NTNU

Norwegian University of Science and Technology

Does media attention affect Bitcoin return, and thus explain investor attractiveness?

A categorization- and demand analysis of Bitcoin

An empirical study

Lars Aasland and Eirik Skei Lerfald

September 2018

Master Thesis

Department of Economics

Norwegian University of Science and Technology

Supervisor: Gunnar Bårdsen

Preface

This thesis completes a two-year master program in Financial Economics at NTNU and was carried out in the spring and over the summer of 2018. It has been a challenging yet rewarding process. Knowing little of the topic on beforehand, we have spent several hours reading relevant literature to better understand the dynamics of Bitcoin. With a subjective positive starting point regarding Bitcoin and its prospects for the future, we are several months later left with a more objective and informed view.

We would like to thank our supervisor Gunnar Bårdsen for valuable feedback, and for always putting time aside to discuss the progress of our thesis. We would also like to thank Siri Østraat for reading the thesis and pointing out easy-to-miss grammatical errors.

This master thesis is a collaboration between Eirik Skei Lerfald and Lars Aasland. The views in this thesis is our own, along with any errors.

Abstract

This thesis aims to analyze how media attention contributes to the demand for Bitcoin, and in so way Bitcoin return. A useful tool in this analysis, is a categorization of Bitcoin. The two main questions to be answered is:

(i) What kind of financial asset can we categorize Bitcoin as?

(ii) How does Media attention affect Bitcoin return?

This is done through firstly laying out a theoretical framework for price formation - where investor attractiveness is captured through a variable for media attention. Building on this framework, Bitcoins function and ability as money today is investigated through a comparison with the traditional monetary framework we know today. This is further investigated with an analysis of the volatility process of Bitcoin and financial assets. Which concludes with Bitcoin being classified as a speculative asset who do not resemble any traditional financial asset. Following this it is found that media attention does make Bitcoin more attractive for investors and being a driver for demand. This speculative drive of demand coheres with Bitcoin being a speculative asset.

Sammendrag

Denne avhandlingens mål er å analysere om medieoppmerksomhet er en drivende faktor i etterspørselen etter Bitcoin, og på så måte avkastning på Bitcoin. Et nyttig verktøy i denne analysen er å kategorisere Bitcoin. De to hovedspørsmålene som da vil bli besvart er:

(i) Hva slags finansielt aktivum kan Bitcoin kategoriseres som?

(ii) Hvordan påvirker medieoppmerksomhet Bitcoin?

Dette er gjort ved å først presentere et teoretisk rammeverk for prisdannelse hvor investorers interesse er forklart i en variable for medieoppmerksomhet. Ved å bygge videre på dette rammeverket blir Bitcoins funksjonalitet som en valuta i samfunnet i dag analysert og sammenlignet ved bruk av det tradisjonelle rammeverket for penger vi kjenner til. Dette er videre analysert ved hjelp av volatilitetsprosessene til Bitcoin og andre finansielle aktivum. Funnene fra denne analysen tyder på at Bitcoin ikke kan klassifiseres sammen med tradisjonelle finansielle aktivum, og på så måte er et spekulativt finansielt aktivum som står på egenhånd. Videre blir det funnet at medieoppmerksomhet gjør Bitcoin mer attraktiv for investorer og er en driver av etterspørsel. Denne spekulative driveren av etterspørsel sammenfaller godt med kategoriseringen av Bitcoin som et spekulativt aktivum.

Contents

1. Introduction

Amid the turmoil of the 2008 financial crisis, Satoshi Nakamoto[1] sent out his "Bitcoin: A Peer-to-Peer electronic cash system", known as the *White paper*, to a mailing list of fellow mathematical cryptography enthusiasts. From a humble beginning with only enthusiasts, Bitcoin grew steadily, with some bumps here and there, until its value skyrocketed in 2017 and Bitcoin suddenly became the household discussion. This is clearly seen by the attention given to Bitcoin by the media and people in general, using Google trends as a proxy, also skyrocketing during 2017. This did of course not go silently in the financial world, and the lack of intrinsic value[2] in Bitcoin has been under fire, by people like Jamie Dimon[3], since Bitcoin made itself relevant. The discussion surrounding the value of Bitcoin, and what Bitcoin really is has been churning and churning, and the sole believers and critics are distanced between Bitcoin being the currency of the future[4]- or just another bubble[5]. This has been an ongoing discussion, accompanied by news about the tremendous return some people have made of Bitcoin[6], the media attention given Bitcoin has been of great magnitude.

1.1 Bitcoin 101[7]

Bitcoin is a decentralized cryptocurrency. Meaning it has no centralized issuer, nor any third-party backing. This exclusion of the third party is made possible through an open blockchain and cryptographical mathematics, which makes all transactions- and transaction history available for all to see. It is not regulated in any way, and the only thing needed to buy Bitcoin is internet and a digital wallet to store the Bitcoins. When talking about the price of Bitcoin, it is the USD-BTC exchange rate which is denominated.

[1] See (The economist, 2018)
[2] Like a fiat currency, Bitcoin has no underlying value, nor promises any payments. This will be further explained and discussed in chapter 4.
[3] See (Bloomberg, 2018)
[4] See (Verhage and Katz, 2018)
[5] See (Mullen, 2018)
[6] See(Bishop, 2018)
[7] A more detailed and technical explanation is found in the appendix

1.2 The aims of this Thesis

"Does media attention affect Bitcoin return, and thus explain investor attractiveness?" is the question that this thesis aims to answer, with an underlying analysis into the categorization of Bitcoin. Broken down, the two problems are;

(iii) What kind of financial asset can we categorize Bitcoin as?

(iv) How does Media attention affect Bitcoin return?

These questions will be answered throughout this thesis, which is structured as follows. Chapter 2 presents a literature review of previous findings in the field, and what this thesis hope to add to the field of study. In section 3 the theoretical framework will be put forward, alongside an introduction and discussion of investor attractiveness. Section 4 provides the building bricks for the quantitative analysis into Bitcoin and investor attractiveness, as it plots out the methodology used for analysis. Section 5 provides a deeper understanding of how the functionality of Bitcoin and how it interacts with the financial world and everyday life. Data and descriptive statistics are shown and explained in chapter 6. Chapter 7 provides a volatility analysis of the variables, and chapter 8 looks at investor attractiveness for Bitcoin using google search query as a proxy for media attention. In chapter 9 a critical point of view is offered with suggestions to further research. Chapter 10 will start with a summery and followed by pulling all the threads together in the conclusion.

2. Literature review

The market for Bitcoin is new and undeveloped, as Bitcoin has only been around since 2008[8], with the first transactions and trades conducted in 2010. Considering these facts, the literature on the topic is not as extensive as more traditional financial assets. How to correctly classify and label Bitcoin has been of academic interest, and so several research studies into the field has been done. Baur et. Al (2017), Ciaian et. Al (2014), Yermack (2015) and Gronwald (2015) have all studied how Bitcoin performs in the market, and how it can be labeled, and have all drawn the conclusion that Bitcoin resembles a speculative asset more than the currency it is set out to be. Baur, Hong et. Al (2017) also put support behind this, as their findings found most Bitcoin are held to speculate in a return on rising Bitcoin price. This speculative nature, and the fact that Bitcoin has no intrinsic value is of great interest as something must drive the Bitcoin price dynamics. Dyhrberg (2016) found that financial market factors did indeed attribute to the return on Bitcoin, but on the other hand Ciaian et. Al (2014) found no relationship between Bitcoin return and traditional financial market factors. Kristofouk (2013), Gronwald (2015), Ciaian et al (2014) and Mai et. Al (2016) all found that Bitcoin return could in fact be driven by demand side dynamics, such as attention and investor attractiveness.

In this thesis, an updated dataset in terms of the development in Bitcoin prices is used when assuming the categorization approach of Baur et. Al (2017) for two reasons. Firstly, because our dataset extends to including the drop of Bitcoin prices during January of 2018. Secondly, if Bitcoin is to be labeled as an inherently speculative asset with the updated dataset, the result substantiates our approach towards expanding the framework of Ciaian et. Al (2014). Our contribution to their paper is examining the investor attractiveness variable through a new theoretical model within their framework. The theoretical model is tested in chapter 8 and may be considered our main contribution to the literature of Bitcoin. Lastly, the results of this thesis questions the framework on which the approach of Ciaian et. Al (2014) is built, due to the results from categorizing Bitcoin.

---

[8] Satoshi Nakamoto`s White paper was sent around late 2008

3. Theoretical framework

In studies done by Kristoufek (2013), Ciaian et. Al (2014) and Gronwald (2015) all found results on news, media attention and investor behavior significantly affect the price of Bitcoin, and the importance of macroeconomic factors on price formation are small or not existing. As previously mentioned, Bitcoin has closer resemblance to a financial asset used for speculation than a currency, but its design and prospects for the future is as a currency. So, analysis is augmented most correctly done by considering Bitcoin to be a fiat currency Ciaian et. Al (2014). With a theoretical framework put forward by Barros (1979), and further made more relevant by Ciaian et. Al (2014), this thesis will try to further investigate how attention around Bitcoin is forming the price of Bitcoin.

The model which is the building stone of the thesis that Bitcoin price formation is highly connected to attention was first put forward by Barros (1979), but the one of relevance to this thesis is the revised model from Ciaian et. Al (2014); *"The economics of BitCoin price formation".* Initially it was a model developed for the study of how prices were formed under the Gold standard. Ciaian et. Al (2014) tweaked this model to explain how the price of Bitcoin are formed, specially focusing on three areas;

1. Supply-Demand interactions
2. Bitcoins attractiveness for investors
3. Global macroeconomic and financial developments

Formally, the model takes form as follows. Money supply for Bitcoin is fixed and transparent, a given amount of Bitcoin is added to the network at an already determined rate until the max amount of 21 million is reached. The money supply of Bitcoin becomes the price of Bitcoin multiplied with the Bitcoins in circulation.

$$M^s = P^b B \tag{3.1}$$

Where B is the amount in circulation, and P^b is the price of Bitcoin. The demand for Bitcoin then is.

$$M^d = \frac{PY}{V} \tag{3.2}$$

The demand for Bitcoin depends on the general prices of goods and serviced P. Y, which is the size of the Bitcoin economy, and V, the velocity of which transactions of one Bitcoin takes place. Equilibrium price condition of Bitcoin implies that the supply and demand of Bitcoin must be equal, which gives rise to the following relation for Bitcoin price.

$$P^b = \frac{PY}{VB} \tag{3.3}$$

It can be read from this relationship that the price of Bitcoin decreases by higher transaction volumes, and with rising stock of Bitcoin. On the other hand, higher general price level and increasing size if the Bitcoin economy will increase the price of Bitcoin.

Second, the attractiveness for investors is something that literature has shown significantly influences the price of Bitcoin. For potential investors gathering information can be costly, both in more technical terms and in finding potential investments. For Bitcoin, the growing interest and consciousness in the media concerning its existence is something that made gathering information on Bitcoin less costly for investors. This can be seen when prices spike, also the attention surrounding Bitcoin spikes[9]. This is also found by Ciaian Et. Al in the building of the framework, as it is stated "Investment opportunities under the attention of the news media may be preferred by new investors. Because they reduce search costs". (Ciaian, 2014:7) A coefficient a_t is modelled in, which catches the attractiveness for investors from attention from news media. By a log transformation of the equilibrium condition, and adding a_t, Ciaian Et. Al (2014) model then becomes:

$$P_t^b = \beta_0 + \beta_1 p_t + \beta_2 y_t + \beta_3 v_t + \beta_4 b_t + \beta_5 a_t + \varepsilon_t \quad ^{10} \tag{3.4}$$

How the coefficient a_t affects and influences Bitcoin price is what this thesis will try to find out and add to existing work on the topic.

The reason for excluding the other variables for the sake of our analysis is two folded. Firstly, extensive literature has found that macroeconomic, and traditional financial assets and factors do not affect Bitcoin return. This is found by Gronwald (2015), Ciaian et. Al (2014) and Kristofouk (2013), who all points at the speculative nature of news in the price formation of Bitcoin. Also, the volatility and size of the Bitcoin economy today is something that does not really make sense in the price formation of Bitcoin, as Bitcoin mainly takes it

[9] See figure 6.1

[10] In the original model, also a coefficient Mt is added for financial factors affecting Price, but that is not of interest to our analysis.

value from the prospect of future value as a currency. The scaling problems when it comes to Bitcoin transactions[11] and the fact that most Bitcoin are bought to be held to speculate in higher future value.

The categorization of Bitcoin in part 7. Will provide valuable knowledge about how robust this framework is for analyzing Bitcoin. Bitcoin is designed, and meant to be a currency, but have so far not been widely used as such, but more as a speculative investment.

3.1 How is supply and demand generated for Bitcoin?

As already known, the supply of Bitcoin is limited to 21 million Bitcoins, and the rate that new Bitcoins will be introduced to the market is known to all. This leaves little unknown about the supply side dynamics, as it is close to as transparent as it can be. The only unknown variable in the supply side of Bitcoin is how many of existing Bitcoin owners are willing to sell their Bitcoin at a given time. Ciaian et. Al (2014) strongly argues that the price driver in Bitcoin is supply and demand, meaning capitalism in its purest form. These supply and demand dynamics are also what often gives rise to the excessive volatility which have been discussed and will be further investigated throughout this paper.

Demand side dynamics are the fascinating part of Bitcoin, as traditional macroeconomic factors have been found by economists to not really play a part in how price is formed. (Ciaian et.al 2014) Our thesis is that the key driver of the demand side of the Bitcoin price formation is of more behavioral sort, it is the attention and the momentum in the market that drives price and so return. As a short summarization of what Bitcoin is, it is a type of FIAT currency which is issued outside of governmental control and is so not part of the traditional financial markets. This separation from the markets closes the door to a lot of macroeconomic factors affecting Bitcoin. However, geopolitical factors are something that can affect the demand side of Bitcoin price dynamics.

[11] See appendix

3.2 Investor attractiveness

"It's worse than tulip bulbs. It won't end well. Someone is going to get killed."

- *Jamie Dimon, J.P. Morgan*

There exists a wide range of strong opinions regarding the subject that is Bitcoin. Some believe that Bitcoin is a fraud and a pyramid scheme which eventually will drive the Bitcoin price to zero. Other believe Bitcoin to be the currency of the future that will render all third-party agents, such as banks, obsolete. Jamie Dimon, CEO of J.P. Morgan belongs to the first category, having voiced his opinion on the matter several times. The quote above is an outtake from a longer statement he made during the Barclay banking conference on 12th of September 2017. The price of Bitcoin dropped by 10% the following 24 hours after. Whether the price fell because of the substance of his statement, or the statement at all, is uncertain, but the price of Bitcoin has proven to be extremely volatile-sensitive to media attention on multiple other occasions. For instance, on the 4th of September, eight days before Jamie Dimon called out Bitcoin to be a fraud, a committee led by China's central bank issues a ban on ICO funding[12], TechCrunch. (2018). This caused the price to drop $4,845 to around $4,350[13], i.e. a 10,2% drop in price. In theory, whether ICOs are allowed or not should not affect the price of Bitcoin, since this does not alter the functionality of Bitcoin as a medium of exchange. Even though companies in China are no longer able to gather funds through token sales, you are still free to trade your Bitcoin whenever.

It is hard to find clear evidence of positive attention being a price driving factor in the same way as with negative media attention. However, when trading in Bitcoin futures were announced the price jumped over $2,000 in an hour. It is unclear as to this being the only reason behind the spike in price, but it is fair to assume that the volatility-sensitivity mentioned with bad news also applies to good news. This is news which started out as being strictly positive- but soon faded as people realized this opened for possibility to short Bitcoin.

[12] ICO is short for Initial Coin Offering. This offers a way for a company to raise funds for a project, and is the equivalent of IPO (Initial Public Offering) in the world of crypto currencies, where instead of buying equity in a company, you buy tokens. Usually these tokens have a function of some sort, however this is no requirement.
[13] https://coinmarketcap.com/currencies/bitcoin/#charts, timeframe 03.09.17-04.09.17

In 1936 John Maynard Keynes used the term "Animal Spirits" in his *The General Theory of Employment, Interest and Money,* to explain how emotions guide our behavior. Keynes see actions done by people during times of volatility as the driver of the said volatility (Keynes, 1936). Looking at the China ban on ICO`s and how this caused a drop in Bitcoin price, it can be said that irrational behavior affects the market response, which possibly could be attributed to animal spirits being present. Looking at Bitcoins bull market it could be argued that the phenomenal rise was fueled by animal spirits, as to there were no fundamentals behind the rise, but people continued to buy Bitcoin. Verto Analytics performed an analysis on the user growth of Coinbase[14] It almost doubled its user numbers from 2,2 million in November 17, to 4,3 million in December 17, Hwong, C. (2018). This was when the Bitcoin price where soaring from around $6,000 to $20,000.

3.3 Google Trends – a proxy for media attention

In this thesis we investigate whether media attention is one factor driving the return of Bitcoin. We illustrate the approach used by a hypothetical example. Consider an investor using the Google search engine to search for the keyword 'Bitcoin'. Pondering the motivation behind his curiosity, the two reasons we could come up with were the following: either he read about Bitcoin in a news article or on a blog, or someone else has spoken of Bitcoin in his presence, which fundaments in some media source. Thus, we hypothesize that both scenarios can be traced back to media coverage of Bitcoin. In either case, he is intrigued enough to investigate the new, unfamiliar crypto currency using Google.

If what we hypothesize is correct, namely that the Google searches made by people reflects what people gather from the media landscape, the scaled and relative size of search volume for the keyword 'Bitcoin' will also reflect the relative size of the volume of news articles and blog posts mentioning Bitcoin in one context or the other. Put in other words: we believe that the interest in a topic exhibited by people in general, measured by google trends, reflects the coverage of this topic by the media. Hence, we believe that Google Trends will approximate media coverage. While this hypothesis is fundamentally based on our logical reasoning, it is also supported by Cervellin, Cornelli and Lippi (2017) who concludes that "Overall, Google Trends seems to be more influenced by the media clamor than by the true

[14] An exchange for buying and selling Bitcoin

epidemiological burden.”. Even though the paper was concerned with the coherence of actual outbreaks of diseases to people using google to search for these diseases, they found that “The search volumes of Google Trends are frequently found to be increased for conditions with large media coverage (…)” Cervellin et al. (2017). These findings are also confirmed by another paper in which the authors explore (among other things) the relationship between public interest and quantities of online news articles. In this paper, it is uncovered that:

> *“The quantity of news articles was related to patterns in Google search volume, whereas the number of research articles was not a good predictor but lagged behind Google search volume, indicating the role of news in the transfer of conservation science to the public.”* Nghiem LTP, Papworth SK, Lim FKS, Carrasco LR (2016).

