1, (\alpha_1 + \beta_1) < 1 \]

GARCH models are commonly used together with the assumption of normal distribution (Bai et al., 2003, p. 349). Nevertheless, as we previously mentioned, financial data is known to display leptokurtosis. This has led some researchers to reject the normality assumption and instead follow Bollerslev’s (1987) assumption of a t-distribution, which he shows is more capable of matching both the volatility dynamics and the kurtosis. Following Bollerslev’s suggestion, a comparison of GARCH (1,1) with a t-distribution and a Gaussian distribution will be made in order to discern if the same conclusion can be made also for bitcoin returns.

To find out whether the factors, identified in section 5.2, have an influence on the bitcoin volatility, the GARCH (1,1) model is modified following the example of Vlastakis and Markellos (2012). This modification is done by adding the identified variables into the conditional variance equation of the GARCH(1,1). Equation 8 below displays the resulting model.

\[ \sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma \pi_t + \delta \phi_t + \zeta \xi_t + \sigma \tau_t + \alpha \varphi + b \nu + c \varnothing + d \eta + e \Omega + f \omega \]

Where:
- \( \pi \) = information demand
- \( \phi \) = trade volume
- \( \xi \) = world market index
- \( \tau \) = trend
- \( \varphi \) = Cyprus
- \( \nu \) = Silk Road
- \( \gamma \) = Baidu
- \( \eta \) = USA
- \( \Omega \) = China
- \( \varnothing \) = MtGox

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By inserting these variables into the model, the study hope to find whether they contribute to the volatility of the bitcoin price in any significant way. In order to determine this the statistical program STATA is utilized. This program is able to estimate the parameters and also generates a p-value, which will, as discussed in section 5.5, disclose if a parameter is statistically significant or not.

5.8 Evaluation of the GARCH Model

5.8.1 Ljung-Box Test Statistic
Once the parameters of the GARCH model have been determined, the model can be evaluated. This evaluation is done according to how well the model removes autocorrelation from the squared return (Hull, 2012, p. 229). This is due to the underlying assumption of volatility persistence, i.e. a period with high volatility is likely followed by a period with similar high volatility (Hull, 2012, p. 224). If a GARCH model is working well, it should be able to remove such autocorrelation. Autocorrelation can also decrease the accuracy of a time-based predictive model, such as the GARCH model. In order to test the GARCH model for autocorrelation, the Ljung-Box test statistic (Hull, 2012, p. 225) is applied. It is defined as a hypothesis test where $H_0$: There is no serial correlation, the data is thus randomly distributed, and $H_1$: The data is not independently distributed.

\[ Q = m \sum_{k=1}^{K} w_k c_k^2 \]

Where:
- $Q =$ Ljung-Box test statistic
- $m =$ number of observations
- $c_k =$ autocorrelation
- $K =$ number of lags
- $w_k =$ ratio of observations depending on the included number of lags

**Equation 9: Ljung-Box test**

\[ w_k = \frac{m+2}{m-k} \]

**5.8.2 Durbin-Watson Test Statistic**
The Durbin-Watson test statistic (Durbin & Watson, 1971, p. 1) is another way of testing for autocorrelation in time series (Saunders et al., 2012, p. 529). Its test statistic ranges from 0 to 4, where 2 indicated zero autocorrelation, 0 a positive autocorrelation and 4 a negative autocorrelation.

\[ d = \frac{\sum_{i=2}^{n} (z_i - z_{i-1})^2}{\sum_{i=1}^{n} z_i^2} \]

Where:
- $d =$ test statistic
- $z_i =$ $y_i - \hat{y}_i$
- $y_i =$ the observed value of the response variable for individual i
- $\hat{y}_i =$ the predicted value of the response variable i
5.9 Chapter Summary

In this chapter the techniques used to practically answer the posed research question have been presented and argued for. It displays a crucial part of the study, since faulty methods will have a direct negative affect on the quality of the study, as it will lack measurement validity (Bryman & Bell, 2007, pp. 40-41). A well-documented practical method is further an important feature of a research, as it will affect its reliability and replicability. These are all quality issues and will be discussed further in chapter 9.

Except for the definition and collection methods of the variables, this chapter outlines the tests performed in this study, which are:

- Pearson’s correlation test
- Significance test
- Augmented Dicker-Fuller test [ADF]
- GARCH (1,1)
- Ljung-Box test statistic
- Durbin-Watson test statistic
6. Empirical Result

This is the chapter where the research result is presented. It does not only display the result of the statistical tests, but also contains a presentation of the different variables and their characteristics. This chapter does thereby initiate the analysis, which will be the focus of the upcoming chapter.

6.1 Descriptive Statistics

Before embarking on the result of the statistical tests and the modelling of the bitcoin price volatility, it will be useful to have a look at the chosen variables and their properties in order to generate a better understanding of them.

6.1.1 Bitcoin Price & Return

Figure 4 displays the average price of Bitstamp and BTC-e. As can be seen, the price of bitcoin has experienced a remarkable development. From a seemingly steady price of around 5 USD/BTC for a long period in the beginning of our sample, the bitcoin price temporarily rose to 200 USD in the beginning of the second quarter of 2013 and then peaked at more than 1000 USD in the end of November the same year. During the following months, the bitcoin price displayed great fluctuation with a negative trend and in the end of the first quarter of 2014, which also denotes the end of the sample period, the registered price of bitcoin was around 500 USD.

Figure 5, which displays the logarithmic return on the studied bitcoin markets, offers another angle of the movement of the bitcoin price. Here it is possible to discern the clustering effect that is common for financial assets, which was discussed in section 5.8. The diagram makes it clear that there is a great spread of return. An extreme example is found in the middle of April 2013 where bitcoin exhibits a 13.83% return, which turned to -45.80% three days later and to 21.58% a week later. This very volatile period can also be spotted in figure 4 above, as the first small peak, and it coincides with the economic unrest on Cyprus mentioned in section 5.2.6.
For more detailed data concerning the bitcoins return distribution, focus is shifted to table 3. A daily mean of 0.5% and standard deviation of 4.5% translate into an average annual return of 517% and average annual volatility of 86%. Compared to the studies by Brière (2013) and Chowdhury (2014), whose studies suggest average annual returns of 371% and 476% respectively and average annual volatility of 175% and 258%, this result displays an even higher return but a far lower volatility. The value of the skewness and kurtosis suggests that the distribution is negatively skewed and is having high leptokurtic characteristics. It is thus suggested that the distribution is not normally distributed.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Variance</th>
<th>Std. Deviation</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logarithmic return</td>
<td>0.005</td>
<td>0.002</td>
<td>0.045</td>
<td>-1.350</td>
<td>16.511</td>
</tr>
</tbody>
</table>

*Table 3: BTC return distribution*

By performing a Kolmogorov-Smirnov and a Shapiro-Wilk test, also know as tests of normality distribution, it is possible to generate further evidence for this assumption. As can be seen in table 4, both tests shows significance suggesting that the distribution of the bitcoin return is not normally distributed. Looking at the histogram of the data, displayed in appendix B, the data exhibits a clear bell shape. Despite a high mean value, the data is corresponding rather well with the normal distribution.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Kolmogorov-Smirnov</th>
<th>Shapiro-Wilk</th>
</tr>
</thead>
<tbody>
<tr>
<td>LogReturn</td>
<td>.144</td>
<td>.842</td>
</tr>
</tbody>
</table>

*Table 4: Normality tests on BTC return data*

### 6.1.2 Trade Volume

The volume of bitcoin traded on the chosen markets has also changed over time. Looking at Figure 6 below it is possible to discern three distinct periods. The first period, reaching from 13th September 2011 to 1st January 2013, represents a period with a relatively low trading volume with an average daily trading volume of 3 968 trades. In the following period, 2nd January 2013 to 1st October 2013, the trade volume increases to an average of 15 592 trades. Our sample period ends with the period starting from 2nd October 2013 to 3rd
May 2014, which displays a strong increase of trade volume, raising the daily average to 41,246 trades. This average still stands in sharp contrast to the 68,000 trades per day accounted for in section 3.1.2 and recorded on April 3rd 2014, at the end of the sample period.

Taking a step back to analyse the complete sample period, the data gives a total average of 15,502 trades per day, see table 5. The volatility is however large with an average standard deviation of 24,017 trades. The value of the skewness and kurtosis further indicates that the trade volume is not normally distributed, but rather positively skewed with fat tails.