3.4 The theoretical model for investors attractiveness

Using Google Trends as a proxy for media attention, figure 3.1 represents our theory of how the variable ‘Investor attractiveness’ might be formed. This is a purely hypothetical framework which is based on the arguments presented thus far.

Figure 3.1: The theoretical model for investor attractiveness

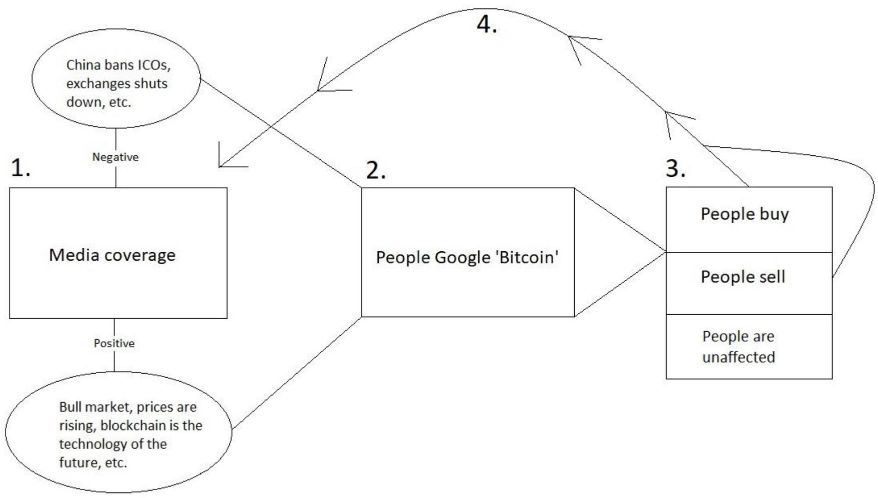


Figure 3.1: *Media coverage of Bitcoin, either positive or negative results in investors seeking out information on the term, using the Google search engine. After becoming informed, the investor decides to purchase a Bitcoin, sell a Bitcoin, or do nothing. The effect of his action generates a feedback-effect so long as he takes action, in which case we return back to the first period.*

The process step by step:

1. Media coverage captures the effect of events that have proved to affect the price of Bitcoin, both good news and bad news.

2. After reading or hearing about Bitcoin, investors want to know more on the topic, and use the Google search engine to explore the term. At this stage, the investors who are already informed will most likely skip this stage and directly act on basis of the news coverage. Therefore, this stage of the figure captures the effect of those investors who are new to the market.

3. Investors will buy, or investors will sell based on the substance of the news, which mirrors the reality of for instance shutdown of exchanges, or different psychological effects of human nature. Due to the time it takes to become informed on the topic, it is likely that there will be a latency which will reflect new investors entering the market. We illustrate this by an example:

An investor is intrigued by the new and unfamiliar cryptographic currency mentioned by some media source. But before the investor does the trade from dollar to Bitcoin, he must first consider two things: He perhaps uses the Google search engine to do the research needed to decide on buying Bitcoin or not. Next, should he decide on buying Bitcoins, the investor needs to create an electronical wallet with an exchange, so he can trade dollars to Bitcoin and store the money during the exchange. Creating a wallet such as this takes time, at least 24 hours, because the verification of identities must be done thoroughly by the exchange to ensure safety of its customers. For many customers, this is not an easy process, so even if it only takes a day or two to have your account with the exchange verified, one would perhaps have to learn the mechanics of the website in the process. We tried creating an account with Coinbase.com, an exchange where you can purchase a variety of different crypto currencies. The process took a few more days than a week, which in turn verifies this theory.

4. Because the price of Bitcoin in terms of dollars is internally driven, people buying or selling Bitcoin will drive the price up or down. At this stage of the figure, the affected price of Bitcoin will generate a feedback effect towards media coverage, for instance by news articles narrating stories of people becoming rich, or people losing a lot of money.

3.5 Formulating the model

In the second stage of the figure investors gather what information they can regarding Bitcoin before they either take action or don't. The time needed to be sufficiently informed will be implied by statistical significant lagged time periods of Google Trends.

To measure the impact of the possible feedback effect illustrated by the fourth stage in figure 3.1, we must also consider an equation in which Google Trends is the dependent variable.

Our suggested measurement of investor attractiveness can therefore be expressed by the following VAR(p) representation:

$$\begin{bmatrix} P_t \\ T_t \end{bmatrix} = \Gamma_0 + \Gamma_1 \begin{bmatrix} P \\ T \end{bmatrix}_t + \Gamma_2 \begin{bmatrix} P \\ T \end{bmatrix}_{t-1} + \Gamma_3 \begin{bmatrix} P \\ T \end{bmatrix}_{t-2} + \cdots + \Gamma_p \begin{bmatrix} P \\ T \end{bmatrix}_{t-p-1} + \bar{\varepsilon}_t \qquad (3.5)$$

$$\Gamma_0 = \begin{bmatrix} \alpha_{10} \\ \alpha_{20} \end{bmatrix} \ , \ \Gamma_1 = \begin{bmatrix} 0 & \gamma_1 \\ \gamma_2 & 0 \end{bmatrix} , \ \Gamma_i = \begin{bmatrix} \gamma_{11,i} & \gamma_{12,i} \\ \gamma_{12,i} & \gamma_{22,i} \end{bmatrix} \ , \ \text{i = 2, 3 ... , p}$$

where P = Logarithmic Bitcoin price in terms of dollar and T = Logarithmic values of Google Trends.

The estimated VAR(p) model will determine the length of time new investors require to gather information before investing, and to what extend the new investors influence the Bitcoin price. We further extend the model on basis of three arguments:

1. Because the datasets applied in the context of testing this theoretical model is on a weekly format, it is highly likely that the Bitcoin price and Google Trends are simultaneously determined, in which case the first and third period of figure 3.1 occur at the same time. To circumvent this, we shall tweak the model represented by equation 3.5 in terms of the methodology presented in chapter 4. In short, we transform the compact matrix form in equation 3.5 to a reduced form.
2. One obvious disadvantage using this method is not being able to measure the contemporaneous effect of investors reactions to news coverage. Our suggested model when transformed to reduced form only considers the lagged effects of media attention, which in turn means that we can only provide some understanding of how the demand for Bitcoin is generated; i.e. when new investors entering the market. In attempt to separate the two groups of investors, we estimate the cointegrating

relationship between the two variables[15]. The procedure is elaborated in chapter 4 and implemented in chapter 8.

3. The second disadvantage of this model rests on the fact that we are not able to distinguish positively and negatively narrated news. Google Trends will capture both sides simultaneously. In chapter 8, we introduce a dummy variable which is set to measure the asymmetric effects regarding the substance of news coverage, with the aim to measure the average effect on Bitcoin return in both scenarios.

Combining the three arguments we can reformulate the VAR(p) model to become a VECM model:

$$\begin{bmatrix} \Delta P_t \\ \Delta T_t \end{bmatrix} = \Pi_0 + \alpha CI_{t-1} + \Pi_1 \Delta \begin{bmatrix} P \\ T \end{bmatrix}_{t-1} + \Pi_2 \Delta \begin{bmatrix} P \\ T \end{bmatrix}_{t-2} + \cdots + \Pi_p \Delta \begin{bmatrix} P \\ T \end{bmatrix}_{t-p} + \bar{D} + \bar{u}_t \quad (3.6)$$

$$\Pi_0 = \begin{bmatrix} c_{10} \\ c_{20} \end{bmatrix} \quad , \quad \Pi_i = \begin{bmatrix} \delta_{11,i} & \delta_{12,i} \\ \delta_{12,i} & \delta_{22,i} \end{bmatrix} \ , \ \alpha = \begin{bmatrix} \alpha_P \\ \alpha_T \end{bmatrix} \ \bar{D} = \begin{bmatrix} D \\ D \end{bmatrix}_t , \ \bar{u}_t = \begin{bmatrix} u_P \\ u_T \end{bmatrix}_t \ \text{i = 1,2, ... , p}$$

where P_t = Logarithmic Bitcoin price in terms of dollar in period t and T_t = Logarithmic values of Google Trends in period t. Δ implies first difference of the coherent variable, Π_0 is the coefficient matrix of the constants, $\bar{u}_t$ is the residual matrix in which the residuals might be correlated. CI_{t-1} is the cointegrating vector[16] , α_P and α_T are the speed of adjustment parameters. Lastly D_t is a dummy variable measuring the asymmetric response to news coverage:

$$D_t = \begin{bmatrix} 1 \ if \ positive \ news \ coverage \\ 0 \ if \ negative \ news \ coverage \end{bmatrix}$$

The model is specified on reduced form[17] to avoid simultaneous bias. When some error distorts the long-term equilibrium between logged Bitcoin price and logged Google trends, we regard the implied shifts in long-term dynamics as the reactions of investors already settled in the Bitcoin market. Building the model is elaborated in chapter 4, and the model is estimated and analyzed in chapter 8[18].

[15] In chapter 8, we employ the Johansen cointegration test and uncover that the two variables are cointegrated. The methods used are presented in chapter 4.

[16] For the method of estimating the cointegrating vector, and a more thorough explanation of the involved coefficients, we refer to chapter 4.

[17] Note that reduced form is implied when using Johansens method for estimating the VECM model.

[18] Under new notations

4. Methodology

In this chapter we present and discuss the different procedures we use to answer the two questions raised by this thesis: How is Bitcoin categorized, and how does media attention influence the return on Bitcoin? The chapter is structured in the following way: first we present the common methods that are applied when answering both questions. Secondly, we review the methods used for analysing the volatility process of Bitcoin and its comparable variables. In the third part of the chapter we present the methods used when estimating the VECM model which was introduced in chapter 3.

4.1 Common method

4.1.1 The Dickey-Fuller test

When estimating single-equation models it is of great importance to the researcher that the estimated variables are stationary. If a given variable is stationary, standard inference methods are plausible when estimating this variable. When a variable contains a unit-root, it is said to be none-stationary, and normal inference methods cannot be used. In such instances the variable is generated by a 'random walk' process, where shocks to the error-term are persistent for all time periods. A formal method of testing whether the variable contains a unit-root has been presented by Dickey and Fuller (1979). The Dickey-Fuller test (DF-test) is performed by investigating whether the variable y_{t-1} in the simple AR(1)-model given by equation 4.1 contains a unit-root:

$$y_t = \alpha_1 y_{t-1} + \varepsilon_t \tag{4.1}$$

$$\varepsilon_t \sim i.i.d.N(0,\sigma^2) \tag{4.2}$$

The null is formulated as such: the variable y_t is not stationary, denoted as I(1). The alternative hypothesis is that the variable y_t is stationary, denoted as I(0). The error-term is assumed to be a white noise process as stated by equation 4.2. If the variable does contain a unit-root, the coefficient, α_1, should be equal to unity. Dickey and Fuller (1979) proposed to subtract y_{t-1} on both sides of equation 4.1, which gives us the equations 4.3 and 4.4:

$$\Delta y_t = (\alpha_1 - 1) y_{t-1} + \varepsilon_t \tag{4.3}$$

$$\Delta y_t = \rho_1 y_{t-1} + \varepsilon_t \tag{4.4}$$

The Dickey-Fuller test is then performed by testing the null, $\rho_1 = 0$, against the alternative that $\rho_1 < 0$. Under the null hypothesis of none-stationarity, normal inference methods cannot be applied when estimating the test statistic:

$$t_{DF} = \frac{\hat{\rho}_1}{sd(\hat{\rho}_1)} \tag{4.5}$$

Instead, Dickey and Fuller presented their own table with critical values based on Monte-Carlo simulations. Estimating equation 4.4 and calculating the test statistic given by equation 4.5, the calculation may be evaluated against the critical values gathered by Dickey and Fuller (1979).

However, it is not always the case that the error-term purely consists of white noise. To avoid serial correlation in the residuals, and general misspecification of the model given by 4.4, an extension to the simple Dickey-Fuller test may be applied. The augmented Dickey Fuller test (ADF-test) includes differenced lags of the independent variable as explanatory variables in the model. Throughout this thesis, this method is used to determine stationarity. The extension to the standard DF-test can be expressed by equation 4.5 and may be further extended by for instance a trend- or a drift term.

$$\Delta y_t = \beta_0 + \rho_1 y_{t-1} + \sum_{i=1}^{p} \varphi_i \Delta y_{t-i} + \varepsilon_t \tag{4.5}$$

$$\text{where } \rho = \sum_{i=1}^{p} \alpha_i - 1, \qquad \varphi_i = -\sum_{k=i+1}^{p} \alpha_k$$

4.1.2 Return series

If a variable is found to contain one unit root, differencing the variable once will render the variable stationary. As we shall see during this thesis, all variables at hand contain one unit root. The formula we use to generate stationary variables is the following:

$$r_t = 100 * [\log P_t - \log P_{t-1}] \tag{4.6}$$

Where r_t is return, and P_t refer to the variable on level form. Multiplied by a hundred, r_t represents the percentage change for any given variable, which will be useful when interpreting the results later. For all variables that are expressed in dollar terms, r_t is mentioned as the return in time t. For the variable that is not denominated in dollar, r_t is mentioned as the percentage change in time t.

4.1.3 Choosing the correct lag length in dynamic single equation models

When deciding how many lags to include in a given dynamic single equation model, we apply the general-to-specific method. Using this method, one would start by estimating a general model, and removing the last lag that is not proven statistically significant. Repeating this process until all estimated lagged variables are statistically significant yields the correct model following this procedure. However, this method alone could result in either including or excluding too many lags, thus either overparameterizing the model[19] or excluding important information in the general model.

By combining the general-to-specific method with the information criteria, we can overcome this particular issue. Therefore, to come closer to the 'true' model when specifying the general model, we shall use the following information criteria which are reported in OxMetrics: Akaikes Criterion (AIC), Schwarz Criterion (SC) and Hannan-Quinn Criterion (HQ). Following Doornik A. Jurgen and Hendry F. David (2013a)[20] these criteria are given by the following equations:

$$AIC = \log \tilde{\sigma}^2 + (2k)\ T^{-1} \tag{4.7}$$

$$SC = \log \tilde{\sigma}^2 + k(logT)T^{-1} \tag{4.8}$$

$$HQ = \log \tilde{\sigma}^2 + 2k\ (\log(\log T))\ T^{-1} \tag{4.9}$$

Using the maximum likelihood estimate of σ^2:

$$\tilde{\sigma}^2 = \frac{T-k}{T}\tilde{\sigma}^2 = \frac{1}{T}\sum_{t=1}^{T}\tilde{u}_t^2 \tag{4.10}$$

The information criteria equations hold two important implications: first, the left side of the equations imply that the greater the number of variables in the general model, the smaller the variance will be. The right side of the equations tells us in what degree the different equations increases in value when more variables are added to the general model. Keeping in mind that the goal is to minimize the values of the information criteria, the right-hand side penalizes the general model that includes excess explanatory variables compared to the true model.

[19] This would mean having too many degrees of freedom when estimating the model, which causes problems when estimating the general model.
[20] For supplementary reading of the respective criteria, see Akaike (1973,1974), Hannan and Quinn(1979), Schwarz (1978) and Rissanen (1978).

The properties of the information criteria are summarized by Lütkepohl, H. and Krätzig, M. (2004) in the following way: AIC asymptotically overestimates the order with positive probability, HQ estimates the order consistently (plim $\hat{p} = p$) and SC is even strongly consistent ($\hat{p} \to p\ a.s.$)[21]. Thus, we write the order of explanatory variables selected by the different criteria in the following sequence:

$$\hat{p}(SC) < \hat{p}HQ < \hat{p}AIC$$

In the multivariate scenario, the information criteria hold the same properties. Following the simulation analysis of Alain Hecq (1996) it is advocated weighting the results of SC relatively to the other information criteria when determining the lag-length of VAR-equations in the presence of GARCH-errors. The multivariate information criteria are listed in the appendix.

4.1.4 Diagnostic testing: post estimation

After specifying the general model in terms of the method presented in 4.1.3, it is important to conduct diagnostic testing. If the general model is correctly specified, there should be no serial correlation in the residual term. However, testing for serial correlation in the post-estimation phase provides confirmation to whether the general model is an adequate representation of the true model. In this section we review the two test procedures that we use throughout this thesis: The ARCH-LM test and the Ljung-Box test. The latter is both used in chapter 7 and 8.

4.1.4.a The ARCH-LM test

Having decided what lag-length the general model should have based on combining the general-to-specific method with looking at the information criteria, we are here concerned with uncovering GARCH-errors in the series. To investigate this matter, the standardized residuals from the estimation of the general model are stored in a standardized quadratic form measured by ε^2, which is then regressed on a constant in addition to m lags of its past observations. That is, a regression on the following equation:

$$\varepsilon_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\varepsilon_{t-2}^2 + \cdots + \alpha_m\varepsilon_{t-m}^2 + white\ noise \tag{4.11}$$

If the autocorrelations of the underlying time series are accounted for by the ARMA-specification in the mean equation, there should be no serial correlation since the residuals

[21] The results are the same in the presence of GARCH-errors, see Hecq, Alain (1996)

in this case are uncorrelated with mean zero. However, there may still be serial dependency in the residuals caused by some nonlinear generating process not captured by the simple ARMA-model, which in this case could suggest the existence of heteroscedasticity in the time series. Uncovering this tendency (heteroscedasticity) can be done by the usage of several different tests, such as the Engle ARCH-LM test (Engle, 1982) and McLeod-Li test (McLeod and Li, 1983). Bollerslev (1986) suggested that the Engle ARCH-LM test should also have power of proving GARCH-effects, which concurs with Enders (2015): "(…) if your lag length is shorter than the true structure, and if you still detect GARCH effects, you can conclude that GARCH effects are present in the data." (Enders, 2015, page 160). Choosing amongst the tests, OxMetrics limits the selection to the ARCH-LM test which is no negative limitation considering the arguments presented.