This view is confirmed by the Kolmogorov-Smirnov and Shapiro-Wilk tests, see table 6, which both show that the distribution of the trade volume data of bitcoin is significant, thus suggesting non-normality. Turning to the histogram in appendix B, it is easy to identify that the distribution is indeed positively skewed.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Variance</th>
<th>Std. Deviation</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trade volume</td>
<td>15502.459</td>
<td>576836016.984</td>
<td>24017.411</td>
<td>4.197</td>
<td>27.6641</td>
</tr>
</tbody>
</table>

Table 5: BTC trade volume distribution

<table>
<thead>
<tr>
<th>Variable</th>
<th>Statistic</th>
<th>df</th>
<th>Sig.</th>
<th>Statistic</th>
<th>df</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Trade volume</td>
<td>.262</td>
<td>963</td>
<td>.000</td>
<td>.583</td>
<td>963</td>
<td>.000</td>
</tr>
</tbody>
</table>

Table 6: Normality tests on BTC trade volume data

6.1.3 Information Demand

The next variable, information demand, represents the amount of search queries on Google for the word ‘bitcoin’ during the sample period and gives an indication of the interest for the topic at a specific moment. As was explained in section 5.2.2, this variable is a relative measure of the total amount of search queries made over the world. As can be noticed, there are similarities between figure 7, representing the Google searches over time and figure 6 displaying the trade volume. It is further possible to, also here, identify similar periods according to the levels of activity.
For simplicity, the same dates as for trade volume are used also here. During the first period the average amount of searches generates a value of 0.40. This number increases by 548% to 2.19 for the second period and an additional 297% for the third period giving an average value of 6.51 per day. Looking at the complete set of data, the average value is 2.26 with a standard deviation of 3.13. See table 7. The skewness and kurtosis, of 2.25 and 5.05 respectively, suggest that the distribution is positively skewed with fat tails. These values suggest that the distribution is non-normal. The histogram of the information demand data, displayed in appendix B, confirms this. Also the Kolmogorov-Smirnov and Shapiro-Wilk tests, see table 8, show result in line with this result, namely a rejection of the null hypothesis of normal distribution.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Variance</th>
<th>Std. Deviation</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Information demand</td>
<td>2.26</td>
<td>9.80</td>
<td>3.13</td>
<td>2.25</td>
<td>5.05</td>
</tr>
</tbody>
</table>

Table 7: Bitcoin information demand distribution

<table>
<thead>
<tr>
<th>Variable</th>
<th>Kolmogorov-Smirnov</th>
<th>Shapiro-Wilk</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Statistic</td>
<td>df</td>
</tr>
<tr>
<td>Information demand</td>
<td>.256</td>
<td>963</td>
</tr>
</tbody>
</table>

Table 8: Normality test of bitcoin information demand data

6.1.4 World Market Index
The last variable examined is the World Market Index. As can be viewed on figure 8, this collection of securities exhibits a relatively stable price of between 40 and 60 USD over the sample period. Unlike the bitcoin price, seen in figure 4, the index is not experiencing any sudden movements. It is however exhibiting a positive trend from the beginning of October 2011, where the index had its lowest price of 38.11 USD, to the end of the sample period.
As can be expected when regarding the price movements in figure 8 above, the variance of the world market index return is limited. This can be also been seen in figure 9, which displays movements of the logarithmic return of the index with a maximum range of -0.05 and 0.04 within a few months of the beginning of the sample period.

This conclusion, of a stable variable, is confirmed by table 9, which presents the distribution data. While the mean and variance are defined as zero, the distribution is suggested to be negatively skewed and strongly leptokurtic. This should come as no surprise considering previous discussion of the characteristics of financial assets.

To control the suggested non-normal distribution Kolmogorov-Smirnov test and Shapiro-Wilk test are performed also here, table 10. Both tests confirm with significance that the index is non-normally distributed.

Table 9: World market index return distribution

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Variance</th>
<th>Std. Deviation</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>World Market Index</td>
<td>0.000373</td>
<td>0.000</td>
<td>0.000</td>
<td>-10.597</td>
<td>389.177</td>
</tr>
</tbody>
</table>

Table 10: Normality tests on world market index data

<table>
<thead>
<tr>
<th>Variable</th>
<th>Kolmogorov-Smirnov&lt;sup&gt;a&lt;/sup&gt;</th>
<th>Shapiro-Wilk</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Statistic</td>
<td>df</td>
</tr>
<tr>
<td>World Market Index</td>
<td>.286</td>
<td>963</td>
</tr>
</tbody>
</table>

6.1.5 Concluding comment

Section 6.1.1 to 6.1.4 show conclusive results of non-normal distribution for all the variables. Despite such clear results, one has to bear in mind the importance of the sample
size. As mentioned, bitcoin has existed for no more than five years. This short existence has in turn affected the amount of data available for this study. According to the central limit theorem [CLT], well known within probability theory, the distribution of any sample will become normally distributed as the number of observations goes towards infinity, regardless of the population distribution (Moore, 2009, p. 299). Due to the limited data and support from the CLT, the variables are nonetheless assumed to be normally distributed.

### 6.2 Correlations Test

As was described in section 5.4, a Pearson correlation test was performed on the variables in order to find out more about the relationship between them. The result of this test, presented by table 11, suggests that there is a negative and significant correlation between trade volume and logarithmic (bitcoin) return, and a positive and significant correlation between trade volume and information demand. None of the other variables displays any significant correlation with each other.

![Correlation Table](image)

*Table 11: Correlation test*

Examining the scatter plots generated and displayed in appendix C, one sees that trade volume and information demand displays the strongest relationship. This corresponds to the result of the correlation test, which also shows the highest significant value of 0.69. The dots of this scatter plot are however rather dispersed, which suggests that the relationship is still not really strong. The scatter plot for trade volume and logarithmic (bitcoin) return displays a significantly weaker relationship, with a high concentration of dots in a half circle-shaped formation. It is however possible to discern a slight inclination towards the left, which corresponds to the negative value of -0.12 from the correlation test. This therefore suggests that the result of the correlation test is evidence of a very weak relationship. Judging from these results, the risk for multicollinearity is considered low.

### 6.3 Unit Root Test

The importance of stationary properties of the employed times series was made clear in section 5.6.1. Here it was further explained that these properties are to be tested through the use of the Augmented Dickey-Fuller [ADF] test. The critical values are given in table 13 and should be compared to the test statistic of the different times series seen in table 12. Since the list of test statistics only displays values with a greater negative value, the correct
conclusion is that all variables are stationary time series. There is thus no need to perform any differencing on the time series data from the variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Test Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>LogReturn</td>
<td>-18.682</td>
</tr>
<tr>
<td>Trade volume</td>
<td>-10.656</td>
</tr>
<tr>
<td>Information demand</td>
<td>-3.066</td>
</tr>
<tr>
<td>World Market Index</td>
<td>-34.055</td>
</tr>
</tbody>
</table>

Table 12: Test statistic

<table>
<thead>
<tr>
<th></th>
<th>1% Critical Value</th>
<th>5% Critical Value</th>
<th>10% Critical Value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-2.580</td>
<td>-1.950</td>
<td>-1.620</td>
</tr>
</tbody>
</table>

Table 13: ADF critical values

6.4 GARCH(1,1)

Having examined the different variables it is now time to present their ability to explain the movement of the bitcoin price and maybe shed some light over its noteworthy volatility. Table 14 below presents the result from the GARCH (1,1). This model was considered the most suitable option for the task on grounds presented in section 5.7. The selected variables are listed as external variables, with the coefficient followed by the belonging p-value. As can be seen, only five of the variables are significant with a 5% significance level. These are the trade volume, information demand and trend variables, as well as the Cyprus and MtGox dummies. With a confidence level of 95%, it is thus very likely that these results did not happen merely by chance. With this conviction in mind, it is interesting to take a closer look at the information provided by the coefficients of the significant variables. The trade volume variable exhibits a slightly positive value of 0.0000325, suggesting a small effect on the bitcoin return.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficient</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logarithmic return</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.00237</td>
<td>0.001</td>
</tr>
<tr>
<td>Lag1</td>
<td>0.69709</td>
<td>0.000</td>
</tr>
<tr>
<td>Lag2</td>
<td>-0.34021</td>
<td>0.000</td>
</tr>
<tr>
<td>Lag3</td>
<td>0.15302</td>
<td>0.000</td>
</tr>
<tr>
<td>External variables</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-6.91107</td>
<td>0.000</td>
</tr>
<tr>
<td>Trade volume</td>
<td>0.00003</td>
<td>0.000</td>
</tr>
<tr>
<td>Information demand</td>
<td>0.18996</td>
<td>0.000</td>
</tr>
<tr>
<td>World Market Index</td>
<td>6.99538</td>
<td>0.234</td>
</tr>
<tr>
<td>Trend</td>
<td>-0.00707</td>
<td>0.000</td>
</tr>
<tr>
<td>Cyprus</td>
<td>1.84762</td>
<td>0.004</td>
</tr>
<tr>
<td>Silkroad</td>
<td>-0.52891</td>
<td>0.534</td>
</tr>
<tr>
<td>Baidu</td>
<td>0.68658</td>
<td>0.405</td>
</tr>
<tr>
<td>USA</td>
<td>-1.37695</td>
<td>0.051</td>
</tr>
<tr>
<td>China</td>
<td>1.25186</td>
<td>0.066</td>
</tr>
<tr>
<td>MtGox</td>
<td>1.60408</td>
<td>0.006</td>
</tr>
</tbody>
</table>