When applying the tests using OxMetrics, we set the lag-length (m) to different values to check the different intervals of the residual-series. The test is carried out by testing the null hypothesis being H_0: α_1= α_2= ,…,= α_m= 0, or rather put in words: all coefficients measuring the impact of the lagged squared residual terms in equation (4.11) are jointly equal to zero. We set three different lag intervals, namely 1-2, 1-5 and 1-10.

4.1.4.b The Ljung-Box test

Even though the general model is specified using the method presented in 4.1.3, there may still be autocorrelation in the residuals. If this is the case, the Q-statistics formed using the correlations of the squared residuals will, if proven significant (i.e. below a p-value of 0,05), imply strong evidence of GARCH effects (Enders, 2015). The Q-statistics in referring to the Ljung-Box test, which is an improved Box-Pierce test set to uncover autocorrelations in large finite time series (G. M. Ljung; G. E. P. Box, 1978). It is worth mentioning that this test has been disputed by Madalla, who argued that when including none exogenous explanatory variables, such as lags of the dependent variable, the properties of the Q-statistics used in the Ljung-Box test will not be asymptotically convergent towards a chi-squared distribution, rendering the test biased toward accepting the null hypothesis of no autocorrelation. He instead suggested to use Breusch-Godfrey test for serial correlation. (Madalla, 2001).

Though the arguments of Madalla (2001) disputes implementing the Ljung Box test, OxMetrics once again limits the assortment of tests to the said test for autocorrelation. Therefore, we use the Portmanteau Q-statistics (Ljung Box test).

Following Doornik and Hendry (2013a), the sampled autocorrelation function (ACF) of a variable x_t is the series {r_j} where r_j is the correlation coefficient between x_t and x_{t-j} for j = 1,…,s:

$$r_j = \frac{\sum_{t=j+1}^{T}(x_t - \bar{x})\left(x_{t-j} - \bar{x}\right)}{\sum_{t=1}^{T}(x_t - \bar{x})^2} \tag{4.12}$$

The Portmanteau statistic is given by:

$$LB(s) = T^2 \sum_{j=1}^{s} \frac{r_j^2}{T-j} \tag{4.13}$$

When reporting the test results, we investigate different intervals of the time series, denoted as Q(5), Q(10), Q(20), and Q(40).

4.2 Method for categorization

4.2.1 GARCH models

In our attempt to categorize Bitcoin, we apply the method of Baur et al. (2017), with two important distinctions. Firstly, instead of assuming each model to be fitted well by one AR lag, we follow the procedure of estimating each variable subject to the comparison separately; using the technique presented in section 4.1.3. When the ARMA(p,q) representation is adequate, the conditional variance is closely examined. The second distinction from the method of Baur et al. (2017), is we fit the best possible GARCH type model to the conditional variance of each variable. This way, the analysis is extended to include a comparison of model selections. The next paragraphs will provide the knowledge one needs to follow the analysis of chapter 7.

Typically, financial time series show tendencies to clustered volatility where if a large value in the variance occurs at some point during the time series, it is expected that the next period of the variance is also large (in absolute values). The GARCH model is an extension of Engle's ARCH-model (1982) presented by Bollerslev (1986). A simple GARCH(1,1) model is given by the following equations:

$$\mathrm{y_t} = \delta + \varepsilon_t \tag{4.14}$$

$$\varepsilon_t = \mathrm{v_t}\sqrt{\mathrm{h_t}} \tag{4.15}$$

$$v_{t} \sim i.i.d. N(0,1) \tag{4.16}$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \tag{4.17}$$

The conditional variance of ε_t is equal to h_t, because the conditional variance of v_t is equal to unity per assumption of it being white noise, stated by equation 4.16. Therefore, the GARCH-model estimates the conditional variance equation as generated by an ARMA-process which need not be constant over time, thus allowing for the variance to depend on previous observed values of itself. Note that a GARCH(0,1) specification is equivalent to setting $\beta_1$equal to zero, which would then transform the model to the original ARCH(1) model of Engle (1982).

With basis in the GARCH model, several extensions have been proposed. These models usually alter the conditional variance equation of the standard GARCH model. An example of properties that are accounted for in these models is the 'leveraged effect' (GJR, EGARCH), i.e. asymmetric responses to shocks in a negative and positive manner measured in the conditional variance[22]. The GJR model, proposed by Glosten, Jagannathan and Runkle (1993) alters the conditional variance by including a dummy variable that captures the different effects from when the variance term ε_{t-1} is positive and negative respectively:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \gamma_1 D_{t-1} \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \tag{4.18}$$

Where D_{t-1} is a dummy variable equal to 1 if ε_{t-1} is greater than zero, and 0 if $\varepsilon_{t-1}$is smaller than zero. A negative and significant estimate of the coefficient γ_1 will imply that negative shocks increase the variance by more than positive shocks do. This is the so called 'leveraged effect'.

A second relevant variation to the GARCH model is the integrated GARCH (IGARCH), in which the conditional variance is persistence for all periods of time during a time series. The IGARCH(1,1) model assumes that is α_1+ $\beta_1$is equal to 1. This gives us the equation for conditional variance equal to:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \tag{4.19}$$

$$\beta_1 = (1 - \alpha_1) \tag{4.20}$$

On many occasions when modelling financial data, one finds that the sum of these two coefficients are approximately equal to unity. This means that the conditional variance

[22] see Black (1976)

estimated exhibits a strong persistence and is categorized as a random walk process. Assuming that the sum of the two parameters equals unity, one would have the advantage of estimating one less coefficient, rendering the IGARCH model more parsimonious than the original GARCH model. At the same time, a GARCH model would capture more of the variation in the underlying time series, so there exist trade-off benefits when comparing the two, in which case the information criteria should decide what model is best. Enders (2015).

4.3 Method for estimating the VECM

Our theoretical model presented in chapter 3.4 is a VECM model. This section will provide information of how we intend to build the VECM which is used to examine how the investor attractiveness variable can be formed. With an example of two variables, in this last part we consider a simple first order vector auto regressive model (VAR(1)). Section 5.3.1 is mostly based on the "Introduction to VAR analysis" chapter of Enders (2015).

4.3.1 VAR: reduced form

In this thesis, it is of importance to determine the relationship among Bitcoin and Google trends. As discussed in chapter 3, the two variables could be simultaneously determined, which means that estimating equation 4.21 and 4.22 by OLS would cause simultaneous equation bias[23]:

$$X_{1,t} = a_{10} - a_{12}X_{2.t} + b_{11}X_{1,t-1} + b_{12}X_{2,t-1} + \varepsilon_{X_{1,t}} \tag{4.21}$$

$$X_{2,t} = a_{20} - a_{21}X_{1,t} + b_{21}X_{2,t-1} + b_{22}X_{1,t-1} + \varepsilon_{X_{2,t}} \tag{4.22}$$

Equation 4.21 and 4.22 constitute a first-order vector autoregression on level form. The error-terms are assumed to follow a white noise process.

In this structural VAR-representation, the variables can affect each other. To avoid simultaneous bias in the estimators of the coefficients, a transformation of the system of equations to a reduced form can be done. The software we use throughout this thesis, 'OxMetrics', conducts reduced form systems automatically when estimating restricted VAR-models. However, we believe it is important to clarify what is meant by 'reduced form'.

First, we obtain the compact form:

[23] In the context of this thesis, let $X_{1,t}$ equal Bitcoin return and $X_{2,t}$ equal percentage change in Google trends

$$Az_t = \Gamma_0 + \Gamma_1 z_{t-1} + \varepsilon_t \tag{4.23}$$

where $A = \begin{bmatrix} 1 & a_{12} \\ a_{21} & 1 \end{bmatrix}$, $x_t = \begin{bmatrix} X_{1,t} \\ X_{2,t} \end{bmatrix}$, $\Gamma_0 = \begin{bmatrix} a_{10} \\ a_{20} \end{bmatrix}$, $\Gamma_1 = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$, $\varepsilon_t = \begin{bmatrix} \varepsilon_{x_{1,t}} \\ \varepsilon_{x_{2,t}} \end{bmatrix}$

Multiplying equation 4.23 with the inverse of the coefficient matrix, A, yields the VAR(1) representation on reduced form:

$$y_t = B_0 + B_1 y_{t-1} + e_t \tag{4.24}$$

where $B_0 = A^{-1}\Gamma_0$, $B_1 = A^{-1}\Gamma_1$, $e_t = A^{-1}\varepsilon_t$.

The condition of stability in this VAR-representation is solving the characteristic equation:

$$|B_1 - \lambda \mathrm{I}| = 0 \tag{4.25}$$

Next, defining a_{i0} as element *i* of the vector B_0, a_{ij} as the element in row *i* and column *j* of the matrix B_1, and e_{it} as the element *i* of the vector e_t, we can rewrite equation 4.21:

$$X_{1,t} = a_{10} + a_{11}X_{1,t-1} + a_{12}X_{2,t-1} + e_{1t} \tag{4.26}$$

$$X_{2,t} = a_{20} + a_{21}X_{1,t-1} + a_{22}X_{2,t-1} + e_{2t} \tag{4.27}$$

Equation 4.26. and 4.27 are the estimated vectors when using the restricted VAR-estimation function in OxMetrics in our two-variable scenario.

4.3.2 Johansens trace test

A formal definition of cointegration was proposed by Engle and Granger (1987) and is here adapted to the two-variable scenario which we shall encounter in this thesis. When analysing two variables that are integrated of the same order, for instance $X_{1,t}$ and $X_{2,t}$ which are both I(1), if there exists a vector $\beta = [\beta_1, \beta_2]$ such that the linear combination $\beta x_t = \beta_1 x_{1,t} + \beta_2 x_{2,t}$ is I(0), the two variables are cointegrated, denoted as CI(1,1). β is called the cointegrating vector (Enders, 2015) (Engle and Granger, 1987). To uncover cointegration, we employ Johansens trace test.

The Johansen cointegration test of Johansen (1988) is based on estimating a reduced VAR process using maximum likelihood procedure. The normal procedure is to reparametrize equation 4.24 using the same method showed in section 4.1.1. Recalling that VAR(1) representation on reduced form can be represented by the following equation:

$$y_t = B_0 + B_1 y_{t-1} + e_t \tag{4.28}$$

Reparametrizing yields:

$$\Delta y_t = B_0 + (B_1 - 1)y_{t-1} + e_t \tag{4.29}$$

$$\Delta y_t = B_0 + \varphi y_{t-1} + e_t \tag{4.30}$$

The stability condition for equation **X** is $|\varphi - \lambda I| = 0$, meaning that all eigenvalues in this characteristic equation are strictly less than unity. To employ the Johansen cointegration, estimating the eigenvalues of the matrix φ is necessary. The rank, r, of the matrix is then examined. Depending on which test statistic one uses[24], the null hypothesis and alternative hypothesis differ. In this thesis, we use the trace statistic of Johansen (1988) which is given by the following equation:

$$\lambda_{trace}(r) = -T\sum_{i=r+1}^{n} \ln\left(1 - \hat{\lambda}_i\right), r = 0,1,2,\dots,n-1 \tag{4.31}$$

The null hypothesis assumes that $r(\varphi) \leq n$ where n is the number of entries of underlying time series vector. The null is tested against the alternative hypothesis that there exists n cointegrating relations, or more precisely; $\varphi = \alpha\beta'$ where alpha and beta are matrixes of dimensions n x r. The elements of the beta-matrix refer to the cointegration vector, of which there only may exist one in the case of two cointegrated variables. The elements of the alpha-matrix refer to the 'speed of adjustment parameters'.

The test is carried out by systematically trace-testing the null of at most r cointegrated relations against the alternative that there is more than r cointegrated relations. Starting with testing $r \leq 1$ against the alternative that $r \geq 1$, if the null is rejected, we continue with testing $r \leq 2$ against the alternative of $r \geq 2$. When the null is not rejected evaluated against the trace statistic, we have successfully determined the rank of the matrix φ.

When testing the cointegration relationship between Bitcoin and Google trends, there can only exist one cointegrated vector. OxMetrics automatically normalize the vector with respect to the first variable by following the method of Doornik and Hendry (2013b), and so the matrix φ can be written:

$$\varphi = \alpha\beta' = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} \begin{bmatrix} 1 & \beta_2 \end{bmatrix} \tag{4.32}$$

[24] Johansen (1988) suggested two different test statistics: λ_{trace} and λ_{max}

4.3.3 VECM and Granger Causality

In the case where the two variables are CI(1,1), there always exists an error correction mechanism[25] (ECM). Following the formulation of Enders (2015), the ECM vectors which constitutes the vector error correction mechanism (VECM)[26] can be given by 4.33 and 4.34:

$$\Delta X_{1,t} = \alpha_1 + \alpha_{X1,t}(X_{1,t-1} - \beta_1 X_{2,t-1}) + \sum_{i=1} a_{11}(i)\,\Delta X_{1,t-i} + \sum_{i=1} a_{12}(i)\,\Delta X_{2,t-i} + \varepsilon_{X1,t} \quad (4.33)$$

$$\Delta X_{2,t} = \alpha_2 + \alpha_{X2,t}(X_{1,t-1} - \beta_1 X_{2,t-1}) + \sum_{i=1} a_{21}(i)\,\Delta X_{1,t-i} + \sum_{i=1} a_{22}(i)\,\Delta X_{2,t-i} + \varepsilon_{X2,t} \quad (4.34)$$

Where the residuals terms are white noise processes that may be correlated, and where $X_{1,t-1} - \beta_1 X_{2,t-1}$is the cointegrating vector. The parameters $\alpha_{X1,t}$ and $\alpha_{X2,t}$ are known as the 'speed of adjustment parameters'. Note that the cointegrating vectors in equation 4.33 and 4.34 (with respective scalars) are equivalent to the notation αCI_{t-1} of equation 3.6 in chapter 3.4. Should $\alpha_{X2,t}$ in equation 4.34 be equal to zero, $\Delta X_{2,t}$ is said to be 'weekly exogenous' with respect to β_1 in the cointegrating vector. When one variable is weekly exogenous, i.e. if a variable does not respond to deviation from the long-run equilibrium relationship, estimating the ECM does not require a VAR-representation, but can be expressed by an ADL model[27] (Enders, 2015).

The reduced form vectors 4.33 and 4.34 can be used to determine Granger Causality. In the presence of cointegration in the two-variable simultaneous equation example, the variable $X_{2,t}$ is said to *not* 'Granger cause' the variable $X_{1,t}$ if all the estimated parameters $\sum_{i=1} a_{12}(i)$ are equal to zero. That is, previous observed values of X_2 does not contributes to explaining current values of X_1. Or rather: if $\{X_{1,t}\}$ does not improve the forecasting performance of $\{X_{2,t}\}$, then $\{X_{1,t}\}$ does not Granger cause $\{X_{2,t}\}$. (Enders, 2015).

The residuals of the two variables that shall constitute the VECM, Bitcoin return and percentage change in Google trends, exhibits GARCH errors. Following the simulation analysis of Alain Hecq (1996), when two variables are affected by GARCH errors in the residual terms, involving the information criteria when determining Granger none-causality does not cause spurious results[28], and are therefore applied in chapter 8.

---

[25] In the literature, ECM is translated to either "Error correction model" or "Error correction mechanism"

[26] Note that the VECM is a system of equation on reduced form (standard form)

[27] Also referred to as 'univariate ECM'

[28] This holds even under the worst circumstances where the volatility parameter (ARCH) is large relative to the moving average parameter (GARCH), and the sample size is relatively large.

5. What is Bitcoin?

5.1 Bitcoin as Money

As previously mentioned, the initial thought, and possibly still the long-term purpose of Bitcoin is to become a global currency with aim to make the third party obsolete in the financial world. (Satoshi, 2008) A currency is money of any form, which is in actual use. (Merriam-Webster) To be able at greater extent to categorize, or to understand Bitcoins role today, the understanding on how it corresponds to the main characteristics of money.

When people think of Money, they think of something that can be exchanged for goods and services. For something to be considered money, it must serve some key functions. It must be trustworthy store of value, it needs to facilitate transactions in ways as a medium of exchange, and to be a unit of account. (Yermack, 2015) By looking at the Dollar, the largest reserve currency in the world today[29], we see that all these criteria are well met. The FED who issues the dollar also guarantee that it has value, and that it can be used as a medium of exchange in transactions. Its position as a global reserve currency shows its stronghold in the world of currencies, as it is also used as a *unit of account* across the globe. But money is also wider than just USD and Fiat Currencies, just because it resembles a global currency, it might not be the best comparison for Bitcoin today. Bitcoin might not even fit into the framework of traditional money, it might be better compared to speculative financial assets. In the following sections the most common forms of money, and the traditional framework, will be laid out and discussed.

5.2.2 Commodity money

Commodity money is considered one of the oldest forms of conducting transactions and storing value we know of. From barter economies where corn and hide where considered currency, to more modern times when gold and silver were the going currency. These goods used as currency usually required work to get a hold of, so it can be said that they had an opportunity cost of obtaining said currency. As bartering with different produce became different, both in terms of setting a value and it being impractical, coins of gold, silver and other metals became the going currency. Leading up to the Gold standard, where a currency

[29] A reserve currency is currency held by governments as a mean of international payments. The dollar is considered a safe haven, and in so way a safe currency to hold to facilitate payments. (Tappe, 2018)

would be backed up by gold reserves, but no gold was actually switching hands. (Dyhrberg, 2016). On 6th of March 2018, a federal judge in the US ruled that Bitcoin can be regulated as a commodity, and not as a currency. (CNBC, 2018)

5.2.3 Fiat Currency

The concept of FIAT money is said to have been around for centuries, with the most famous story being "The Stones of YEP", but there is no clear evidence either way of that ancient FIAT money had intrinsic value or not. (Goldberg, 2005) However, in 1971 the international Gold standard was abolished for good, and since then money has only been pieces of metal and paper used for facilitating transactions between parties and are not redeemable for anything but such. (Hoppe, 1994) Bitcoin can also in so manner be thought of as a FIAT currency, as it does not hold any intrinsic value besides the value people believe it has. Investors in Bitcoin trust the technology and put their belief into this being something for the future, this is where its true value lies. As with a FIAT currency, if no one believes it can be used for holding value or transactions, it is virtually worthless. And it is with FIAT money that the all so important concept of trust makes itself most relevant, the holder of FIAT money trusts that it can be exchanged and accepted by a counterpart. A FIAT currency is usually backed by a government ensuring that trust to hold. As has been put forward, Bitcoin does not have similar backing as a FIAT currency do. This is what is replaced by mathematics and market dynamics, the only trust needed to make the market function is the trust in technology instead of government. But Bitcoin fails to conduct the everyday tasks we expect from a currency in a satisfactory way. The high transaction fee and time [30]for conducting a transaction makes Bitcoin not suitable as a day to day medium of exchange. As a store of value, Bitcoin has shown itself to be extremely volatile. These significant fluctuations make Bitcoin unsuitable as a store of value, as it lacks consistency. Bitcoin are traded on numerous exchanges around the world, often at different prices. This gives rise to arbitrage opportunities, as well as confusion around its value. This shows its uselessness as a Unit of Account, as we must choose which to believe in the moment. (Yermack, 2015)

[30] As of 07.08.18 each transaction takes on average 28 minutes, and cost $0.10. (https://www.blockchain.com/charts/avg-confirmation-time?timespan=30days, https://bitcoinfees.info/)

5.2.4 Electronic Money

Electronic Money is defined by *The European Central Bank* as "An electronic store of monetary value on a technical device that may be widely used for making payments to entities other than the e-money issuer". Electronic Money could easily be seen as a predecessor of Bitcoin, but the main similarity here is that the monetary value is stored on a technological devise. Traditional E-money needs to have an issuer, and so it has someone responsible for the issuance, and for the functionality. In Bitcoin, no one is in charge and reliable. E-Money is usually just digitally represented FIAT currency, such as the Euro E-money issued by ECB. (European Central Bank)

5.3 Bitcoin as a currency today

5.3.1 As a medium of exchange

For Bitcoin it seems harder to meet the three key functions of money. First, for Bitcoin to become a global and widely used currency it must as a minimum have the functionality and stability of the currencies we use today. This is something we do not observe in satisfactory manner at the time of writing. The scarcity of retailers and others accepting Bitcoin is a big obstacle for it to cement itself as a currency for the masses. When examining the volatility process of Bitcoin in chapter 7, we see that this will impose substantial risk on both retailers and consumers accepting- and using Bitcoin as payment, as it does not hold a stable value very well. It is also pointed out by Yermack (2015) that the time taken for a transaction to go through the system is something of a challenge for a retailer, as it can choose to trust that the customer has correctly transferred the Bitcoins and let the transaction of goods go through, but is then again left with risk on the downside that no such transfer has occurred.

Processing and confirming payments are something of a growing pain for Bitcoin, which must be fixed for it to properly function as a medium of exchange. Bitcoin can simply not compare itself to its competitors when it comes to processing payments for its users. VISA can at most process roughly 56,000 transactions a second, the Bitcoin protocol however, are processing 3,3-7 transactions a second at most. (Croman et. Al, 2016) For Bitcoin to have use as a traditional currency, this does not hold. the cost of a single transaction in the Bitcoin network is on average between $1,4 and $2,9. Both the fact that it is so volatile, and the scalability of the transaction chain will have to be improved for it to function proper as a medium of exchange.

5.3.2 As a Unit of account

The problems of Bitcoin being so volatile, translates in even greater account into its usefulness as a unit of account. For something to be of use as a unit of account it is important that it is easy comparable to goods and services denoted in different terms or currency (Yermack, 2015) and for something to be compared with another, it is important that you can trust the value of what you are comparing, which is something of a challenge when it comes to Bitcoin. Both the volatility issue, and the fact that we have numerous prices of Bitcoin on numerous exchanges around the world makes it tough to accurately make comparisons. In fact, the price of Bitcoin can fluctuate several hundred dollars across exchanges. (WorldcoinIndex.com, 2018) Implying that *The law of one price* does not hold for Bitcoin, so there are vast arbitrage opportunities.

5.3.3 As a store of value

For something to be a good store of value, it must have the ability to be acquired at a given time and saved for later consumption without the prospect of significant loss. It is of the greatest importance that the owner of the asset does not lose consumption power over the time he holds it. With the mention of Bitcoin being the "Internet age equivalent to gold" in mind, it is possible that Bitcoin in the future might become a safe-haven for storing value. Today however, Bitcoin faces two main threats to it being a good choice for storing value; it is how to securely store it, and the significant volatility experienced. The storage problem is not of greater extent, as hackings and theft of Bitcoin is not common. And, the wallets have become sophisticated with time. [31] However, as pointed out by Blackrock (2017), Bitcoin annualized daily realized volatility was 70% when to comparison US stocks during the 2008-2009 financial crisis showed about 30% annualized daily realized volatility. So, to say that Bitcoin is volatile would be an understatement. Yermack (2015) pointed out that it is almost impossible to find a good hedge against Bitcoin, which also shows how hard it would be to maintain belief and healthy exposure to the markets while holding value in Bitcoin.

[31] https://www.coindesk.com/information/how-to-store-your-bitcoins/

5.3.4 Does Bitcoin hold as a currency?

From the above analysis, considering the three key characteristics of money and Bitcoin, Bitcoin do not perform well in the monetary framework used today. As pointed out, in both the functionality as a medium of exchange, unit of account and as a store of value, the volatility of Bitcoin is an issue. This brings up the timely question of Bitcoin today resembling more of a speculative asset than a currency, which is supported by the findings of Yermack (2015). Financial assets tend to have greater volatility and more of a speculative nature to it than most developed currencies. For the sake of analysis, and to get greater knowledge, it is however reasonable to include exchange rates in the quantitative analysis into the categorization which is done in chapter 7. This is due to the high volatility experienced in Bitcoin is key as to why it does not function as a currency, and so comparing volatility processes would be useful.

5.3.5 Bitcoin as a speculative investment?

As argued, the volatility experienced with bitcoin makes it resemble more a financial asset than a traditional currency. Assets which such volatility as Bitcoin is often very suitable for risky investing with high possible returns, and almost infinite lower bound. A speculative investment is defined by the Cambridge dictionary as "An investment that carry a high level of risk of loss, or the activity of investing in these types of investments" (Cambridge dictionary) Which arguably fits as a glove on what investing in Bitcoin has been like, as it has shown great volatility over time with both great return and loss. As found by Baur. et Al (2017), most investors do only hold Bitcoin. This indicates speculation in the volatility, as holders of an asset believe that they will get a return by holding, they believe they will experience positive volatility (Baur et. Al, 2017). This is of course no different than speculation in stocks, but in Bitcoin it is only the volatility which will grant you a return, or loss, on your investment. The pure supply and demand driver of return comes as Bitcoin have no intrinsic value, nor promises any future payments apart from resell value. This makes it difficult to theoretically compare it with any other class of financial asset, such as stocks. A quantitative analysis, which will be done in chapter 7, finds that bitcoin do not resemble traditional financial assets used for speculation today.

The lack of intrinsic value in Bitcoin is important when it comes to how attention and hype play a part in the price formation of Bitcoin. The fact that Bitcoin is a supply and demand market in its purest form makes market manipulation highly possible. Gandal et. Al (2018) found that during Bitcoins early days in 2013, one agent in the market single handily drove the price from $250 to $1,000 (Gandal et. Al, 2018). The Bitcoin and cryptocurrency markets have matured since then, but it cannot be excluded that investors in the market today have such power. Griffin and Shams (2018) found support for the claim that Tether[32] was used to manipulate Bitcoin, paired with their other findings this gave evidence to that price manipulation is behind "substantial distortive effects in cryptocurrencies". (Griffin & Shams, 2018).

Price manipulation is something that is done in a speculative manner. Volatility, price manipulation and arbitrage opportunities all make Bitcoin perfect for speculative investments. Bitcoins failure to satisfactory meet the three key requirements for a currency, and its highly speculative market goes to show that it has more in common with speculative financial assets than a currency. This will also be checked in chapter 7., where the volatility processes of speculative assets[33], and non-speculative assets[34] will be compared to that of Bitcoin.

The four variables chosen to further extend the analysis of this chapter in a quantitative matter are two currency pairs, a stock market index and a risk-free asset. In the next chapter, the chosen variables are laid out and compared through a basic statistical analysis.

[32] A cryptocurrency pegged to USD

[33] Stock market index

[34] 1 year T-Bill, referred to as the risk-free rate

6. Data and descriptive statistics

6.1 Introducing the variables

In this chapter, we present the variables we have chosen to compare Bitcoin amongst[35], and have a first look at similarities and differences between them. The variables introduced in this section are Google trends, S&P500 (stock market proxy), 1-year treasury bill[36] and lastly two currency pairs: dollar to euro and dollar to sterling pound. Besides the Google Trends-variable, all variables are retrieved from Thomson Reuters data stream. The variables contain daily observations starting at 2013.03.04 and ending at 2018.03.02, adding up to a total of 1306 observation per variable. To have a meaningful comparison of the data, there is not included any weekend observations for Bitcoin, even though Bitcoin trading is not limited to weekdays only.

The google trend data is extracted from google servers per API-request using python 3 to sort the data into a csv file[37]. This data is restricted to containing weekly observations only, due to data extraction rules set by Google. Therefore, the total number of observations for this variable adds up to 261, during the same time interval as for the daily data.

Google-trend data are generated in the following way[38]: you start off by choosing a keyword, setting a time-period and choosing either to generate for the whole world, or a specific region of choice. The volume of all Google-searches using this keyword is measured relatively to the volume to that of all other Google-searches at the same point in time, and this relationship is then multiplied by a factor which scales the dataset to a value between 0 and 100. 100 represents the week with the most interest in the keyword, and 0 means there is not enough data available to create a meaningful value. Not to be mistaken by actual search volumes, Google-trend data measures the relative popularity in Google search query.

[35] See chapter 4
[36] which will be referred to in this thesis as the risk-free rate
[37] The code is added to the appendix
[38] A description of how the data is generated can be found following this link: https://newsinitiative.withgoogle.com/training/lesson/6507480104304640?image=trends&tool=Google%20Trends

6.2 Graphing the variables

In this section, the variables used throughout this thesis is graphed and discussed. Due to the categorization, and analysis of media attention on Bitcoin return, the series of interest are the return series. It is useful to create logarithmic time series to represent the variables on level form. Using logarithmic time series has advantages such as normalizing price development in Bitcoin and makes it possible to compare lever format to the return format later in the thesis. Therefore, logarithmic time series as graphed by figure 6.2 and 6.5 will be referred to as "level form". In this section, the raw series are presented as to get an overview of the variables.

6.2.1 The daily datasets on level-form

The time series graphed in Fig. 6.1 shows the development during all daily datasets, for all variables on standard level form. Notice that the 1 Y Tr. yield is denominated in percent, whilst the other variables are denominated in levels. To be able to graph the daily Trends-series, each day of the week has been assigned the weekly value, i.e. the average value. Fig. 6.2 views the daily log-level development during the same time horizon.

From viewing figure 6.1, Bitcoin (pBTC) shows nothing near the behaviour of the other variables we wish to compare it to, except for the Trends-variable. As a currency, Bitcoin seems to diverge from the depicted relationship between the US dollar and the two other currencies.

Figure 6.1: Daily raw series

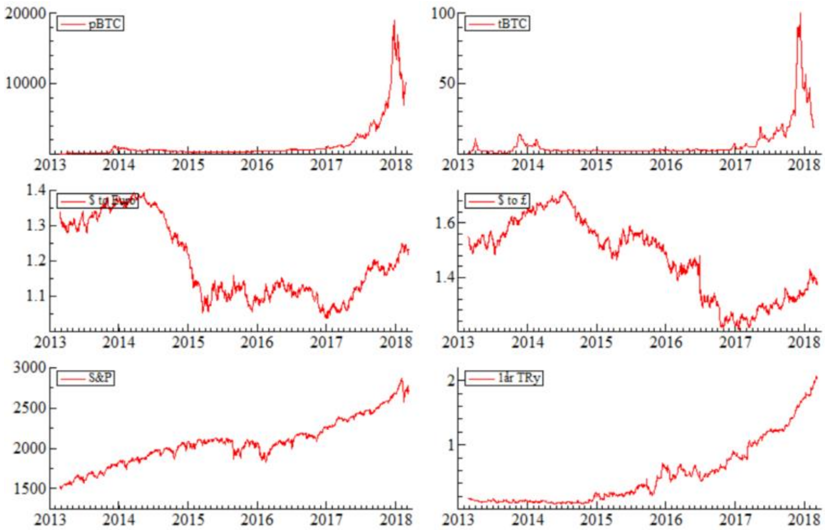


__Figure 6.1:__ The graphed series of Bitcoin price in terms of dollar (pBTC), the Google-Trends variable (tBTC), dollar to euro exchange rate ($ to Euro), dollar to pound exchange rate ($ to £), the S&P500 stock market index (S&P) and the one-year risk free rate in the US (1år Try). The daily raw datasets contain 1305 observations.

When viewing figure 6.2, the logged variables offers a visualisation of the time series which points to Bitcoin being more like the stock market proxy than we initially expected. The logged Google Trends variable is also a candidate which seems to match the time patterns reflecting the behaviour of Bitcoin.

Figure 6.2: Logarithmic daily raw series

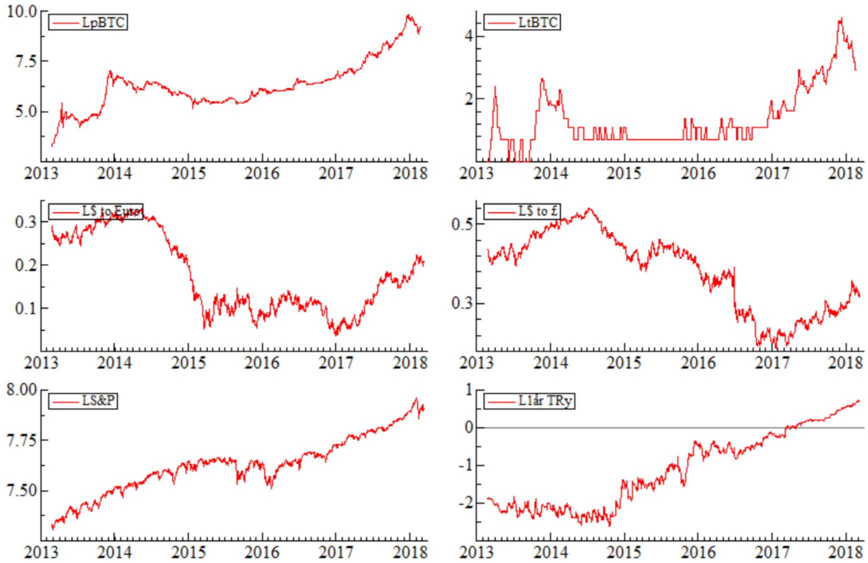


__Figure 6.2:__ The graphed daily logarithmic series of Bitcoin price in terms of dollar (pBTC), the Google-Trends variable (tBTC), dollar to euro exchange rate ($ to Euro), dollar to pound exchange rate ($ to £), the S&P500 stock market index (S&P) and the one-year risk free rate in the US (1år Try). The daily logarithmic raw datasets contain 1305 observations..

6.2.2 The daily return variables

To create return series, we apply the method elaborated in chapter 5.1.2. Because the risk-free rate is already given in percent, this return series for this variable is generated by the logarithmic first difference only. The graphed daily return series are found in figure 6.3:

Figure 6.3 shows the graphed returns generated by daily data for each asset during their respective lifespan. Trends-variable is not represented by the daily return series figure, since the variable holds only weekly data. If we were to graph this variable, it would contain at least 4 zero-observations per week. Comparing the daily return series to the original daily raw series, Figure 6.3 shows that all variables seems to have stabilized around a close to zero mean-value, which is no surprise given the fact that these are return-series.

Figure 6.3: Daily return series

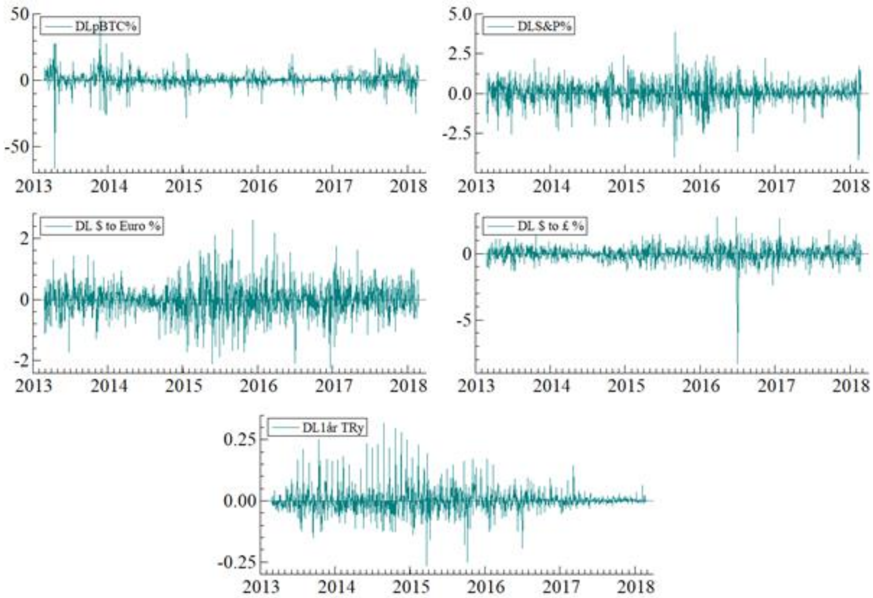


Figure 6.3*: The graphed daily return series of Bitcoin (DLpBTC%), S&P500 (DLS&P%), the dollar to euro exchange rate (DL $ to Euro %), the dollar to pound exchange rate (DL $ to £ %) and the risk-free interest rate in the US (DL 1år TRy). Percentage change in the Google Trends variable on a daily format is not obtainable due to data extraction rules set by Google.* The daily return datasets contain 1304 observations per variable.

6.2.3 The weekly variables on level form

The weekly time-series are gathered by estimating the weekly average using the daily time series. The Trends-variable is downloaded in a weekly format in its original state. The weekly variables on level form are found in figure 6.4 and 6.5.