Table 14: Results from GARCH(1,1)
When the trade volume increases, so does the bitcoin return. The information demand has a larger coefficient, 0.190, suggesting a greater impact. As it is also positive, an increased amount of search queries suggests greater volatility of the bitcoin. The trend variable is however exhibiting a negative coefficient, -0.007. As explained in section 5.2.5, this is a, by us, constructed variable increasing linearly as time passes. The result of the GARCH(1,1) suggest that an increasing trend, symbolizing an increasing acceptance of bitcoin, has a dampening impact on the bitcoin volatility. The Cyprus dummy variable has the largest of the coefficients. With a coefficient of 1.848 it suggests a relatively strong influence, increasing the bitcoin volatility. In addition, the variable representing the failure of the MtGox bitcoin exchange displays a relatively large and positive coefficient, leading to the same conclusion, that it has increased the bitcoin volatility.

The calculation above was performed using the assumption of normal distribution. A second calculation was however performed, following the suggestion by Bollerslev (1987) that this would lead to a better fit of the model. The result of this second calculation, which can be provided upon request, does however not display any noteworthy indications that this would be the case for this study. The discussion of the most suitable distribution thereby ends with the choice of the common assumption of normal distribution.

### 6.5 Fitness of Model

#### 6.5.1 Ljung-Box Test

As described in section 5.8.1, the Ljung-Box test is utilized to evaluate the above GARCH (1,1) model, by displaying its ability to remove autocorrelation from the squared bitcoin return (Hull, 2012). As can be seen from table 15 below, the first p-value is significant leading to a rejection of the null hypothesis. The model is thus suffering from autocorrelation. In order to include the possibility that the bitcoin returns are autocorrelated, the conditional mean equation of the GARCH model can be written as an autoregressive model with lags (Alexander, 2008, p. 136). Table 15 below shows the test result for the same GARCH (1,1) model, but with one, two and three lags in the conditional mean equation. The Q-statistic is decreasing for every lag that is included. However, they are all significant and the null hypothesis is thereby rejected. Adding additional lags would also not improve the result, since the fourth lag was found non-significant.

<table>
<thead>
<tr>
<th></th>
<th>No lag Q-stat</th>
<th>P-value</th>
<th>One lag Q-stat</th>
<th>P-value</th>
<th>Two lags Q-stat</th>
<th>P-value</th>
<th>Three lags Q-stat</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ljung-Box</td>
<td>337.85</td>
<td>0.0000</td>
<td>217.41</td>
<td>0.0000</td>
<td>92.30</td>
<td>0.0000</td>
<td>84.19</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

*Table 15: Ljung-Box test*

#### 6.5.2 Durbin-Watson Test

Making use of the additional lag in the conditional mean equation of the GARCH (1,1) model an improvement becomes obvious. From a value of 1.07, indicating negative autocorrelation, the inclusion of additional lags leads to values of the d-statistic of round about 2. This suggests that the autocorrelation is removed.

<table>
<thead>
<tr>
<th></th>
<th>No lag d-statistic</th>
<th>One lag d-statistic</th>
<th>Two lags d-statistic</th>
<th>Three lags d-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Durbin-Watson</td>
<td>1.0752</td>
<td>1.7318</td>
<td>2.0554</td>
<td>2.0990</td>
</tr>
</tbody>
</table>

*Table 16: Durbin-Watson test*
6.5.3 Corrgram
With two seemingly contradicting test results, a corrgram was generated in STAT. The Corrgram, which is a table of the autocorrelations first result, with a model with no lags included. This suggests autocorrelation, since all p-values of the corrgram’s lags are significant. The same result is given for the GARCH (1,1) model with one lag. The model with two lags is similar, but shows indications of change, as the first lag of the corrgram is non-significant. It is however not enough to disregard the significance of the rest of the lags of the corrgram, but it is an indication. With three lags included in the model, all lags have a positive value, however not significant.

<table>
<thead>
<tr>
<th>Corrgram</th>
<th>No lag for LogReturn</th>
<th>One lag for LogReturn</th>
<th>Two lags for LogReturn</th>
<th>Three lags for LogReturn</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lags</td>
<td>P-value</td>
<td>Lags</td>
<td>P-value</td>
<td>Lags</td>
</tr>
<tr>
<td>Lag 1</td>
<td>0.0000</td>
<td>Lag 1</td>
<td>0.0000</td>
<td>Lag 1</td>
</tr>
<tr>
<td>Lag 2</td>
<td>0.0000</td>
<td>Lag 2</td>
<td>0.0000</td>
<td>Lag 2</td>
</tr>
<tr>
<td>Lag 3</td>
<td>0.0000</td>
<td>Lag 3</td>
<td>0.0000</td>
<td>Lag 3</td>
</tr>
<tr>
<td>Lag 4</td>
<td>0.0000</td>
<td>Lag 4</td>
<td>0.0000</td>
<td>Lag 4</td>
</tr>
<tr>
<td>Lag 5</td>
<td>0.0000</td>
<td>Lag 5</td>
<td>0.0000</td>
<td>Lag 5</td>
</tr>
<tr>
<td>Lag 6</td>
<td>0.0000</td>
<td>Lag 6</td>
<td>0.0000</td>
<td>Lag 6</td>
</tr>
<tr>
<td>Lag 7</td>
<td>0.0000</td>
<td>Lag 7</td>
<td>0.0000</td>
<td>Lag 7</td>
</tr>
<tr>
<td>Lag 8</td>
<td>0.0000</td>
<td>Lag 8</td>
<td>0.0000</td>
<td>Lag 8</td>
</tr>
<tr>
<td>Lag 9</td>
<td>0.0000</td>
<td>Lag 9</td>
<td>0.0000</td>
<td>Lag 9</td>
</tr>
<tr>
<td>Lag 10</td>
<td>0.0000</td>
<td>Lag 10</td>
<td>0.0000</td>
<td>Lag 10</td>
</tr>
<tr>
<td>Lag 11</td>
<td>0.0000</td>
<td>Lag 11</td>
<td>0.0000</td>
<td>Lag 11</td>
</tr>
<tr>
<td>Lag 12</td>
<td>0.0000</td>
<td>Lag 12</td>
<td>0.0000</td>
<td>Lag 12</td>
</tr>
<tr>
<td>Lag 13</td>
<td>0.0000</td>
<td>Lag 13</td>
<td>0.0000</td>
<td>Lag 13</td>
</tr>
<tr>
<td>Lag 14</td>
<td>0.0000</td>
<td>Lag 14</td>
<td>0.0000</td>
<td>Lag 14</td>
</tr>
<tr>
<td>Lag 15</td>
<td>0.0000</td>
<td>Lag 15</td>
<td>0.0000</td>
<td>Lag 15</td>
</tr>
<tr>
<td>Lag 16</td>
<td>0.0000</td>
<td>Lag 16</td>
<td>0.0000</td>
<td>Lag 16</td>
</tr>
<tr>
<td>Lag 17</td>
<td>0.0000</td>
<td>Lag 17</td>
<td>0.0000</td>
<td>Lag 17</td>
</tr>
</tbody>
</table>

*Table 17: Corrgram*

6.5.4 Concluding Comment
Despite indications of reduced autocorrelation, the result of the above tests are somewhat inconclusive. It is however clear that the model has unknown autocorrelation. The coefficients of the variables, can however be estimated securely using a consistent covariance matrix estimate (Zeileis, 2004, p. 2). This is a common method within econometric analyses and have been advocated in econometrics literature for the last 30 years.
7. Analysis

A thorough review of literature, previous research and background information about bitcoin ensured the identification of five main variables that could offer insights into the bitcoin price volatility. The ones most likely to contribute to the BTC price volatility were found to be: trade volume, information demand, the effects of six major events, a trend of rising acceptance, and a world market index. In this chapter, we provide a deeper analysis into the significance of these variables and offer theoretical support for our findings.