Figure 6.4: Weekly raw series

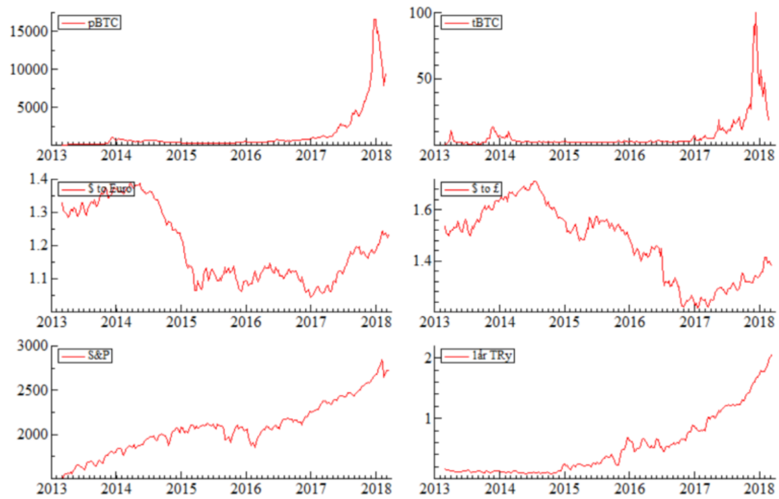


Figure 6.4: *The graphed weekly series of Bitcoin price in terms of dollar (pBTC), the Google-Trends variable (tBTC), dollar to euro exchange rate ($ to Euro), dollar to pound exchange rate ($ to £), the S&P500 stock market index (S&P) and the one-year risk free rate in the US (1år Try). The weekly raw series contain 261 observations.*

Figure 6.5: Weekly logarithmic raw series

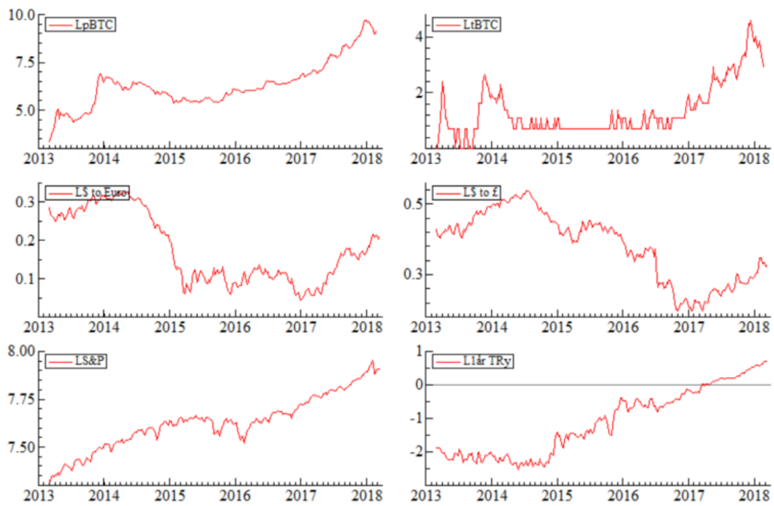


Figure 6.5: *The graphed daily logarithmic series of Bitcoin price in terms of dollar (pBTC), the Google-Trends variable (tBTC), dollar to euro exchange rate ($ to Euro), dollar to pound exchange rate ($ to £), the S&P500 stock market index (S&P) and the one-year risk free rate in the US (1år Try). The weekly logarithmic raw series contain 261 observations.*

6.2.4 The weekly return variables

All weekly return variables are generated using the formula in chapter 5.1.2, except for the risk-free rate variable[39] which is generated by the logarithmic first difference.

Figure 6.6: Weekly return series

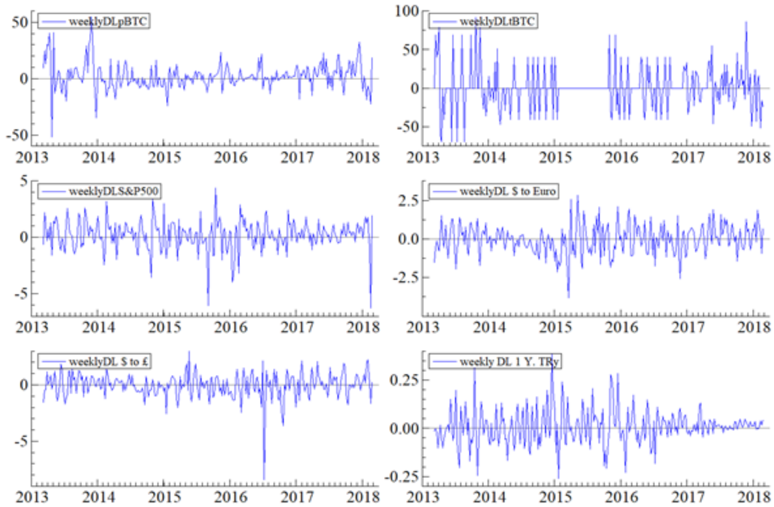


Figure 6.6: *The graphed weekly return series of Bitcoin (weeklyDLpBTC), Google Trends (weeklyDLtBTC), S&P500 (weeklyDLS&P500), the dollar to euro exchange rate (weeklyDL $ to Euro), the dollar to pound exchange rate (weeklyDL $ to £) and the risk-free interest rate in the US (weekly DL 1Y. Try). The weekly return series contain 260 observations.*

Figure 6.6 displays the weekly return series. These time series do appear to have stabilized at some mean-value close to zero. When viewing the Trends-variable, the graph seems somewhat unordinary. This is due to the Trends dataset holds multiple zero-values. The series we are looking at in Fig. 6.6 are percentage changes in the google search popularity. This means that during the periods which are flat the popularity for Bitcoin searches has been stable. It is seen in Fig. 6.4 that the values are in fact close to zero, not equal to zero.

The observed tendency to volatility clustering in figure 6.3 and 6.6 is a known phenomenon in financial time-series. It occurs when one period in the dataset represents a shock in the series, the following period will also be affected by this. In chapter 7 this will be analysed more closely, as there is likely to be an underlying persistency of shocks in the dataset.

[39] weekly DL 1 Y TRy

6.2 Stationarity

In this section, the variables on log-level form and on return form are tested using the ADF-test explained in chapter 6.1.1, to determine whether the variables contain a unit root. Using the information criteria[40] to decide the lag length (p) of the first differences, the following general equation for all variables are estimated:

$$\Delta y_t = \beta_0 + \rho_1 y_{t-1} + \sum_{i=1}^{p} \varphi_i \Delta y_{t-i} + \varepsilon_t \tag{6.1}$$

The null hypothesis is that the variable is I(0), while the alternative hypothesis is that the variable is I(1). The lag-lengths, t-ADF, and ρ-values are reported in table 6.1.

Table 6.1: ADF-tests

Variables on level form: daily				Variables on level form: weekly			
p	Variable	t-adf	ρ	p	Variable	t-adf	ρ
0	Bitcoin	-0,58	-0,0008	0	Bitcoin	-0,89	-0,05
0	Trends	-1,99	-0,007	0	Trends	-2,19	-0,04
4	S&P500	-0,98	0,002	2	S&P500	-0,81	-0,01
1	$ to Euro	-1,23	0,002	1	$ to Euro	-0,98	-0,01
0	$ to £	-1,02	-0,001	1	$ to £	-1,25	-0,01
3	Risk free rate	-0,11	0,0001	8	Risk free rate	0,33	0,002
Critical values: 5% = -2,864 1%=-3,438				Critical values: 5%=-2,873 1%=-3,457			
Return variables: daily				**Return variables: weekly**			
p	Variable	t-adf	ρ	p	Variable	t-adf	ρ
3	Bitcoin	-16,35***	-0,9	0	Bitcoin	-11,83***	-0,71
0	Trends	-36,08***	-1	2	Trends	-10,89***	-1,26
0	S&P500	-36,65***	-1,02	1	S&P500	-12,01***	-0,98
4	$ to Euro	-16,29***	-1,04	0	$ to Euro	-12,43***	-0,75
0	$ to £	-34,07***	-0,94	1	$ to £	-11,64***	-0,95
8	Risk free rate	-12,25***	-1,02	7	Risk free rate	-6,18***	-1,1
Critical values: 5% = -2,864 1%=-3,438				Critical values: 5%=-2,873 1%=-3,457			

***Table 6.1**: The table views the results of ADF-tests for each variable, on both daily and weekly format, where level form refers to the logged variables, and the return form refers to the logged first differenced variables. 'p' tells how many differenced lags are used, determined by the information criteria. 'ρ' is the coefficient value which is subject to the ADF-test. 't-adf' is the test statistic value when conduction the t-test. *** denotes significance at a 1% level, ** denotes significance at a 5% level. The critical values used are listed in the bottom of each square bracket, as gathered by Dickey and Fuller (1979).*

[40] Recall that thought the residuals of the variables might exhibit GARCH-errors, using the information criteria is still the best option to determine lag-length in this scenario. For more information, see chapter 5.

The results from the ADF-tests shows that the variables on level form contain a unit root which means they are I(1). The return variables do not contain a unit root, and are classified as I(0). Neither variable on level form is stationary and must therefore be differenced once to become stationary. Hence, estimating all the return series by OLS will yield unbiased estimators. Moving forward with the descriptive statistics will therefore only examine the return series for each variable on a daily- and weekly format.

6.3 Descriptive statistics

In this section, basic descriptive statistics of each return variable is reviewed[41]. Table 6.2 contains the descriptive statistics for all our return variables on daily and weekly basis. The mean return on Bitcoin is more than ten times the return on the stock-index both for the daily and the weekly dataset, and nowhere near the return on the two exchange rates, which trades on average close to zero. Obviously, risk-free treasury bills hold the lowest return amongst the other assets in its category. In both our daily and weekly observed data, Bitcoin return holds the highest standard deviation, followed by S&P500 return, the return of the exchange rates and lastly the risk-free rate.

Table 6.2: Descriptive statistics

Daily return series	Mean	SD	Skewness	Kurtosis	Min	Max
Bitcoin ($ / BTC)	0.45528	5.9832	-0.991	20.28	-66.395	48.478
S&P500	0.04498	0.75906	-0.61622	3.6926	-4.1843	3.8291
$ / Euro	-0.0053674	0.53318	0.0066055	2.0921	-2.2594	2.6
$ / £	-0.0074797	0.58846	-2.1297	31.876	-8.312	2.7631
1 Y Tr. Yield (US)	0.0019631	0.049017	1.0756	8.0733	-0.2662	0.31736
Observations	1305					

Weekly return series	Mean	SD	Skewness	Kurtosis	Min	Max
Bitcoin ($ / BTC)	2.2201	11.556	0.49444	4.0508	-51.715	54.696
Trends	1.1325	26.685	0.43233	1.5486	-69.315	91.629
S&P500	0.22141	1.3045	-0.98548	4.3031	-6.2824	4.3997
$ / Euro	-0.026937	0.93909	-0.11922	0.69504	-3.8161	2.8466
$ / £	-0.036755	1.0904	-1.8050	12.658	-8.4297	2.9960
1 Y Tr. Yield (US)	0.0097871	0.089630	0.49615	2.1498	-0.26018	0.38431
Observations	260					

***Table 6.2**: The table contains basic descriptive statistics which are gathered from OxMetrics using "Descriptive Statistics using PCgive".*

[41] Descriptive statistics for the logged variables are gathered in the appendix.

The estimated skewness suggests that most variables are moderately skewed, and the excess kurtosis suggest that Bitcoin return and the dollar-pound exchange rate return holds the highest probability of assuming daily extreme values relative to their respective means. In the weekly datasets, the excess kurtosis has declined relatively to the daily datasets, suggesting that the weekly observations are closer to a normal distribution.

6.3 The correlation matrix

In the following section the correlation matrix, and the implications of the significant coefficients relevant to the thesis are discussed. The correlation matrix is generated by dividing the covariance between two variables on the product of their respective standard deviations, whilst restricting the estimation to be contemporaneous[42]. The results are displayed in table 6.3.

The results indicate that daily Bitcoin returns are uncorrelated with all explanatory variables, i.e. all the coefficients are close to zero, which makes these results insignificant. The close-to-zero value of the coefficient belonging to S&P500 return provides a risk-management opportunity for an investor who seeks to mitigate risk. Even though this coefficient is not significant, it is indeed an interesting relationship that in theory could contribute to a better diversification when one decides to invest among different financial assets. The other variables seem to have significant relationships compared to one another, indicating that Bitcoin could be an asset outside of the traditional financial framework.

The correlation matrix representing the weekly dataset depicts that the correlation coefficient between S&P 500 return and Bitcoin return is highly significant. The coefficient assumes a value closer to zero than unity, indicating that grouping these assets in a portfolio could be a useful hedge.

The correlation coefficient of the Trends-variable indicates a significant correlation viewed under the 5% significance level, which corresponds to the hypothesis that that Trends should have explanatory power on Bitcoin return.

[42] To calculate the p-values related to the different estimated coefficients, we use Stata

Table 6.3: The correlation matrix

Daily returns						
Bitcoin ($/Bitcoin)	1					
S&P500	0.0090647	1				
$/Euro	-0.023571	-0.064855***	1			
$/£	-0.019406	0.10789***	0.52092***	1		
1 Y Tr. Yield (US)	0.0093012	0.089794***	-0.12448***	0.015138	1	
Observations	1306					
Weekly returns						
Bitcoin ($/Bitcoin)	1					
Trends	0.0985**	1				
S&P500	0.1622***	0.1732***	1			
$/Euro	-0.0448	-0.0443	-0.0301	1		
$/£	0.0051	0.0946	0.2387***	0.5200***	1	
1 Y Tr. Yield (US)	0.0704	0.0221	-0.0779	0.2105	0.0218	1
Observations	260					

***Table 6.3**: The correlation matrix shows that all variables are uncorrelated with Bitcoin on a daily basis. On the weekly format, Bitcoin is correlated with percentage change in Google Trends, and the stock market index. *** denotes significance at a 1% level, ** denotes significance at a 5% level.*

6.4 Summary

By the first look at our data, we have seen that Bitcoin price- and daily return history looks entirely different from that of (what we assume to be) its comparable peers, being the stock market proxy, the two exchange rates and the risk-free rate. Creating the return series, we have seen that both the daily and the weekly logged variables are stationary all together when being differenced once. In other words, the return series of each variable is stationary, and can be estimated by using OLS. This result shall be referred to several times throughout this thesis.

Creating the correlation matrix, we made the discovery that there is a relatively strong relationship between Bitcoin return and the S&P500 return (on a weekly basis). While the correlation matrix is a very basic statistical analysis, the result could imply that the return of S&P500 can contribute to explaining the variation in Bitcoin return.

Lastly, the properties of our data points towards Bitcoin behaving more like a speculative asset rather than a currency, due to its high mean return. However, one can argue that the categorization of Bitcoin (in terms of known financial assets) purely on basis of this argument is imprecise. To further extend the categorisation of Bitcoin, and to compare the financial assets in a greater detail, we shall investigate the volatility patterns across the different assets, using univariate GARCH modelling. This leads us to the next chapter.

7. An analysis of volatility across the variables

To some extent, this chapter will follow the methodology of Baur et al. (2017) as discussed in chapter 2. This chapter can be viewed as an elaborated descriptive statistic analysis, in which the volatility processes of the variables introduced in chapter 6 are compared. The aim of this chapter is to attempt a categorization of Bitcoin. This chapter proceeds as follows; first the mean equation[43] is specified using methods put forward in chapter 5. When the mean equations are adequately expressed by an ARMA(p,q) model, each residual term are tested for GARCH-effects and autocorrelations using the ARCH-LM test and the Ljung-Box test. Last, the best GARCH-model in terms of the volatility process of each variable is fitted, and further it is checked if the GARCH-effects are accounted for using the ARCH-LM test.

Because all variables on level form are I(0) when differenced once, we shall use the return series presented in chapter 6, using both daily and weekly data[44].

7.1 Specifying the mean equations

Because there are 5 days of recorded trading each week for all variables, we set the maximum ARMA(p,q) lag length to p = 5 and q = 5, i.e. Monday through Monday. For the weekly datasets, we set the lag-threshold to be 4, accounting for approximately one month of data. Combining the general-to-specific method with regarding the information criteria, we determine the adequate lag-lengths for each model. The reader should be advised that a more correct method to use when fitting an ARMA-equation is to apply the Hannan-Rissanen procedure of Hannan & Rissanen (1982). We follow the procedure partly by first choosing the proper lag-length of the auto regressive part, before adapting the moving average lag-length to this result. If an additional MA-variable changes the estimates of either one of the AR-parameters that are already declared statistically significant in the model, the MA-variable is not included in the mean equation.

Using the information criteria to decide respective error-distributions, all daily variables follow a normal distribution, except the $/Euro return series, which follows a t-distribution. In the case of our weekly data, the information criteria choose a t-distribution for all

[43] The mean equation is referred to as the ‘general equation’ throughout chapter 4.

[44] Recalling that we do not have daily data for Google Trends, examining the volatility process of the Trends-variable is only done using weekly data.

variables except for the Trends-variable which is normally distributed. These results are applied when determining the proper lag-lengths of the different mean equations. The selected lag-length included in the mean equation for each respective variable are presented in Table 7.1.

Table 7.1: Lag-length selection for each mean equation

Daily return data			*Weekly return data*		
Variable	AR	MA	Variable	AR	MA
Bitcoin	2	1	Bitcoin	1	0
S&P500	1	1	S&P500	2	0
$ to Euro	1	1	$ to Euro	2	0
$ to £	2	0	$ to £	1	0
Risk free rate	2	2	Risk free rate	2	0
			Trends	0	0

Table 6.1: The selected lag-lengths for the mean equation of each variable. The method used is first determining the number of relevant auto regressive lags using the general to specific method combined with looking at the information criteria. Then, we have fitted the correct amount of moving average variables without distorting the statistical significance of the auto regressive parameters.

7.1.1 Diagnostic testing

Table 7.2 displays the results gathered regarding diagnostic testing of the mean equations as specified by table 7.1. An elaboration of both tests can be found in chapter 5.