7.1 Information Demand

Taking the stance of researchers such as Fama (1965) and Malkiel (2003), information should not affect an investor’s ability to earn above-average returns. Prices should always reflect the fundamental value of the asset. Since the bitcoin price is dependent solely upon supply and demand and lacks a fundamental value (ECB, 2012, p. 21; Kristoufek, 2013, p. 1), it indicates an increased reliance on information published about it. In addition, the efficient market hypothesis only suggest that information is irrelevant when investors are not willing to take on additional risk (Malkiel, 2003, p. 60). As it has been suggested that above average risk-taking may be a characteristic of bitcoin investors (Moore, 2013, p. 148), this implies an increased importance for them to keep up with the information flow.

Madhavan (2000, p. 207) argues that the informational structures and informational efficiency of a market are important for understanding investor behavior and thus explaining market outcomes. The vast amount of information published about bitcoin since its introduction (e.g. ECB, 2012; Naughton, 2013; The Economist, 2013) ensures that investors have a great deal of information to sort through in order to find the information relevant to them. Given the fact that investor attention is a scarce resource (Barber & Odean, 2008, p. 786) and that acquiring all available information is too costly for investors despite today’s technological advancement (Grossman & Stiglitz, 1980, p. 405; Moscarini & Smith, 2002), one cannot assume that bitcoin investors are able to absorb all information supplied to them. In accordance with researchers such as Vlastakis and Markellos (2012), Da et al. (2011) and Moscarini and Smith (2002) we concluded that information demand is the most appropriate proxy for the information investors actually absorb and consider valuable.

In accordance with Miller (1977, p. 1164), the visibility of bitcoin and the attention it receives from its investors are vital for the investor to even consider trading in the first place. Thus, the fact that bitcoin figures extensively in the media is potentially positive. As found by Barber and Odean (2008, pp. 788-789), non-professional, individual investors are often more affected by attention. As such investors upholds the majority of the bitcoin market, it suggests that it should be more important for bitcoin. In addition, as high investor attention can instigate high investor sentiment (Da et al., 2011 p. 1471), which can cause price volatility (De Bondt & Thaler, 1987, p. 557) it is easy to see why information demand (Da et al., 2011; Drake et al, 2012; Vlastakis & Markellos, 2012) might offer valuable insight into bitcoins high volatility. In accordance with Baker and Wurgler (2007, p. 130), the emergent nature of the market intensifies this conclusion.
As suggested by the literature review, our empirical results confirmed that information demand has a strong influence on BTC volatility. The relationship is positive, implying that as information demand increases, the bitcoin price becomes more volatile. With a foundation in bounded investor rationality in uncertain situations (Simon, 1955), and the investor instinct to reduce ambiguity surrounding their investments (Illeditsch, 2011; Vlastakis & Markellos, 2012), this result is not surprising. As previously noted, the ambiguity of the bitcoin market is extreme. Thus, the bitcoin investor is subject to bounded rationality and will most likely base decisions partly on heuristics causing an imperfect market. The great proportion of individual, non-professional investors also increases the likelihood that trades are made based on noise instead of real information (Barber et al., 2009; Black, 1986; De Bondt & Thaler, 1989). This creates market inefficiencies and volatile prices (De Long et al., 1990, p. 706). However, theory suggests that such noise traders have also contributed to the increased trade volume (Li & Wu, 2011, p. 1511) displayed on the bitcoin market. Therefore, noise traders are important to consider (Mendel & Shleifer, 2010) for a market such as bitcoin.

Spikes in bitcoin information demand seem to correspond with major events. As argued by Vlastakis and Markellos (2012, p. 1810) this is the natural response from investors wanting to reduce the ambiguity caused by the event. Also in line with their argumentation, the increased information demand is only temporary and soon decreases again. This further corresponds to the working paper by Garcia et al. (2014, p. 10) who found support that negative events will create an increased information demand before it affects the bitcoin price. This allowed them to identify a certain predictive power in bitcoin information demand in relation to negative events. Thus, a deeper look into the correlation between events, information demand and BTC price could offer some interesting conclusions and offer a more thorough explanation for the event effects discussed in the upcoming section. Nevertheless, that is something left for future research to consider.

### 7.2 Event Effects

The information sensitivity of the bitcoin market indicated through the literature review (e.g. Brière et al., 2013, p. 4; Garcia et al., 2014, p. 14), the background information search (e.g. Bloomberg News, 2013; Strauss, 2013) and historical prices is, perhaps surprisingly, not fully displayed in the GARCH(1,1) results. The time studied, 13.09.2011 – 03.05.2014, was a period where several major events occurred that one might initially believe would have a substantial impact on bitcoin volatility. Instinct tells us that the news that bitcoin would be forbidden for a market as big as China or the closing down of one of its largest market places Silk Road, should not go unnoticed by the bitcoin community. As expected, the graph below demonstrates that it did not. Even so, the lasting effects appear rather low. A closer examination by using GARCH(1,1) shows that only two out of the six events studied are indeed significant for the bitcoin price volatility.

![Figure 10: Bitcoin information demand and events](image)
Studies of semi-strong form market efficiency often focus on the effects of particular events (Fama, 1970, pp. 383, 404), suggesting that events is a good indicator of investor knowledge and market beliefs. However, the presence of anomalies discussed by other researchers (e.g. Malkiel, 2003; Shiller, 2003), implies that these events may not always have such a large impact after all. An attempt to apply these traditional theories to bitcoin proves to be even more complicated when considering that the base of the EMH lies with the fundamental value of the asset (Shleifer, 2000). As bitcoin lacks a fundamental value, or at least an easily identified one (Bloomberg News, 2013; Garcia et al., 2014, p. 13; Kristoufek, 2013, p. 1), the theories of efficient markets and random walk serves merely as guidelines for a study about BTC volatility. Thus, the theoretical framework brought us into behavioral finance where investor psychology is an important factor (Kahneman & Tversky, 1979; Ritter, 2003; Simon, 1955).

It is important to note that the period where all these events occurred is rather short. Bitcoin is a new asset class and studies of investor psychology such as heuristics and sentiment are usually performed over a larger time span. Nevertheless, the unique characteristics and rapid price changes indicates that this is a market that does not operate according to traditional rules. Further, bitcoin exhibits many of the characteristics Baker and Wurgler (2007, p. 130) argue ensures the greatest sensitivity to investor sentiment. The first bitcoin exchange opened in 2010 (History of Bitcoin, 2014), it did not reach a significant trading volume until 2013 (see figure 6), exhibits a high volatility at 86% and it has a total market capitalization of 5,421 million USD (Table 1).

As discussed in the news (Naughton, 2013; The Economist, 2013) and suggested by researchers such as Briére et al. (2013, p. 4) the Cyprus event had a significant impact on the bitcoin market. With a p-value of 0.004, our findings concur with these results. By merely viewing the graph, it is easy to see that a bitcoin price surge occurred around the time that the Cypriot savings levy was imposed and savers were refused the right to withdraw their money from the bank. Within a month, the price dropped again, but it has never again dropped to the levels before the Cyprus event. Instead, the price soared to unexpectedly high levels at the end of the year. One can hypothesize that investors feeling frustrated by the traditional banking system after the Cyprus event sought out bitcoin as an alternative placement for their money. It appears that this event caused investors to open their eyes to this innovative and denationalized investment opportunity. It is thus reasonable to assume that it has continued to serve as a starting-point in the decision-making process for many bitcoin investors. If true, this is a clear example of anchoring heuristics described by Tversky and Kahneman (1974, p. 1128). Investors may thus be biased by failing to adjust their decisions to

![BTC price curve and events](image-url)
new information, such as price data indicating the riskiness of a bitcoin investment, and instead conservatively focusing on the positive option it proved to be around the time of the Cyprus event.

In the final months of 2013, bitcoin was heavily discussed in the news due to some major events (see Figure 10). Within a relatively short time span, the bitcoin price surged which spurred further discussions in the media and among investors. Our research found that none of these events had any greater effect on the bitcoin price individually. However, perhaps together their effect is larger. Availability heuristics explains that investors often group together small events and make decisions based on an overall estimate of their combined significance (Tversky & Kahneman, 1974, pp. 1127-1128). The closing of Silk Road (Greenberg, 2013), the Baidu decision to accept payments with bitcoin (Clinch, 2013b; Chang, 2013), and Ben Bernanke’s statement of bitcoins potential (Strauss, 2013) can together be interpreted as bitcoin was moving towards a more legitimized and customary use at the end of 2013. As will be discussed later, this could be connected to an increased acceptance of bitcoin as an asset. These positive events appear to have created optimistic investor sentiment which allowed for a continuous BTC price increase and perhaps even overpricing (Barberis et al., 1998, pp. 232-233; Stambaugh et al., 2012, p. 297).