Table 7.2: Post estimation diagnostic testing

Dependent variable	**Q-statistics on Squared Standardized Residuals**				**ARCH-LM-test**		
	Q(5)	Q(10)	Q(20)	Q(40)	1-2	1-5	1-10
			Daily returns				
Bitcoin	5,67* (P-value=0,0587)	8,28	36,23**	53,69**	119,06***	48,24***	24,13***
S&P500	5,84	8,53	18,28	37,68	78,05***	43,75***	22,31***
$ to Euro	1,79	11,35	24,63	46,12	8,00***	8,24***	5,91***
$ to £	9,32*	13,76	23,22	47,24	11,08***	7,72***	4,11***
Risk free rate	2,33	12,34	66,99**	109,53***	8,73***	4,45***	2,74***
			Weekly returns				
Bitcoin	3,74	4,97	10,89	29,78	1,33	3,6***	2,67***
S&P500	1,37	9,96	14,08	41,25	3,16**	1,51	1,92***
$ to Euro	7,69*	11,52	24,76	40,34	4,87***	2,81**	2,72***
$ to £	3,16	5,27	16,08	35,46	1,01	0,45	0,23
Risk free rate	21,15***	56,23***	115,31***	239,13***	1,94	7,10***	4,62***
Trends	4,09	5,21	11,11	29,68	0,93	3,38***	2,69***

*Table 7.2: In this table, the post estimation diagnostic testing results are presented. *** denotes significance at a 1% level, ** denotes significance at a 5% level and * denotes significance at a 10% level.*

7.1.1.1 Daily return diagnostic tests

For most variables on a daily format, the autocorrelation in the early stages of the ACF[45] are accounted for by the specified ARMA equations, though these results might be skewed due to the containment of endogenous variables in the estimated mean equations. However, there still exists heteroscedasticity tendencies captured by the residuals of the means; creating disturbances in the model. All daily series show confirmed GARCH-errors given by the ARCH LM test, i.e. we reject the null hypothesis of no (G)ARCH-effects present in the datasets for all variables.

7.1.1.2 Weekly return diagnostic tests

For our weekly set of variables, it is worth noticing that the risk-free rate return shows strong evidence of autocorrelation. Adding more lags of the AR-term does not remove the autocorrelation, which means that the variable is very likely to be fitted well by a GARCH-model. We reject the null of no GARCH-effects present in the datasets for all variables, except for USD/EUR exchange rate return. For this variable, we expect to find non-significant coefficients measuring the conditional variance in the next part of this chapter.

7.2 Applying GARCH modelling

7.2.1 The models

The results from the last section validate the usage of GARCH-models for all variables except the weekly USD/EUR exchange rate return. By using the information criteria to determine the adequate GARCH-model for each variable, we found the models selected to be GARCH, IGARCH and GJR. The results are listed in table 7.3.

The variance of the weekly return data of Bitcoin proved to be fitted well by both the IGARCH model[46] and the GJR model[47]. Both models are listed in table 7.3 for the purpose of comparing volatility pattern of Bitcoin return to that of the percentage change in Google Trends. As expected, none of the coefficients involved in the conditional variance equation of the weekly USD/GBP exchange rate return are statistically significant.

[45] for the squared residuals

[46] selected by HQ and SC

[47] selected by AIC

Table 7.3: The estimated GARCH models

	Mean equation					Variance equation				
	Constant	AR(1)	AR(2)	MA(1)	MA(2)	Constant	α	β	γ	**Model**
Daily return variables										
Bitcoin	0,21*	-0,83***	0,05	0,85***	-	0,94**	0,19***	0,81***	-	IGARCH(1,1)
	(0,11)	*(0,06)*	*(0,04)*	*(0,04)*	-	*(0,44)*	*(0,04)*	*(0,04)*	-	
S&P500	0,04***	-0,91***	-	0,87***	-	0,05***	0,01	0,74***	0,36***	GJR(1,1)
	(0,02)	*(0,26)*	-	*(0,29)*	-	*(0,01)*	*(0,06)*	*(0,06)*	*(0,08)*	
Dollar to Euro	-0,01	0,49	-	-0,49	-	-	0,03***	0,97***	-	IGARCH(1,1)
	(0,01)	*(0,72)*	-	*(0,73)*	-	-	*(0,01)*	*(0,01)*	-	
Dollar to Pound	-	0,02	-0,01	-	-	-	0,05	0,095	-	IGARCH(1,1)
	-	*(0,03)*	*(0,03)*	-	-	-	*(0,02)*	*(0,02)*	-	
Risk-free rate	0,003***	-0,93***	-0,97***	0,93***	0,98***	0,01	0,02	0,95***	0,08*	GJR(1,1)
	(0,0007)	*(0,03)*	*(0,06)*	*(0,03)*	*(0,04)*	*(0,01)*	*(0,01)*	*(0,01)*	*(0,04)*	
Weekly return variables	**Mean equation**					**Variance equation**				**Model**
Bitcoin	1,14**	0,26***	-	-	-	6,34	0,36***	0,64***	-	IGARCH(1,1)
	(0,54)	*(0,08)*	-	-	-	*(4,14)*	*(0,08)*	*(0,08)*	-	
Bitcoin	1,58***	0,26***	-	-	-	5,44	0,46***	0,68***	-0,27**	GJR(1,1)
	(0,64)	*(0,07)*	-	-	-	*(4,21)*	*(0,13)*	*(0,08)*	*(0,12)*	
S&P500	0,22***	0,26***	-0,08	-	-	0,36*	-0,04	0,48**	0,86**	GJR(1,1)
	(0,07)	*(0,07)*	*(0,07)*	-	-	*(0,18)*	*(0,08)*	*(0,22)*	*(0,44)*	
Dollar to Euro	-	0,31***	-0,18**	-	-	-	0,09**	0,89***	-	GARCH(1,1)
	-	*(0,06)*	*(0,08)*	-	-	-	*(0,04)*	*(0,08)*	-	
Dollar to Pound	-	0,2***	-	-	-	-	0,12	0,88	-	IGARCH(1,1)
	-	*(0,06)*	-	-	-	-	*(0,13)*	*(0,13)*	-	
Risk-free rate	0,01***	-0,13**	-	0,38***	-	-	0,1**	0,9***	-	GARCH(1,1)
	(0,003)	*(0,06)*	-	*(0,06)*	-	-	*(0,05)*	*(0,03)*	-	
Google Trends	3,14*	-	-	-	-	21,55	0,18**	0,89***	-0,21***	GJR(1,1)
	(1,61)	-	-	-	-	*(18,53)*	*(0,08)*	*(0,08)*	*(0,08)*	

Table 7.3: **** denotes significance at a 1% level, ** denotes significance at a 5% level and * denotes significance at a 10% level. Standard deviations are listed in parenthesis. In the case where the intercept terms are insignificant and measured very small, the coefficient values with respective standard deviations are not listed. For more information regarding the different type of models, see chapter 4.*

The post estimation diagnostic test results can be found in the appendix. In summary, all GARCH-errors are accounted for by modelling the conditional variance using the different type of GARCH models listed in table 7.3. The only variable that exhibits significant autocorrelation is the daily risk-free rate return variable.

7.3 The results

7.3.1 Daily return datasets

The constant of the Bitcoin return variance equation takes the largest value compared to that of the other variables, thus confirming the relatively high volatility of Bitcoin. When comparing the constant of each variable, we see that the volatility of S&P500 return is the coefficient that finds itself closest to that of Bitcoin return. The constant of the two exchange rate returns is further away in comparison. The ARCH-coefficient of Bitcoin return[48] is larger relatively to the other ARCH-coefficients, which suggests that the volatility of Bitcoin return cohere more to its own past observations than the volatility of the compared variables. The GARCH-coefficient[49] shows that Bitcoin return holds a persistency of shocks in the conditional variance somewhere in between S&P500 return and risk-free rate return.

The gamma coefficient belonging to S&P500 return is highly significant, suggesting the existence of a leverage effect in the time series. The IGARCH-model used to model Bitcoin return does not account for a leverage effect. When exploring different specifications of the GJR-model for Bitcoin return, we found that none of the gamma coefficients proved to be significant. Therefore, we cannot compare the two variables on this subject, using the daily format, though it is worth mentioning that Baur et. Al (2017) in their study found that the gamma coefficient for Bitcoin return was positive and highly significant when using a GJR(1,1) model with one AR lag on daily return series. The reason for this might be that the dataset used by Baur et. Al (2017) do not account for the decline in Bitcoin price throughout January 2018. In addition to this, the G@RCH package in OxMetrics we have used is predetermined to estimate robust standard deviations, whereas Stata offers a menu of different ways to estimate the standard deviations. In their paper, it is offered few details explaining the method that was used to achieve the results they base their discussion on.

When comparing the model selections for the different variables, the IGARCH format suggests that Bitcoin and the two exchange rates share the similarity of a persistent response to shocks, implying a shared variance pattern across the currencies. This could point towards Bitcoin resembling a currency. However, this is the only similarity we could find when comparing the volatility processes of the different currencies. The fact that the constant in the conditional variance equation for Bitcoin return is very large, does rather point towards Bitcoin being an asset which could be described as speculative.

As discussed in chapter 3, the price determination of Bitcoin is driven by buyers and sellers and is thus internally driven. Because the measured conditional variance is large, there is reason to believe that speculative investors are attracted to Bitcoin. This reasoning concurs

[48] Alpha
[49] Beta

with Baek and Elbeck (2014) who find Bitcoin to be a highly speculative asset due to its volatility being internally driven.

Using the same tool for categorizing Bitcoin, namely the GARCH-type models, Baur et al. (2017) found that the volatility process of Bitcoin return was nowhere near that of the compared exchange rates[50], and it was concluded that Bitcoin prove to resemble a "highly speculative asset". As mentioned earlier, this study did solely rely on GJR-models, and could therefore not compare the different fitted GARCH-type models across the variables.

7.3.2 Weekly return datasets

When examining the volatility process of the weekly return dataset of Bitcoin, we found that both the GJR-model and the IGARCH-model are good candidates when modelling the conditional variance. The conditional variance of dollar to pound exchange rate return was, as expected, poorly modelled by the selected IGARCH-model, and is therefore not involved in this discussion. Though the sum of the alpha and beta parameters in the conditional variance equation of USD/EUR exchange rate return is almost equal to unity, the information criteria all together chose the GARCH-model rather than the IGARCH model.

The constants of the conditional variance of Bitcoin return are relatively large to the other assets but are not proven statistically significant. The constant of the percentage change in Google Trends holds the largest value, reflecting that this variable is the most volatile, thought the constant is not statistically significant.

The ARCH-coefficients of Bitcoin return in both models have increased in value when compared to the ARCH-coefficient estimated using daily data. Similarly, the GARCH-coefficient has decreased, meaning that the volatility pattern of Bitcoin return on a weekly basis is relatively more influenced by sudden, more slowly decaying shocks, rather than the actual persistency of the shocks measured by the GARCH-term[51].

On weekly format, there are few similarities to be pointed out between Bitcoin return and the exchange rate returns. Though the model selection for Bitcoin return and USD/GBP

[50] $/Euro and $/£
[51] Compared to the results for daily return data

return is similar, modelling the conditional rate of return on the USD/GBP is not necessary, because its variance can be considered constant due to the test results in section 7.1.1.[52]

The GJR-models selected for Bitcoin return[53], S&P500 return and percentage change in Google trends opens up for discussion. The ARCH- and GARCH-coefficients of the percentage change in Google Trends lie closer to those of Bitcoin return compared to the ARCH- and GARCH-coefficients of the S&P500 return. The gamma-coefficient measuring the leverage effects[54] suggests that for Bitcoin return and percentage change in Google Trends, positive shocks increase the variance by less than negative shocks. The gamma-coefficients also assume almost the same values. This effect is asymmetric in terms of the gamma-coefficient of S&P500 return, for which positive shocks increase the variance by more than negative shocks. This is the opposite to the findings of Baur et al. (2017) in which MSCI World index was used as the stock market proxy. Their estimations proved a positive and significant gamma-coefficient for Bitcoin return, and a negative and significant gamma-coefficient for the MSCI World index return.

When comparing the conditional variance equations of the three GJR-models, percentage change in Google Trends is the one candidate that resembles the variance pattern of Bitcoin return the most. The results suggest that the two variables are almost equally respondent to 'good news' and 'bad news' and that in general, the volatility pattern of the variables look very much alike.

7.4 Summary and conclusion

In summary remarks, the purpose of this chapter has been to compare the volatility process of Bitcoin return to that of USD/EUR return, dollar to pound return, the S&P500 stock index return and the risk-free rate return. We have seen that the daily Bitcoin return shares few similarities with the compared variables, other than its variance partly resembling the persistency pattern to that of the two exchange rates. In another context, this could open

[52] The constants of both exchange rate returns are statistically insignificant and too small to be viewed relevant to this discussion, and therefore not included in the table
[53] by AIC
[54] See chapter 4

for research using multi variate GARCH analysis when exploring shared patterns in the conditional variance of the exchange rate return variables.

On the other hand, the three exchange rates[55] differ due to the high volatility of Bitcoin return relative to the two other exchange rates. The high volatility of Bitcoin could classify Bitcoin as a highly speculative asset, which carries more risk than the stock market proxy.

By comparing the volatility processes amongst the weekly datasets, we found that the largest constants in the conditional variance equations belongs to Bitcoin return and percentage change in Google Trends, though they were not statistically significant. The best model to employ for Bitcoin return for comparison among variables, was the GJR-model. When comparing the three GJR-models[56], the conditional variance of Bitcoin return seems to share many of the properties found in the conditional variance equation for the percentage change Google Trends variable.

With Google Trends 'return' being the closest variable related to Bitcoin return in terms of the conditional variances, the results of this chapter suggest that Bitcoin is an asset hardly categorized in terms of any known financial asset classes. The results from the GARCH modelling of the conditional variances point towards Bitcoin resembling a speculative asset rather than a currency or a financial asset with an underlying cash flow on which the asset might be valuated. This concurs with the findings of Baur et al. (2017), and Baek & Elbeck (2014).

In chapter 3 we raised the hypothesis that the demand for Bitcoin, and thus eventually the Bitcoin return, is driven by media attention. When viewing the results of this chapter in this narrative, the percentage change in Google search queries could be an indicator of future Bitcoin return, due to its similar responses to shocks in the conditional variance. In the next chapter, we shall further explore the possibility of a coherence between the two variables.

[55] $/BTC, $/Euro, $/£

[56] Bitcoin return, percentage change in Google Trends, S&P500 return

8. Investigating investor attractiveness

Having analyzed and compared each variable's respective modelled conditional variance, we found that the volatility pattern of percentage change in Google Trends appeared closest to that of Bitcoin return. We concluded that Bitcoin does resemble an asset which is inherently speculative, rather than a currency or a normal financial asset. In this chapter, we move on from looking at the conditional variance estimations, to examine the general coherency between the two variables. Should our categorization of Bitcoin be correct, it is highly likely that percentage change in media coverage (Google Trends) might contribute to explaining some of the variation in Bitcoin return.

Turning now to the theoretical model on investor attractiveness derived in chapter 3, the goal with this chapter is to determine whether media attention is a factor; driving Bitcoin return, and to what extent. In chapter 3, we discussed the possibility of Bitcoin and Google Trends being jointly determined. By estimating the two variables using a restricted VAR model, we circumvent the simultaneous problems caused by their contemporaneous relationship. As we shall see in this chapter, the two variables are indeed cointegrated. Therefore, we shall investigate the relationship between Bitcoin return and percentage change in Google Trends using the VECM. By introducing a dummy variable in section 8.1, we attempt to distinguish positively and negatively narrated news. The results are presented in section 8.3 and discussed in section 8.4.

8.1 Dummy variable

Before we initiate the cointegration test of this chapter, we introduce a dummy variable which can help us to distinguish between the effects on Bitcoin return by media attention of a positive and a negative substance. With basis in the idea of Kristoufek, L. (2013) on how the dummy variable might be formed, we employ the algebra editor in OxMetrics:

dummy = movingavg(DLtBTC, 3, 0) < DLpBTC ? 1 : 0;

which can be read as "If the 4-week moving average of percentage change in Google Trends search queries is less than the Bitcoin return, the dummy variable takes the value 1, and 0 otherwise". Thus, if Bitcoin return is above its trend level measured by the 4-week MA of percentage change in Google Trends, the search queries should reflect people seeking information due to increasing prices. Reversely, when Bitcoin return is below its trend level this should reflect people seeking information due to reducing Bitcoin prices, in which case the dummy variable assumes a zero value. The idea is that because the two variables are cointegrated (as we shall see in the next section), the percentage change in Google Trends indicates whether Bitcoin return is trending upwards or downwards. The dummy variable will be unrestricted when estimating VAR so it isn't altered by the transformation when applying reduced form to the VAR.

Lastly, we should address that Juselius (2006) argues that when involving a dummy variable in the equations of Johansens' cointegration test, the asymptotic distribution of Johansens test statistics is likely to be skewed. On the other hand, when time series contain GARCH-errors, Lee and Tse (1996) and Kosapattarapim et. Al (2018) reports that applying Johansens' test is preferred to the alternatives.

8.2 Johansens' test for cointegration

In the methodology chapter (5.3.1) we derived the reduced form VAR(1) equations which could be represented by the equation:

$$y_t = B_0 + B_1 y_{t-1} + e_t \tag{8.1}$$

To further extend equation 8.1 in terms of finding the correct VAR(p) model (with new notations), we rewrite equation 8.1:

$$\begin{bmatrix} P_t \\ T_t \end{bmatrix} = \Gamma_0 + \Gamma_1 \begin{bmatrix} P \\ T \end{bmatrix}_{t-1} + \Gamma_2 \begin{bmatrix} P \\ T \end{bmatrix}_{t-2} + \cdots + \Gamma_p \begin{bmatrix} P \\ T \end{bmatrix}_{t-p} + \bar{D} + \bar{\varepsilon}_t \tag{8.2}$$

$$\Gamma_0 = \begin{bmatrix} \alpha_{10} \\ \alpha_{20} \end{bmatrix} \quad , \ \Gamma_i = \begin{bmatrix} \gamma_{11,i} & \gamma_{12,i} \\ \gamma_{12,i} & \gamma_{22,i} \end{bmatrix} \quad , \quad \text{i = 1,2, … , p}$$

where P = Logarithmic Bitcoin price in terms of dollar and T = Logarithmic values of Google Trends. $\bar{D}$ is an unrestricted dummy variable matrix introduced in section 7.1, Γ_i is the coefficient matrix and α_{10} and α_{20} are constants. The residuals are assumed to be white noise[57] and may be correlated.

[57] The residuals are not actual white noise, because of the non-linear disturbances caused by GARCH-errors. The serial correlation is removed, however, when including specifying the VAR(p) model as VAR(1). For a discussion on the interference of GARCH-errors when testing for cointegration, see chapter 4.