Such overpricing is congruent with the bitcoin market consisting mainly of non-professional noise traders (Kristoufek, 2013, p. 1), whose actions can instigate bubble behavior of the BTC price (Balibouse, 2014). This implies a higher likelihood of market inefficiencies (Stambaugh et al., 2012, p. 301) than more established markets. Thus, the bitcoin market is more likely to experience fads (Bikhchandani et al., 1992; West, 1988) and mimetic contagion (Topol, 1991). Further, the actions of merely a few investors, perhaps those seeking refuge from traditional banking after the Cyprus event, could have triggered an informational cascade (Bikhchandani et al., 1992, p. 1006). Guillaume Babin-Trembley, a bitcoin spokesperson argued in an article with Forbes (Kitco News, 2013) that this event is in fact the reason behind bitcoins later successes. A glance at Figure 11 above makes this statement credible. At the time, the perceived underlying value of traditional currencies appear to have changed in line with Bikhchandani et al. (1992), making bitcoin a valued alternative.

Despite bitcoin’s 2013 successes, when the Chinese government prohibited banks and financial institutions to deal with bitcoin, the BTC price decreased considerably. Still, with our 5% significance level, this news had no significant impact on volatility. This could be explained by the research by Stambaugh et al. (2012, p. 297) whom concluded that low, i.e. negative, sentiment leads to underpricing less often than high, i.e. positive sentiment leads to overpricing. However, a few months later when MtGox was hacked and many investors lost their money, the reaction was different. As only a few months had passed since the negative news from China, investors were more prone to a negative reaction. Our results show that the failure of the MtGox exchange has had a significant impact on the BTC price volatility. Perhaps investors were relying on representativeness heuristics. Thus, placing too much weight on their recent experience with the Chinese news instead of allowing for a probability assessment based on the combined events and developments over the previous years.
7.3 Trade Volume

Market microstructure theory offers many insights into an assets trade volume and price formation (Garman, 1976; Madhavan, 2000, pp. 205-206). We have seen that bitcoins trade volume exhibited a significant increase during 2013 (Figure 7). The descriptive statistics displays a story of a quickly rising number of trades per day. Nonetheless, bitcoin still exhibits a rather low volume at about 68,000 trades/24 hours (Table 1). The fixed final supply of bitcoin (Chowdhury, 2014, p. 3) ensures that at some point, this increasing trend will subside. At this point however, the market still has room to grow and investors demand for bitcoin is continuously increasing.

As revealed by the GARCH (1,1) test, trade volume is positively related to bitcoin volatility. Thus, as trading of BTC increases, the price becomes more volatile. Perhaps this can be explained by what Robert Shiller identified as bubble-like behavior of the bitcoin price during the end of 2013 (Balibouse, 2014). The increase in information demand at the time, which our tests showed to be positively correlated with trade volume, indicates that investors were seeking out unusual amounts of information. Theoretically, all the positive events discussed in the news at this time could explain the increase in both the demand for information and trade volume. The Mixture of Distribution Hypothesis [MDH] (Kalev et al., 2004, p. 1446; Vlastakis & Markellos, 2012, p. 1809) supports such a relationship. This can be further connected to Black’s (1986) arguments that noise in the market creates increased trading volume. Further, since noise trading leads to market inefficiencies and not optimal decisions, volatility increases (De Long et al., 1990, p. 706).

As most bitcoin investors are unsophisticated noise traders (Kristoufek, 2013, p. 1), they are easily affected by the behavior and expectations of others. This increases the chance for uniform herding behavior (Lux, 1995, p. 882). By relying too much on the information published and the behavior of others, decisions are made based on heuristics and does not represent actual probability assessments (Scheinkman & Wei Xiong, 2003, p. 1186; Schwert, 1990, p. 30; Tversky & Kahneman, 1974). By overestimating the value of information and following the behavior of others, a trading frenzy among bitcoin investors could be a contributor to the bubble-behavior of the BTC price.

An increased trading volume is intimately related to an increased liquidity (O’Hara, 1995, p. 223). From the MDH (Clark, 1973; Li & Wu, 2011, p. 1511) we know that the large presence of noise traders in the bitcoin market should increase liquidity and eventually reduce volatility. Nevertheless, our empirical study suggests another reality. Perhaps some of the unique characteristics of the bitcoin market can offer support for this result. Market microstructure tells us that the trading mechanism itself is a vital aspect of liquidity (O’Hara, 1995, pp. 215-216). The low transaction fees, as well as the direct and quick transactions of bitcoin (Bitcoin Project, 2014a) would suggest a high liquidity. However, the bitcoin trading mechanism further exhibits many problems such as difficulties for investors to withdraw their money (Wong, 2014), a low trading volume on individual exchanges (Moore, 2013, p. 148; Moore & Christin, 2013, p. 7), and many exchanges failing, ensuring a high exchange risk (Moore & Christin, 2013, p. 3). Hence, trade becomes difficult, and arbitrage opportunities (Shleifer, 2000, p. 3) are lower. This suggests that so far, the increased trade volume may not have simplified bitcoin trading.
In addition, the negative correlation identified between BTC trade volume and return shows that the growth of the bitcoin market may not have provided benefits to bitcoin investors. This is opposite to the conclusions drawn by Gervais et al. (2001, p. 877) who found that increased trading volume creates a return premium on prices. However, they also stated that this effect grows with time, so perhaps the time period studied is simply too small and the bitcoin market too immature for this effect to be present. Nevertheless, the BTC average annual return appears to have increased with time in line with each new study performed. The study by Briére et al. (2013, p. 5) found a return of 371%. By adding a few additional months Chowdhury (2014, p. 6) results displayed a higher return of 476%. Finally, by covering a somewhat later time-period, our study identified an even higher return of 517%. Thus, the extremely high BTC average annual return now displayed seem to have other explanations than the increasing trade volume.

### 7.4 Trend

Theoretically, investors should seek to avoid ambiguity and uncertainty in their investment decisions (Fama et al., 1969, p. 2; Illeditsch, 2011). Then, one might wonder why so many have sought out bitcoin as an investment objective. It has been argued that initially bitcoin investors mainly consisted of technology enthusiasts, liberalists and criminals (Grinberg, 2011, p. 165; Yermack, 2014, p. 7) and that still today it mainly consists of individual noise traders and speculators (Kristoufek, 2013, p. 1). Thus, the market is far from mature. Its lack of regulation and transparency further makes the outcome of an investment uncertain (Chin, 2014; Illeditsch, 2011; Moore & Christin, 2013).

However, as trade volume grows, more information is published and institutions open their eyes to bitcoin the acceptance of bitcoin as a currency and an asset class seem to be increasing. Support can be found in Prospect Theory of the importance of framing for the investment decision (Kahneman & Tversky, 1979; Tversky & Kahneman, 1986). News about bitcoins increased acceptance is widespread as many news sources have discussed the establishment of the Bitcoin Investment Trust (Matonis, 2013), Exchange-Traded Funds (Chin, 2014), as well as the increased acceptance of bitcoin as payment for goods and services (Bradbury, 2014; Holpuch, 2013). Both traditional media outlets and specific bitcoin news sources publish information about bitcoin on a daily basis (Arthur, 2013; Bitcoin Magazine, 2014; Bitcoin Project, 2014a; The Economist, 2013). This indicates that people are becoming increasingly used to news about bitcoin and the ambiguity of the market is reduced.

As predicted by the literature review, our empirical data confirmed that a rising trend of acceptance would have a negative effect on the bitcoin price volatility. In more illustrative terms, a higher belief that bitcoin is a valid investment objective causes its price to stabilize. Bihchandini et al. (1992) argues that investors often rely on the social information provided by the behavior of others in their investment decisions. Thus, as more and more people begin to openly express their belief in bitcoin and increase their trade volume, investor imitation will ensure a more stable price formation. The social media loop present in the bitcoin market suggested by Garcia et al. (2014) further supports this line of argument.
7.5 World Market Index

Interestingly enough, the state of the overall market appears to have no significant influence on the bitcoin market. The empirical result identified that the WMI, our proxy for the state of the market, had no significant impact on bitcoin price volatility. Literature suggests that volatility tends to move between markets and that prices are contagious (Bekaert et al., 2005; Lin et al., 19941), but this is apparently not the case for bitcoin. When investors are uncertain about the state of the market, aggregate investor sentiment could affect prices in individual markets creating increased volatility (Baker & Wurgler, 2007; Ozoguz, 2009). As argued by Baker and Wurgler (2007, p. 129) this effect is especially present for young and highly volatile assets. However, in line with the studies performed by Brière et al. (2013) and Chowdhury (2014), BTC appear unaffected by market events.