Using the information criteria for multivariate model selection[58], 8 different lag lengths are examined to have included approximately two months of observed history. HAC standard errors are used to avoid possible spurious estimations caused by heteroskedasticity or wrong lag determination relative to the true model. The results are gathered in table 8.1:

Table 8.1: The different VAR(p) models

VAR(p)	1	2	3	4	5	6	7	8
AIC	-1,8686	-1,9292	-2,0089	-2,1273	-2,1421	-2,1954	-2,1625	-2,2061
SC	-1,7578	-1,763	-1,7873	-1,8504	-1,8097	-1,8065	-1,7168	-1,7034
HQ	-1,824	-1,8624	-1,9198	-2,0159	-2,0084	-2,039	-1,9832	-2,0038

Table 8.1*: The different information criteria are listed for each reduced form VAR(p) representation for logarithmic values of Bitcoin and Google Trends, with p representing 1-8 lag lengths. SC selects VAR(4), AIC selects VAR(8) and HQ selects VAR(6).*

Following Alain Hecq (1996), the SC should be weighted in presence of GARCH errors, when the information criteria select different model types. We also observe that the second largest absolute value of HQ selects a VAR(4) model. Therefore, four lags of p are used.

Moving forward, we reparametrize equation 8.6 by using four lags:

$$\begin{bmatrix}\Delta P_t\\ \Delta T_t\end{bmatrix} = \Pi_0 + \Pi_1\begin{bmatrix}P\\ T\end{bmatrix}_{t-1} + \Pi_2\Delta\begin{bmatrix}P\\ T\end{bmatrix}_{t-1} + \Pi_3\Delta\begin{bmatrix}P\\ T\end{bmatrix}_{t-2} + \Pi_4\Delta\begin{bmatrix}P\\ T\end{bmatrix}_{t-3} + \bar{D} + \bar{u}_t \quad (8.3)$$

where the matrix $\Pi_1 = \Gamma_1 - \mathrm{I}$ in which I is the identity matrix.

We further explore the rank of the matrix Π_1, which is expected to be one, due to our two-variable scenario. The null hypothesis is that the rank is equal to or less than 1, compared to the alternative that the rank is equal to or larger than one. We observe that the trace statistics indicates that the rank of the matrix Π_1 is one with a 98,9% success rate. Bitcoin and Google Trends are indeed cointegrated, denoted as CI(1,1).

Table 8.2: Johansens trace test statistics

$H_0 : r \leq$	Trace statistic	P-value
0	19,41	[0,011]**
1	0,57	[0,499]

[58] These are listed in the appendix.

__Table 8.2__: The trace statistics are presented, the null of zero cointegrated vectors is rejected. We cannot reject the null of the rank being larger or equal to one, which means that the determined rank of the matrix under examination is one. Thus, Bitcoin and Google Trends are CI(1,1).

Before presenting the cointegrating vector, we raise one concern with the results. When attempting to employ the Johansens cointegration test using a VAR(8) model as selected by the AIC, the p-value of one cointegrating vector is 0,238, in which case the two variables should be modelled using first differences. However, because we follow the suggested methodology of Alain Hecq (1996) of weighting the Schwartz criterion, we continue with assuming the two variables to be CI(1,1).

The cointegrating relationship between Bitcoin and Google Trends that is estimated using the Johansen method on the form $\begin{bmatrix}\alpha_1\\ \alpha_2\end{bmatrix}\begin{bmatrix}1 & \beta_2\end{bmatrix}\begin{bmatrix}P\\ T\end{bmatrix}_t$ is displayed in table 8.4. The results are discussed in section 8.4.

Table 8.3: The cointegrating vector

	$\alpha\beta'$			
	α_1	α_2	β_1	β_2
	-0,0297	0,0472	1,0000	-1,5216
Standard Dev.	0,0100	0,0292	0,0000	0,1416

__Table 8.3__: OxMetrics automatically normalizes the cointegrated vector with respect to logged Bitcoin price, see Doornik and Hendry (2013b). The alpha coefficients are referred to as the speed of adjustment parameters, that is, the correction toward the long-term equilibrium stated by the beta coefficients. See section 8.4 for a discussion of the results.

Figure 8.1 The cointegrating vector estimated by Johansen method

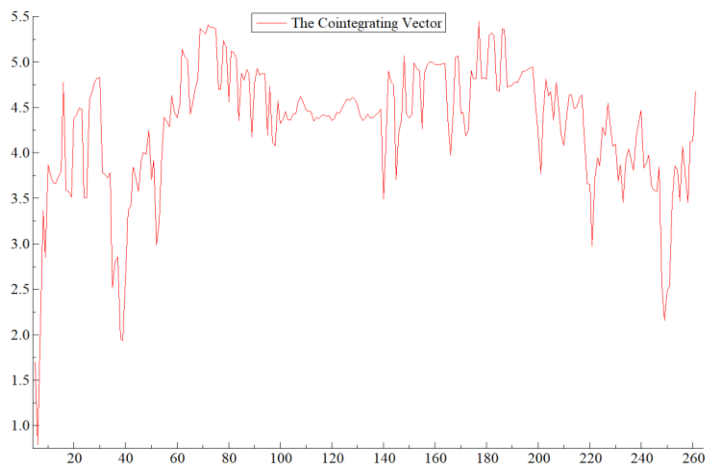


Figure 8.1: The graphed cointegrating vector estimated using the Johansen method. Thought the graph views many fluctuations, the long-term relationship between the two variables seem to be stable.

Next, using the function *"Map CVAR to I(0) model"* in OxMetrics, the cointegrating vector is stored as the variable CI. Combining the cointegrating vector with the first differences of the logarithmic values of Bitcoin and Google Trends, we arrive at the VECM model. It is very important to highlight that during this transformation; the return series are not multiplied by 100. Thus, the dummy coefficient, the constants and the speed of adjustment parameters must be multiplied by one hundred to be interpreted as a percentage values. The results are presented in table 8.4.

Table 8.4: The estimated VECM model

ΔP_t	Constant	ΔP_1	ΔP_2	ΔP_3	ΔT_1	ΔT_2	ΔT_3	CI_1	Dummy
Coefficient	0.08424	0.01634	0.03244	0.008958	0.1425***	*0.1347****	*0.1006****	*- 0.0159***	*0.108****
HACSE	(0.0455)	(0.0554)	(0.0532)	(0.0516)	(0.0241)	(0.024)	(0.0246)	(0.00536)	(0.0118)
ΔT_t	Constant	ΔP_1	ΔP_2	ΔP_3	ΔT_1	ΔT_2	ΔT_3	CI_1	Dummy
Coefficient	0.1068	0.196*	0.1247	0.0267	0.09254	- 0.1243**	- 0.1897**	0.02533	- 0.1695***
HACSE	(0.133)	(0.162)	(0.155)	(0.151)	(0.0705)	(0.0702)	(0.0719)	(0.0157)	(0.0345)

***Table 8.4**: The results from estimating the VECM model are displayed. Variable_i denotes the i lagged value of the variable. *** denotes significance at a 1% level, ** denotes significance at a 5% level and * denotes significance at a 10% level. HAC standard deviations are listed in parenthesis.*

8.3.1 Narrowing down the VECM model

Next, we need to decide the optimal value of p and q in equation 8.4 and 8.5:

$$\Delta P_t = \alpha_1 + \alpha_P CI_{t-1} + \sum_{i=1}^{p} a_{11}(i)\,\Delta P_{t-i} + \sum_{i=1}^{q} a_{12}(i)\Delta T_{t-i} + D + \varepsilon_{Pt} \tag{8.4}$$

$$\Delta T_t = \alpha_2 + \alpha_T CI_{t-1} + \sum_{i=1}^{p} a_{21}(i)\,\Delta P_{t-i} + \sum_{i=1}^{q} a_{22}(i)\Delta T_{t-i} + D + \varepsilon_{Tt} \tag{8.5}$$

Where CI is the cointegrating vector estimated by Johansens method. Because the two equations are stationary due to the cointegrating vector as well as the first differences being I(0), normal inference methods can be applied to the model. Therefore, we combine the general-to-specific method with the multivariate information criteria when looking at the different values of p and q. We keep the threshold value of p and q at 3.

In all models we estimate, percentage change in Google Trends is statistically significant for all 3 lags of q. Reducing the lag-length of Bitcoin return starting with p=3, the information criteria of the five different models are listed in table 8.5:

Table 8.5 Information criteria values from estimating five different models

	Different values of (p,q)			
IC	(3,3)	(3,2)	(3,1)	(3,0)
AIC	-2.1265	-2.1419	-2.1541	-2.1617
SC	-1.8780	-1.9210	-1.9608	-1.9959
HQC	-2.0266	-2.0531	-2.0763	-2.0950

***Table 8.5**: Using 3 statistical significant lags of percentage change in Google Trends (q), we compare the information criteria of five different models with different lag lengths of Bitcoin return (p).*

In addition to the fact that neither one of the models contain significant values of the lagged values of Bitcoin return, each and all information criterion select zero lags of Bitcoin return. The simulation study of Alain Hecq (1996) in which the series exhibit GARCH-errors to the error terms proves that using the information criteria to decide Granger non-causality does not cause spurious results. The model-selection of the multivariate information criteria indicates that Bitcoin return does not Granger cause percentage change in Google Trends. This is confirmed by using a f-test excluding the three lags of Bitcoin return[59]. Reversely, we observe that percentage change in Google Trends does in fact Granger cause Bitcoin return. This holds two implications: Simulating values of percentage change in Google Trends on basis of shocks to Bitcoin return cannot be done, because there are no lagged values of Bitcoin return. An impulse-response analysis of both variables is therefore not possible using the model suggested by the information criteria. Secondly, the theoretical model derived in chapter 3 on investor attractiveness must be revised. Because there is no feed-back effect towards media attention, the fourth period of the model is disregarded.

8.3.2 The results

Having decided the lag-lengths of our model, we present the results from estimating equation 8.6 and 8.7 in table 8.6.

[59] With p-value equal to 0,012.

$$\Delta P_t = \alpha_1 + \alpha_P CI_{t-1} + \sum_{i=1}^{3} a_{12}(i)\Delta T_{t-i} + D + \varepsilon_{Pt} \quad (8.6)$$

$$\Delta T_t = \alpha_2 + \alpha_T CI_{t-1} + \sum_{i=1}^{3} a_{22}(i)\Delta T_{t-i} + D + \varepsilon_{Tt} \quad (8.7)$$

Table 8.6 The estimated VECM model

ΔP_t	Constant	ΔT_1	ΔT_2	ΔT_3	CI_1	Dummy
Coefficient	0.09578	0.1407***	0.1365***	0.1062***	- 0.01726**	0.1089***
HACSE	(0.0419)	(0.0234)	(0.0223)	(0.0227)	(0.00495)	(0.0116)

ΔT_t	Constant	ΔT_1	ΔT_2	ΔT_3	CI_1	Dummy
Coefficient	- 0.04931	- 0.0939	- 0.09953	- 0.1492*	0.01844	- 0.162***
HACSE	(0.123)	(0.0686)	(0.0655)	(0.0666)	(0.0145)	(0.0341)

Table 8.6*: The table views the result from estimating the VECM model proposed by equation 8.10 and 8.11. Variable_i denotes the i lagged value of the variable. *** denotes significance at a 1% level, ** denotes significance at a 5% level and * denotes significance at a 10% level. HAC standard deviations are listed in parenthesis.*

In the estimated model, only the third lagged percentage change in Google Trends is statistically significant in the second equation. However, because this variable is restricted in the VECM model, we cannot remove any of the insignificant lags. Thought the constants are not significant, they are not excluded.

8.4 Discussing the results

8.4.1 The speed of adjustment parameters and the cointegrating vector

First it must be addressed that the values of the speed of adjustment parameters has changed after narrowing down the VECM. Considering the information criteria, the model displayed in table 8.6 should be closer to the true model. Therefore, we regard this model when discussing the results.

The short-run dynamics of the cointegrated system are given by the estimated coefficients α_P and α_T[60]. The two estimates reflect transitory adjustments when the long-run equilibrium is distorted by some error. While compared to the long-term estimation of beta in table 8.3 (β_2 = - 1,5216), the reaction towards reconstructing the long-term equilibrium is relatively small, and not significant in the second equation. The statistical insignificance of the α_T-coefficient does in fact imply that Bitcoin prices does all the error correction towards long-term equilibrium. Combining the estimated alphas with the estimated cointegrated I(1) system from table 8.3[61] we isolate the cointegrating relationship:

$$\Delta P_t = -0{,}017(P_{t-1} + 1.52T_{t-1}) + v_{1,t} \tag{8.8}$$

$$\Delta T_t = \quad 0{,}018(P_{t-1} + 1.52T_{t-1}) + v_{2,t} \tag{8.9}$$

Assuming the error terms to be white noise, setting the cointegrating vector to zero and solving for P_t yields:

$$(P_{t-1} + 1.52T_{t-1}) = 0 \tag{8.10}$$

$$P_t = -1.52T_t \tag{8.11}$$

Solving for P_t is only possible using equation 8.8, because α_T in equation 8.6 is equal to zero, implying a long run non-causality. The interpretation of the cointegrating vector is therefore that a positive shock to Google Trends gives fuel to a decrease in contemporaneous demand for Bitcoin. This demand is hypothetically driven by investors already established in the Bitcoin market, reacting to different news coverage. The negative long-term relationship is an unexpected result. And because the 'contemporaneous' effect is a 5 days average through a week, we conclude that the cointegrating relationship does not provide a causal explanation to the behavior of established Bitcoin investors.

8.4.2 The dummy variable

The dummy variable captures investor attractiveness during the weeks of positive media coverage. When this variable assumes the value 1, bitcoin return level is above its trend level, meaning that the media is assumed to cover stories such as investors in the market realizing high returns.

[60] Equation 8.6 and 8.7, coefficient values in table 8.4
[61] Recall that the cointegrating vector is stored in the variable CI_t

In equation 8.6, Bitcoin return is positively affected by this particular state of the dummy variable, which is an expected result. Because the dummy variable is statistically significant, we observe that there is an asymmetric effect of news coverage to the evolving Bitcoin return. The isolated effect of positively narrated news on Bitcoin return is suggested at large 10,89% higher than if news coverage is of a negative substance.

Contrary to our expectations, percentage change in Google Trends is negatively affected by Bitcoin return being above its trend level. When media coverage is assumed positive, the results indicate that the volume of potential investors searching out information regarding Bitcoin is declining.

Since the fundament of the dummy variable is built upon the cointegrating relationship, one weakness to this analysis is the size of the speed of adjustment parameters. The correction towards long-term equilibrium between the two variables is relatively small, and only significant in equation 8.6. Hence interpreting the two coefficients measuring the asymmetric effect of positive media coverage should be done cautiously. Nevertheless, it is worth presenting two graphs which views the impact with and without the dummy variable in the VECM model, to interpret the goodness of fit for both equations. The graphs can be found in figure 8.2 and 8.3 on the next page.

When graphing the fitted values from estimating the VECM model (fig. 8.2 and 8.3) it is not hard to tell that percentage change in Google Trends is poorly modelled in the VECM framework suggested by this thesis. Though the dummy variable is highly significant, during the period of 2015-2016, the dummy variable overstates the development in the percentage change of Google Trends.

As for the Bitcoin return equation, the dummy variable seems to provide a better understanding in terms of the negative returns of Bitcoin. The downwards fluctuations are poorly explained without the dummy variable, hence the graph suggests that there is indeed an existing asymmetric effect of media coverage on Bitcoin return. The VECM model suggested for Bitcoin return seems to be an appropriate representation of the underlying dataset.

Figure 8.2: Bitcoin return modelled with and without the dummy variable

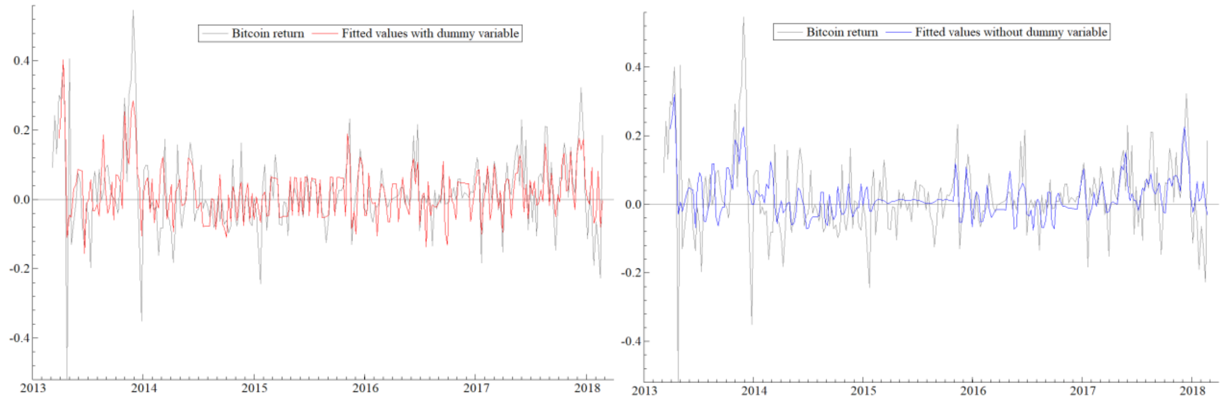


Figure 8.2: *The left graph displays the fitted values from estimating the VECM model with the dummy variable (the red graph), and on the right side the fitted values from estimating the VECM model without the dummy variable are graphed (the blue graph). The black graph represents the reference curve for Bitcoin return based on actual data.*

Figure 8.3: Percentage change in Google Trends modelled with and without the dummy variable

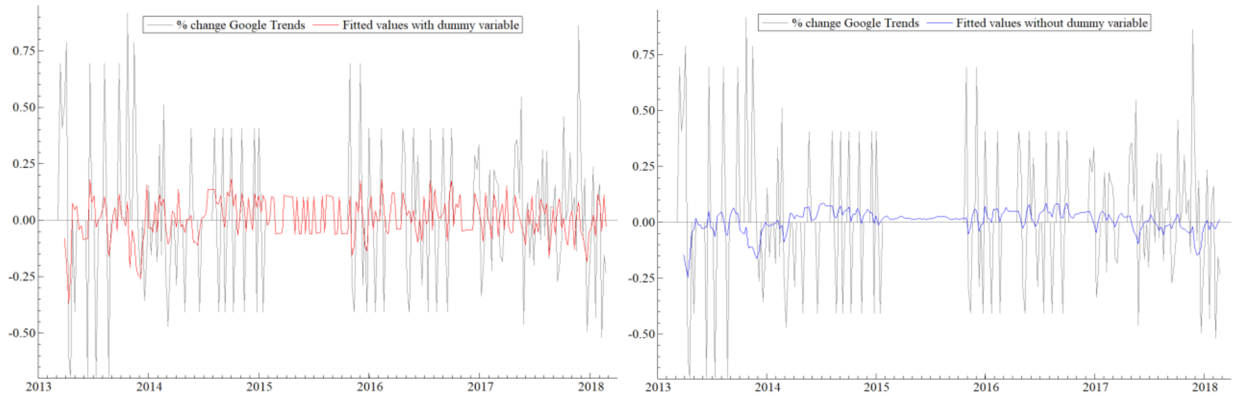


Figure 8.3: *The left graph displays the fitted values from estimating the VECM model with the dummy variable (the red graph), and on the right side the fitted values from estimating the VECM model without the dummy variable are graphed (the blue graph). The black graph represents the reference curve for percentage change in Google Trends based on actual data.*

8.4.3 Lagged percentage change in Google Trends

The significant lags of the ΔT variable suggests that there is some latency in the effect on Bitcoin return caused by percentage change in Google Trends. It is likely that the latency reflects new investors entering the market, as discussed in chapter 3[62]. This interpretation relies on the assumption that the information provided by some media source is fetched by the investor in period t. The reaction in Bitcoin return is then caused by investors lagging behind due to required investigations before investing. The result suggests that the aggregated effect of a simultaneous 10% increase in Google search quires in the three weeks prior to the current yields a 3,83% increase in Bitcoin return.