These researchers have suggested that bitcoin might offer a potential hedge against crisis and present an opportunity for well-diversified portfolios. They base these conclusions on BTC high skewness, which Brière et al. (2013, p. 5) found to be 1.99 and Chowdhury (2014, p. 6) found to be even higher at 2.30. Our results however indicated a much lower skewness of 1.35. Still, Chowdhury (2014) and Brière et al. (2013) offer some interesting suggestions and upon completion of their research, their published work will be an interesting read. Until then, we reserve any conclusions based on their results and simply use it as a topic for discussion.

Despite the remarkably high average annual return of a BTC investment, and its possible benefit to a well-diversified portfolio, a bitcoin investment comes with extreme risks. A comparison to the average annual volatility found by Brière et al. at 175% (2013, p. 5) and Chowdhury (2014, p. 6) at 258%, shows that our results are substantially lower at 86%. Nevertheless, the volatility is still high and makes the outcome of a BTC investment very uncertain. Further, the high exchange risk and lack of regulation (T. Moore, 2013; T. Moore & Christin, 2013) adds to this reasoning. Perhaps when trading volume and liquidity are increased, a wider acceptance is reached and improved security for investors can be ensured, BTC will be a more commonly used source of portfolio diversification.

7.6 Chapter Summary

By combining the information in the preceding chapters, this analysis has aimed to offer a discussion into bitcoins price volatility. The bitcoin market is growing, which can be seen from its increased trade volume and positive trend. Supported by both literature and our own empirical results we found that both these variables have a significant impact on bitcoin volatility. In addition, we found that two of the chosen event variables have a significant impact on bitcoin price, the failure of MtGox and the capital controls imposed in Cyprus. Thus, the information sensitivity of the bitcoin market is perhaps lower than initially assumed after the extensive information search. However, looking at information in a more general term, through the proxy information demand, we still found an explanatory power for the extreme BTC price volatility.
8. Conclusions

We have now reached the end of this thesis. A theoretical framework has been built, the bitcoin market has been described and an empirical study have been performed. These parts were all connected in the previous chapter, and here we will now offer an answer to the research question posed and offer some concluding comments.

8.1 Answer to Research Question

This study set out to identify the drivers behind the extreme price volatility of bitcoin. With a basis in the philosophical standpoints of objectivism and positivism a quantitative study with a deductive research approach was performed. An extensive literature and information review into price formation and the bitcoin market guides the choices throughout the empirical study. In accordance with market microstructure theory (Garman, 1976), the details of the bitcoin trading mechanism and the characteristics of the bitcoin investor were carefully considered. By combining ideas from traditional financial theories such as the efficient market hypothesis (Fama, 1965) with the more recently introduced behavioral finance (Tversky & Kahneman, 1974), a comprehensive theoretical foundation was built.

To allow for a more exhaustive study with a higher explanatory power, the posed research question is formulated in an inclusive manner. This question was broken down into two parts in order to provide a clear answer. The first sub question was answered through an analysis of literature and secondary information. Consistently following the theoretical arguments with a close link to the bitcoin market aided in the identification of ten variables, see table 10, which could offer insight into the extreme price volatility of bitcoin.

<table>
<thead>
<tr>
<th>Event effects</th>
<th>Sub question 1</th>
<th>Sub question 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Which variables can explain bitcoin price volatility?</td>
<td>Do the identified variables have a significant effect on bitcoin price volatility?</td>
</tr>
<tr>
<td></td>
<td>Identified variable</td>
<td>Is it significant?</td>
</tr>
<tr>
<td>Information demand</td>
<td>Yes</td>
<td>Positive</td>
</tr>
<tr>
<td>Trade volume</td>
<td>Yes</td>
<td>Positive</td>
</tr>
<tr>
<td>A positive trend of acceptance</td>
<td>Yes</td>
<td>Negative</td>
</tr>
<tr>
<td>A world market index</td>
<td>No</td>
<td>-</td>
</tr>
<tr>
<td>Event effects</td>
<td>Yes</td>
<td>Positive</td>
</tr>
<tr>
<td>• Cypriote crisis involving capital controls</td>
<td>No</td>
<td>-</td>
</tr>
<tr>
<td>• The FBI’s closure of the Silk Road market place</td>
<td>No</td>
<td>-</td>
</tr>
<tr>
<td>• Baidu’s decision to accept payment with bitcoin</td>
<td>No</td>
<td>-</td>
</tr>
<tr>
<td>• A positive statement about bitcoin from the Federal Reserves’ chairman Ben Bernanke</td>
<td>No</td>
<td>-</td>
</tr>
<tr>
<td>• China’s prohibition of bitcoin as a means of payment</td>
<td>No</td>
<td>-</td>
</tr>
<tr>
<td>• The bankruptcy of the largest bitcoin exchange, MtGox</td>
<td>Yes</td>
<td>Negative</td>
</tr>
</tbody>
</table>

| Table 18: Answers to sub question 1 & 2 |
Their significance and explanatory value was further examined through financial modeling using GARCH(1,1). The empirical study was inspired by the research by Vlastakis and Markellos (2012) and Kristoufek (2013). However, as we set out to form a wider description of BTC price volatility, our variable selection is adjusted and more extensive. By inserting the ten variables identified in sub question 1 into the GARCH(1,1) model, sub question 2 was answered. Table 18 displays which variables have a significant effect on bitcoins price volatility as well as if this effect is positive or negative. Despite initial indications that the stated variables would have an influence on BTC volatility, the empirical result suggest that only five of them carry significant explanatory powers. By using price data from Bitstamp and BTC-e, we included 50% of the BTC market in our study. Thus, we have covered a significant part of the total bitcoin market ensuring trustworthy results. In this way, we were able to answer our research question as followed:

**What drives bitcoin price volatility?**

Our research have identified information demand, trade volume, a positive trend of acceptance, and the effects of events such as the capital controls on Cyprus and the failure of the largest bitcoin exchange MtGox to be significant drivers of bitcoin volatility.

Just as Vlastakis and Markellos (2012) found for stocks on NYSE and NASDAQ, and Kristoufek (2013) for bitcoin on MtGox, our empirical research revealed a close positive connection between information demand and BTC price volatility. When bitcoin investors are uncertain about their investment, they seek to reduce this ambiguity. High investor attention, here represented by increased information demand, creates high investor sentiment (Da et al., 2011; De Bondt & Thaler, 1987). In turn, this elevates BTC volatility. This seem to correspond with events such as the Cypriot banking crisis and the bankruptcy of MtGox (Figure 10). A general connection can be drawn to the work of Garcia et al. (2014) who found that spikes in information demand often stem from the occurrence of negative events. Even though this is interesting to discuss, our focus has been the effect of events on price volatility.

The empirical study revealed that both these events had a significant effect on BTC price volatility. As others have already suggested (Brière et al., 2013; The Economist, 2013) we argue that the difficulties with the traditional banking system in Cyprus spurred an interest in the bitcoin alternative. It is possible that an informational cascade was created, and investors anchored their future decisions on this event creating a positive bias for bitcoin. After this, the bitcoin price exhibited a rapid increase. As displayed in Table 11, several events occurred in this time, such as the closing of Silk Road, Baidu’s decision to accept payment with bitcoin, Ben Bernake’s positive statement and the Chinese prohibition of bitcoin use. However, none of these had any significant effect on their own. However, when MtGox failed, not too long after the Chinese announcement, price volatility increased. A feasible explanation could be that people had become worried creating representativeness heuristics and bias. Alternatively, the realization that a bitcoin investment could be lost in an instant due to hacks and technological difficulties may have hit hard with investors. The characteristics of the bitcoin investor ensures a high likelihood of such heuristics and biases influencing their decision making process.
The empirical study also indicated that increased trade volume creates additional volatility. This is somewhat contradictory to the theoretical arguments by of the MDH (Clark, 1973; Li & Wu, 2011), which we argue could be an effect of the unique characteristics of the bitcoin market. We suggest that our results are more supported by Black (1986) and De Long et al. (1990b), implying that the high presence of noise traders ensures an increased trade volume and non-optimal decisions, which in turn generates high BTC volatility.

In line with Garcia et al. (2014), the rising positive trend of acceptance for bitcoin is reducing its price volatility. We suggest that as the market becomes more mainstream and mature, it becomes less ambiguous for the investor. As theory suggest (Baker & Wurgler, 2006; Illeditsch, 2011), such markets should exhibit a more stable price. Thus, the risk of fads, herd behavior, mimetic contagion, sentiment and bubbles should reduce over time.

Just because a variable is not significant does not mean it is not important for the understanding of bitcoins price volatility. A lack of significance may be just as important. For example, supporting the studies by Brière (2013) and Chowdhury (2014), our empirical results indicate that the bitcoin price is not influenced by the overall state of the market. A more thorough study into this particular variable could offer valuable insights to investors seeking a hedge against financial crisis as it would not be subject to market contagion.

Today, bitcoin investors are forced to accept extreme risks and its investors are said to exhibit quite different characteristics than those investing in traditional assets. However, the market is also claimed to have immense potential under the right conditions. Even though the market is developing quickly it is far from becoming a mainstream addition to a well-diversified portfolio. It is exciting to see what the future holds for this fringe asset class that many have dismissed as something for criminals, liberals and technology enthusiasts.

8.2 Fulfillment of Purpose

A benefit of studying such an unexplored market is the possibility to creatively build a study by allowing for many variables. We have consistently anchored our arguments on theory and performed an empirical study based on a careful selection of variables and reputable financial methods. In this way, we have built a descriptive story of the bitcoin market. Hence, we have fulfilled our purpose to widen the knowledge of the bitcoin market and to discuss the theories of price volatility in the light of this new market.

8.3 Contribution to Literature

In varying ways, one of the root causes of price volatility is some type of information or the understanding of information. Everything from news reports, historical prices, trade volume, the occurrence of events both within the particular market as well as within others, to the combined information provided about the overall state of the market and the beliefs of others. Whether or not there is predictability in prices or they follow a random walk, information is a contributing factor. From a general perspective, we have offered price volatility theories additional insights by applying them to a study of the bitcoin market. In addition, by using the methods of Vlastakis and Markellos (2012) we widened the scope of their conclusions, as our results regarding information demand were consistent with theirs.
Concerning bitcoin specific literature, not much research has been performed to this date. Even fewer have been published and peer-reviewed. We built on the work of Kristoufek (2013) about information demand and added additional insights to Brière et al. (2013) and Chowdhury (2014) which suggests a low correlation between the BTC market and other assets. In addition, we offered another perspective to the bitcoin market than researchers such as Christin (2013), Christine and Moore (2013), Chowdhury and Mendelson (2013) and Garcia et al. (2014). They have all have offered insights into this risky and unique market, which our study has further added to.

8.4 Contribution to Practice

We have added one more piece of the puzzle towards explaining the mystery of the bitcoin market. Most investors seek to reduce the ambiguity surrounding their investments and this thesis offer insight to those wanting to learn more about bitcoin to base their investment decisions upon. The bitcoin market is risky and many are uncertain about its properties and how its price will react to different forms of information. By using our conclusions, a wider understanding of the extreme bitcoin price volatility can be gained. Hence, this thesis has provided a small step towards reducing the ambiguity of the bitcoin market.

8.4 Suggestions for Future research

Many questions remain surrounding the variables studied here, and potentially additional significant variables exist. Hence, future researchers interested in this market have a lot to choose from in terms of study direction. This is one of the first studies of its kind and to uncover the mystery of bitcoin, many more are needed. Below we offer some suggestions.

Previous research has suggested a bidirectional relationship between volatility and information demand (Vlastakis & Markellos, 2012). However, we contended by confirming a correlation. Further study could reveal if increased volatility in itself will also raise information demand. In our research, we also touched upon the idea that information demand is effected by events, as was suggested by Garcia et al. (2014). As they suggested predictability from negative events, a more thorough study into this connection could prove informative. Similarly, we are curious as to the existence of event effects on volume.

Despite bitcoins innovative nature, there are other digital currencies on the market. Even though none of them are as extensively traded as bitcoin, it would be interesting to see how our results hold up on markets such as litecoins or Mezacoins.

In addition, perhaps other researchers with a different background have ideas for other drivers of BTC price volatility. We further suggest additional research into each variable in order to learn even more. We have offered a wide scope as to provide a foundation and we leave it up to the next researcher to continue adding to the story of bitcoin. Finally, if the bitcoin market continues to mature, an examination of these same variables with a longer time span would be valuable. At that point, any differences in results could be compared and analyzed and hence offer insights into the differences and similarities between an emerging market and a mature market.
9. Assessment of Research Quality

This chapter covers ethics and social aspects of the research as well as its reliability, replicability and validity. Despite the placement in the last chapter, these are important issues to discuss as they all concern the quality of the research in different ways. Having gone through all previous chapters it is hopefully clear that great considerations have been made to safeguard the highest quality of this research.

9.1 Ethical & Social Considerations

There are many ethical issues to consider when performing a research study (Saunders et al., 2009, p. 183). Taking ethics into consideration is not supposed to be seen as a way of limiting a study, but rather as ways of making sure that the study is performed in the best way possible for everybody involved (Diener & Crandall, 1978, pp. 151-152). What constitutes ethical actions depends on the social norm present and its philosophical foundation (Saunders et al., 2012, pp. 226-227). For example, in some countries child labour is socially accepted, while punishable by law in others. To help guide researchers in the ethical jungle, codes, such as the European Union’s Respect Code of Practice for Socio-Economic Research, have been drawn (Respect Project, 2014).

There is a large focus on ethics within research involving human participants, including considerations such as informed consent, harm to participants, invasion of privacy and deception. This is due to the close relationship between researcher and participants within such research (Bryman & Bell, 2007, p. 132; Saunders et al., 2012, p. 208). Since this research does not include any participants other than ourselves, no further discussion will be made upon these aspects. Instead focus will be directed towards matters such as honesty, accuracy, issues of affiliations, conflicts of interests, data management and copyright, which are ethical considerations of more importance for this study.

External parties may have interest in the research result, which according to Remenyi et al. (1998, p. 232) could influence the final outcome. It is therefore of interest to emphasize that this study is performed independently, without funding. There are further no connections to the bitcoin community or other party of interest to declare. All sources used have further been thoroughly declared as to respect and acknowledge the work of others and thereby avoiding plagiarism (Remenji et al., 1998, p. 232; Saunders et al., 114-115). When collecting the data, it is important to stay objective, as fabrication and manipulations of information and data are unethical behaviour that could have large implications for the results (Saunders et al., 2012, p. 245). It is further clear that the question of honesty also covers the parts of analysis and conclusions. To add to the integrity of this research, we declare that we have performed the study with greatest objectivity and therefore only employed objective data that we deem reliable, which we have provided with references in case of doubt.

By working with and publicizing this research paper, new knowledge about the bitcoin market is unfolded. This contribution may be small, but still of value for the development
of society. The knowledge provided is sprung from methods generalizable and could therefore be applicable also within other areas.

9.2 Quality Criteria

It is important to evaluate the quality of the performed business research, since it provides value in the form of credibility of the findings (Saunders et al., 2009, p. 156). When generating new knowledge by performing research it is essential that what is said to be tested also is tested, and that the same results is generated if repeating the study. The matter of research quality is, thus, largely concerned with the transparency of and the argumentation for the chosen research process. There are different approaches to evaluate research quality (Bryman & Bell, 2007, p. 40). We have chosen to do it in the light of the well-known criteria of reliability, reliability and validity, since they have proven to apply well to quantitative studies (Bryman & Bell, 2007, p. 42).

9.2.1 Reliability

The criteria of reliability concerns the consistency of the study, which suggests how repeatable it is (Bryman & Bell, 2007, p. 40-41). If this quality criterion is fulfilled, the generated result would be consistent over time if repeated by different observers. Therefore, transparency as to data and methods are important.

We argue that our study is reasonably stable over time. We believe the same result would be reached if we were to perform the study at a later point in time, e.g. by using the test-retest method (Bryman & Bell, 2007, p. 162). We dare to claim this since we are using historical data on the price of bitcoin for a certain period, which makes it independent of when it is retrieved from the system. The same is true for the data of the magnitude of the information demand. We further claim that our study is reliable since the process was built on standardized and pre-specific criteria. This means that the result is not affected by who is performing the actual data collection.

9.2.2 Replicability

This is a criteria closely related to the former, in that it concerns the possibility for other researchers to replicate the study (Bryman & Bell, 2007, p. 41). The emphasis here is on the disclosure of the procedures in great detail. We believe that we fulfil also this criterion by careful and thorough descriptions and explanations of the study.

9.2.3 Validity

Validity is the criterion that focuses on whether the conclusions provided by the study are sound and thereby gives the study credibility if satisfied (Bryman & Bell, 2007, pp. 41, 165). In order for a study to be considered valid it first needs to be deemed reliable. Considering that we view our research reliable we can proceed with analysing its validity. There are different possibilities of evaluating the validity of a study. Measurement validity is for example concerned with whether the study is constructed to measure what it says it will measure. In our study we have looked at the relationship between the information demand and the volatility of the bitcoin price. Since well-established theories suggest a relationship between information and price volatility and discussions with university
professors deemed our measurement plausible we argue that we fulfil the criterion of measurement validity through face validity (Bryman & Bell, 2007, p. 165).

*Internal validity*, on the other hand, is concerned with whether the study demonstrates *causal relationship* between two variables and is therefore closely related to positivist and quantitative studies (Saunders et al., 2012, p. 193). In our study we have, based on existing theory, made the assumption that information (demand) is the independent variable and price volatility is the dependent variable. Following these assumptions, we have in accordance with our research question set out to test this relationship between information demand following significant events and the price volatility of bitcoins. We are, thus, investigating whether there is a causal relationship between these variables and thereby fulfilling internal validity.

Another aspect of validity concerns how generalizable and transferable the results are (Bryman & Bell, 2007, p. 41). In order to satisfy this criterion of *external validity* it is important that the chosen sample is large enough and representative of the population studied. By using (daily) data for the last four years, we have included the largest amount of data available. Further, by using the largest bitcoin exchange platform, Bitstamp, our study is arguably the best indicator of the bitcoin market volatility. Due to the special features of the bitcoin it can be hard to argue for the applicability on the more traditional exchanges. Bitcoin is, however, not the only digital/alternative currency and it is possible that our results are transferable to currencies such as litecoin and Mazacoin.

A final consideration of validity is that of *ecological validity*. It concerns the applicability if the findings to people’s everyday life (Bryman & Bell, 2007, p. 42). With a investor perspective our research will have implications for people who are looking to invest their or others money. Our study thereby has ecological validity.
References


APPENDIX A: The Bitcoin Network

The Bitcoin System

In 2008, a paper was published under the pseudonym Satoshi Nakamoto, explaining the functions of a new peer-to-peer electronic cash system called bitcoin (Nakamoto, 2008). In January 2009, the bitcoin system was released (Chowdhury & Mendelson, 2013, p. 2; History of Bitcoin, 2014). It is based on an open-source software and in just a few years, it has grown into an ever-expanding network. There is no central clearing house or financial institution involved in the transactions of bitcoin (ECB, 2012a, p. 21). Instead, it operates internationally through the collective efforts of the user network.

The creators of bitcoin “define an electronic coin as a chain of digital signatures” (Nakamoto, 2008, p. 2). By using individual keys to sign transactions digitally, coins are transferred and verified. Through cryptography, each transaction is connected to two keys, a public key that encrypts incoming payments, and a private key that decrypts them (Woo et al., 2013, p. 13). Through a process called mining, high performance computers can be programmed to ‘dig’ for bitcoins by solving complex mathematical equations (Chowdhury, 2014, p. 3; Rogojanu & Badea, 2014, p. 107). In this way, transactions made are validated and new bitcoins are created and given as rewards to the miners (ECB, 2012, p. 24). However, most bitcoin users do not mine themselves (Chowdhury, 2014, p. 3). Instead, they purchase or trade their bitcoins from miners or on exchanges.

To ensure the transparency of the bitcoin system and limit counterfeiting or double spending, every bitcoin transaction is recorded in what is termed a blockchain (Chowdhury, 2014, p. 4). Miners gather batches of bitcoin transactions, which they then attach to the end of the chain (Woo et al., 2013, p. 3). This blockchain is publicly distributed and new transactions are regularly checked against the blockchain in order to ensure the integrity of the system (Brito & Castillo, 2013, p. 3). Even though each transaction is recorded, the system ensures privacy to its users by keeping the public keys anonymous (Nakamoto, 2008, p. 6). Accounts are not registered and the public keys cannot be tied to anyone’s identity (Brito & Castillo, 2013, p. 5; ECB, 2012a, p. 21). This reliance upon technical storage capacity could potentially cause problems if the network cannot keep up with the continuously growing blockchain and transaction volume (The Economist, 2014).

To prevent inflation, the monetary base is controlled through limiting the creation of bitcoins by making the equations progressively more complex to solve (Brito & Castillo, 2013, p. 5; T. Moore, 2013, p. 147). The system is constructed as to have a limited final supply of 21 million bitcoins. Miners are expected to reach this amount in the year 2140. Today, there are approximately 12.6 million bitcoins in circulation (Bitcoincharts, 2014c). However, the mining process will not stop here (Brito & Castillo, 2013, p. 5). Transactions will still need to be verified, and to ensure a reward for these miners, transaction fees instead of mined bitcoins will likely be offered. In this way, the system provides miners with an incentive to keep the network running indefinitely.
The Debate About Bitcoin

The ASA Institute for Risk and Innovation (Luco, 2013) published a report stating that although it has many positive aspects such as low transaction costs and instant transfers, the high volatility of the bitcoin price is a concern for its use as a currency. The report argues that bitcoin is an unstable market with many speculative investors and questions its practical use. Similarly, governmental rulings and reports further strengthens this view. In the US, there were regulatory reports stating that bitcoin is a legitimate financial instrument and the Federal Reserve Chairman Ben Bernake stated that bitcoin may hold long term promise if innovations can facilitate a payment system that is faster, safer and more efficient than currently (Rizza, 2013). Recently, Germany declared bitcoin as ‘private money’ subject to capital gains tax (Finextra, 2013). At the end of 2013, Norway went in a similar direction and declared a wealth tax on profits from Bitcoin investments ensuring its validity as an investment objective. However, a Chinese ruling determined it not being a currency and included a prohibition from financial institutions from handling it.

An ECB (2012a) report discussed its value as a currency in terms of three criteria; as a medium of exchange, as a unit of account and as a store of value. They concluded that within a particular virtual community, it could function as both a medium of exchange and as a unit of account. However, due to its unregulated nature and volatile price they question its use as a store of value. Finally, they state that bitcoin falls within the central banks’ responsibility since it has similar characteristics to other payment systems. In contrast, another report by Bank of America Merrill Lynch (Woo et al., 2013) states that bitcoin may become a serious competitor to traditional money-transfer providers. Still, their arguments are in line with those of the ECB (2012) and they question its role as a store of value due to the high price volatility and speculative activities by investors.

Research by Moore and Christin (2013, p. 3) suggest that close to half of bitcoin exchanges close. Chowdhury (2014, p. 7) warns investors of investing more than they can bare to lose, since it is extremely complicated to manage the high risks of bitcoin investments. He further states that the anonymity of the bitcoin market makes it incompatible with banks and regulators’ quest for transparency and accountability. As stated by Chin (2014) “without regulatory certainty, bitcoin will remain largely a fringe speculative asset class”.

APPENDIX B: Histograms
APPENDIX C: Reconstruction

Google Trend is as mentioned organized to only display daily data of the search queries for the three most recent months. The older data is instead displayed on a weekly basis. Since this study is focusing on bitcoing volatility, an extremely volatile type of financial asset, we are interest in using daily data. It is therefore necessary to reconstruct the data retrieved from Google Trend.

The reconstruction starts by summarizing all values for the different weekdays in our 3 months daily sample, Mondays in one group, Tuesdays in one etc. These values were later turned into percentages of the total value of the latest 3 months. These calculations give the following result:

<table>
<thead>
<tr>
<th>Day of the week</th>
<th>Of total search queries</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mondays</td>
<td>12.77%</td>
</tr>
<tr>
<td>Tuesdays</td>
<td>16.47%</td>
</tr>
<tr>
<td>Wednesdays</td>
<td>15.64%</td>
</tr>
<tr>
<td>Thursdays</td>
<td>15.16%</td>
</tr>
<tr>
<td>Fridays</td>
<td>16.55%</td>
</tr>
<tr>
<td>Saturdays</td>
<td>12.14%</td>
</tr>
<tr>
<td>Sundays</td>
<td>11.26%</td>
</tr>
</tbody>
</table>

The next step is to divide the weekly values that we have for the rest of our sample equally between the days of the week. The last step is then to multiply the percentages from the table above with the corresponding weekday of the sample. All Mondays from the weekly sample is thus multiplied with 12.77%, all Tuesdays with 16.47% etc.
APPENDIX D: Scatterplots