One disadvantage when analysing these variables lies in the composition of the Google Trends variable. Because the variable contains both positive and negative media attention simultaneously, we cannot distinguish the effect of positive and negative media coverage when analysing the coefficients.

According to data from Atlanta Digital Currency Fund, the number of accounts registered with Coinbase.com grew from 5.5 million in January 2017 to 11.7 million at the end of October the same year. (Popper, 2018) In addition, according to Verto Watch data, the Coinbase app had 407 000 downloads as of January 2017, which grew to 4.3 million in December 2017, Hwong, C. (2018). Thus, there is evidence to state that there has indeed been a wave of new people entering the market during the year of 2017. However, whether the new accounts have been used to purchase Bitcoin, or what quantity, is not public information[63]. What we do know is that the price of Bitcoin increased to its all-time high during December of 2017, and that the growth in price of Bitcoin throughout the same year has happened simultaneously with the growth of new registered users with Coinbase. We also know that Google Trends suggests an increase in public interest on the topic during the same year, meaning that the media coverage of the term has also increased. These facts substantiate the results we have found in our empirical analysis of this chapter.

[62] In chapter 3, we discuss a scenario in which a new investor ponders entering the crypto currency market.
[63] And can therefore not be measured in our model.

8.5 Summary

By employing the VECM framework, we disregard the fourth stage of our theoretical figure presented in chapter 3 representing investor attractiveness, due to non-Granger causality. Percentage change in Google Trends does not Granger cause the development in Bitcoin return. The theoretical which has been tested must therefore be revised:

Figure 8.4: Investor attractiveness and media attention

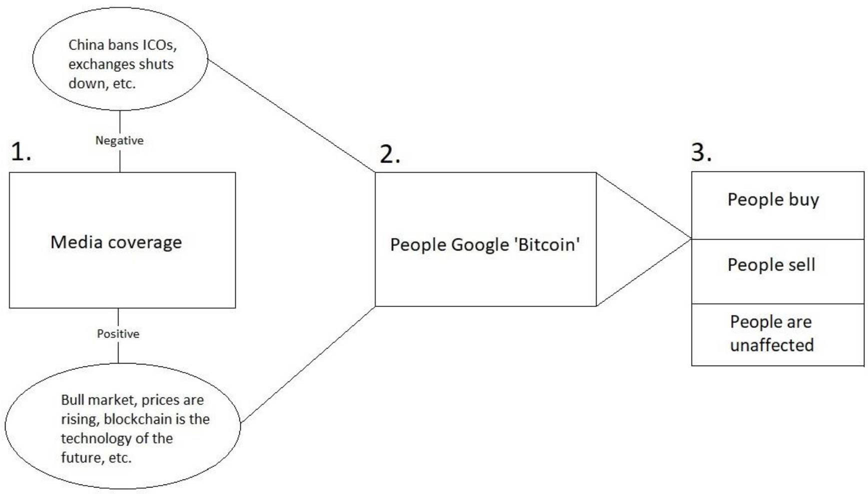


Figure 8.4: *Because Bitcoin return does not Granger cause percentage change in Google Trends, the fourth stage in our theoretical model is dismissed. We find no feedback effect from Bitcoin return towards Media coverage.*

Investors already settled in the market seem to respond negatively to media attention in general surrounding Bitcoin. A positive shock to media coverage (both positive and negative) is associated with contemporaneous decreasing Bitcoin return.

We find an asymmetric effect in the series of Bitcoin return and percentage change in Google trends caused by media coverage. Graphing the fitted and actual values of the variables, we have seen that the asymmetric effect is best captured in the equation for Bitcoin return. Thought the coefficients measuring this effect are highly significant, they should be interpreted with caution.

The lagged values of percentage change in Google trends are interpreted as new investors entering the market as reaction to positive media coverage. The analysis suggests that these investors drive the demand for Bitcoin upwards, due to the significant positive coefficient values entering in the equation for Bitcoin return.

9. A critical point of view

While this thesis attempts to answer how media attention affects the price, and so the return of Bitcoin, actual media attention is not regarded in the modelling process. Google trends is applied as a proxy for the said media attention surrounding Bitcoin. In addition, the data basis is weekly, meaning that sudden responses to news coverage cannot be measured in our model. Should the proxy be an adequate representation of actual media attention, our data mirror the average media attention throughout one week; constituting one observation not regarding the actual substance of news coverage. Adding up to a total of 261 observations excluding weekend observations, the applied time series of Bitcoin prices can be regarded weak. Therefore, the results found in this thesis should be weighted with caution.

Our main contribution to the literature of Bitcoin is a new approach towards interpreting the investor attractiveness variable of Ciaian et. Al (2014). Providing a framework on which some of the demand for Bitcoin can be examined, the theoretical model of investor attractiveness can be re-estimated with a better data basis. An analysis of daily news coverage with the underlying datasets being labeled positive or negative based on substance of news articles or blog posts will provide a much better understanding of how investor attractiveness drives the price of Bitcoin.

10. Summary and conclusion

In this thesis it has been built a theoretical model for analysing "investor attractiveness" in Bitcoin, using a framework put forward by Ciaian et. Al (2014). It is found evidence for, and confirmed, that media coverage on the term *Bitcoin* does affect demand for Bitcoin. By distinguishing between positively- and negatively narrated news, an asymmetric effect that to some extent confirms the hypothesis that positively narrated news has a positive effect on Bitcoin return. Findings from the VECM model analysis indicates that investors new to the market are the main drivers of Bitcoin demand. In addition, no feedback effect towards media attention are found when Bitcoin prices rise, though it is confirmed that a percentage change in Google Trends Granger causes Bitcoin return.

Comparing the volatility process of Bitcoin to stock market indices and currencies, it is found that Bitcoin cannot be categorized as neither, and it should not be viewed as a traditional financial asset. The variable with a conditional variance closest to Bitcoin return variance was found to be the change in Google Trends, which almost mirrors Bitcoins response to shocks regarding the asymmetric measuring effect of the GJR model of Glosten et. Al (1993). This substantiates the findings that new investors do drive the demand for Bitcoin. However, the results also question the framework of Ciaian et. Al (2014), where Bitcoin is considered as a fiat currency, which is disregarded in this thesis.

Considering the results found in this thesis, and to answer the two questions presented in the introduction; Bitcoin must be classified as a speculative financial asset. As we find that it does not meet any of the requirements of a currency of today, neither does it fit the framework of traditional financial assets.

Media attention is in fact a driver of investor attractiveness for Bitcoin. We find that media attention does affect the formation of Bitcoin price, and in so way Bitcoin return. New investors in the market are the main drivers in Bitcoin demand, which enters the market through attention in the media. Positive media attention for Bitcoin increases investor attractiveness.

References

Akaike, H. (1973). *Information theory and an extension of the maximum likelihood principle*. 2nd ed. Budapest, pp.267-281.

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, [online] 19(6), pp.716-723. Available at: https://ieeexplore.ieee.org/document/1100705/.

Baek, C. and Elbeck, M. (2014). Bitcoins as an investment or speculative vehicle? A first look. *Applied Economics Letters*, [online] 22(1). Available at: https://econpapers.repec.org/RePEc:taf:apeclt:v:22:y:2015:i:1:p:30-34.

Barro, R. (1979). Money and the Price Level Under the Gold Standard. *The Economic Journal*, [online] 89(353). Available at: https://www.jstor.org/stable/2231404?seq=1#metadata_info_tab_contents [Accessed 13 Jul. 2018].

Baur, D., Dimpfl, T. and Kuck, K. (2017). Bitcoin, Gold and the Dollar - A Replication and Extension. *SSRN Electronic Journal*. [online] Available at: https://www.bedicon.org/wp-content/uploads/2018/01/finance_topic4_source2.pdf.

Baur, D., Hong, K. and Lee, A. (2017). Bitcoin: Medium of exchange or speculative assets?. *Journal of International Financial Markets, Institutions and Money*, [online] 54, pp.177-189. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2561183 [Accessed 22 Jun. 2018].

Bishop, J. (2018). *Meet The Man Traveling The World On $25 Million Of Bitcoin Profits*. [online] Forbes.com. Available at: https://www.forbes.com/sites/bishopjordan/2017/07/07/bitcoin-millionaire/.

Bitcoinfees.info. (2018). *Bitcoin Transaction Fees*. [online] Available at: https://bitcoinfees.info/.

Black, F. (1976). Studies of Stock Market Volatility Changes. *Proceedings of the American Statistical Association, Business and Economic Statistics Section*, pp.177-181.

Bloomberg.com. (2018). *Jamie Dimon Slams Bitcoin as a 'Fraud'*. [online] Available at: https://www.bloomberg.com/news/articles/2017-09-12/jpmorgan-s-ceo-says-he-d-fire-traders-who-bet-on-fraud-bitcoin.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, [online] 31(3), pp.307-327. Available at: https://www.sciencedirect.com/science/article/pii/0304407686900631.

Box, G. and Pierce, D. (1970). Distribution of Residual Autocorrelations in Autoregressive-Integrated Moving Average Time Series Models. *Journal of the American Statistical Association*, [online] 65(332), p.1509. Available at: https://www.jstor.org/stable/2284333.

Cervellin, G., Comelli, I. and Lippi, G. (2017). Is Google Trends a reliable tool for digital epidemiology? Insights from different clinical settings. *Journal of Epidemiology and Global Health*, [online] 7(3), pp.185-189. Available at: https://www.ncbi.nlm.nih.gov/pubmed/28756828.

Ciaian, P., Rajcaniova, M. and Kancs, d. (2014). The economics of BitCoin price formation. *Applied Economics*, [online] 48(19), pp.1799-1815. Available at: https://arxiv.org/ftp/arxiv/papers/1405/1405.4498.pdf [Accessed 22 Apr. 2018].

Croman, K., Decker, C., Eyal, I., Gencer, A., Juels, A., Kosba, A., Miller, A., Saxena, P., Shi, E., Gün Sirer, E., Song, D. and Wattenhofer, R. (2016). On Scaling Decentralized Blockchains. *Financial Cryptography and Data Security*, [online] pp.106-125. Available at: https://www.researchgate.net/publication/307507650_On_Scaling_Decentralized_Blockchains.

CNBC. (2018). *Cryptocurrencies like bitcoin are commodities, US judge rules*. [online] Available at: https://www.cnbc.com/2018/03/07/cryptocurrencies-like-bitcoin-are-commodities-us-judge-rules.html [Accessed 9 Jun. 2018].

CoinDesk. (2018). *Are 51% Attacks a Real Threat to Bitcoin?*. [online] Available at: https://www.coindesk.com/51-attacks-real-threat-bitcoin/ [Accessed 9 Mar. 2018].

CoinDesk. (2018). *How Does Blockchain Technology Work? - CoinDesk*. [online] Available at: https://www.coindesk.com/information/how-does-blockchain-technology-work/ [Accessed 1 Feb. 2018].

CoinDesk. (2018). *What is Blockchain Technology? - CoinDesk*. [online] Available at: https://www.coindesk.com/information/what-is-blockchain-technology/ [Accessed 3 Feb. 2018].

CoinDesk. (2018). *How to store your bitcoins - bitcoin wallets - CoinDesk*. [online] Available at: https://www.coindesk.com/information/how-to-store-your-bitcoins/.

Coinmarketcap.com. (2018). *Bitcoin (BTC) price, charts, market cap, and other metrics | CoinMarketCap*. [online] Available at: https://coinmarketcap.com/currencies/bitcoin/#charts.

Dickey, D. and Fuller, W. (1979). Distribution of the Estimators for Autoregressive Time Series With a Unit Root. *Journal of the American Statistical Association*, [online] 74(366), pp.427-431. Available at: https://www.jstor.org/stable/2286348.

Dictionary.cambridge.org. (2018). *speculative investment Meaning in the Cambridge English Dictionary*. [online] Available at: https://dictionary.cambridge.org/dictionary/english/speculative-investment [Accessed 11 Jun. 2018].

Doornik, J. and Hendry, D. (2013). *). Empirical Econometric Modelling - PcGive 14*. 1st ed. London: Timberlake Consultants.

Doornik, J. and Hendry, D. (2013). *Modelling Dynamic Systems - PcGive 14*. 2nd ed. London: Timberlake Consultants.

Dyhrberg, A. (2016). Bitcoin, gold and the dollar – A GARCH volatility analysis. *Finance Research Letters*, [online] 16, pp.85-92. Available at: https://www.sciencedirect.com/science/article/abs/pii/S1544612315001038 [Accessed 11 Feb. 2018].

Enders, W. (2015). *Applied econometric time series*. New York: John Wiley & Sons Inc.

Engle, R. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, [online] 50(4), pp.987-1007. Available at: https://www.jstor.org/stable/1912773.

European Central Bank. (2018). *Electronic money*. [online] Available at: https://www.ecb.europa.eu/stats/money_credit_banking/electronic_money/html/index.en.html [Accessed 26 Jun. 2018].

Gandal, N., Hamrick, J., Moore, T. and Oberman, T. (2018). Price manipulation in the Bitcoin ecosystem. *Journal of Monetary Economics*, [online] 95, pp.86-96. Available at: https://www.sciencedirect.com/science/article/pii/S0304393217301666 [Accessed 7 May 2018].

Gerolimetto, M. and Procidano, I. (2003). The Cointegration Analysis in Hypothesis Of Heteroscedasticity: The Wild Bootstrap Test. *Statistica, anno LXIII*, [online] 3. Available at: https://rivista-statistica.unibo.it/article/viewFile/372/365.

Glosten, L., Jagannathan, R. and Runkle, D. (1993). On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *The Journal of Finance*, [online] 48(5). Available at: https://faculty.washington.edu/ezivot/econ589/GJRJOF1993.pdf.

Gronwald, M. (2015). The Economics of Bitcoins: News, Supply vs Demand and Slumps. [online] Available at: https://abdn.pure.elsevier.com/en/publications/the-economics-of-bitcoins-news-supply-vs-demand-and-slumps [Accessed 1 Sep. 2018].

Goldberg, D. (2005). Famous Myths of "Fiat Money". *Journal of Money, Credit, and Banking*, [online] 37(5), pp.957-967. Available at: https://www.jstor.org/stable/3839155 [Accessed 12 Jul. 2018].

Google News Initiative Training Center. (2018). *Google News Initiative Training Center*. [online] Available at: https://newsinitiative.withgoogle.com/training/lesson/6507480104304640?image=trends&tool=Google%20Trends.

Griffin, J. and Shams, A. (2018). Is Bitcoin Really Un-Tethered?. *SSRN Electronic Journal*. [online] Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3195066 [Accessed 2 Aug. 2018].

Hannan, E. and Quinn, B. (1979). The Determination of the Order of an Autoregression. *Journal of The Royal Statistical Society*, [online] 41(2), pp.190-195. Available at: https://www.jstor.org/stable/pdf/2985032.pdf.

Hannan, E. and Rissanen, J. (1982). Recursive Estimation of Mixed Autoregressive-Moving Average Order. *Biometrika*, [online] 69(1), pp.81-94. Available at: https://www.jstor.org/stable/2335856.

Hecq, A. (1996). IGARCH effect on autoregressive lag length selection and causality tests. *Applied Economics Letters*, [online] 3(5), pp.317-323. Available at: https://www.tandfonline.com/doi/abs/10.1080/135048596356438.

Hwong, C. (2018). *Chart of the Week: Coinbase and the Rise of Cryptocurreny*. [online] Verto Analytics. Available at: https://www.vertoanalytics.com/chart-week-dogecoin-bitcoin-rise-cryptocurrency/ [Accessed 30 Mar. 2018].

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control*, [online] 12(2-3), pp.231-254. Available at: https://www.sciencedirect.com/science/article/pii/0165188988900413.

Juselius, K. (2006). *The cointegrated VAR model*. Oxford: Oxford University Press.

Keynes, J. (1936). *The General Theory of Employment, Interest and Money*. [ebook] pp.103-104. Available at: https://cas2.umkc.edu/economics/people/facultypages/kregel/courses/econ645/winter2011/generaltheory.pdf [Accessed 5 Apr. 2018].

Kristoufek, L. (2013). BitCoin meets Google Trends and Wikipedia: Quantifying the relationship between phenomena of the Internet era. *Scientific Reports*, [online] 3(1). Available at: https://www.nature.com/articles/srep03415.

Kosapattarapim, C., Lin, Y. and McRae, M. (2018). Size and power of cointegration tests with non-normal GARCH error distributions. *International Journal of Statistics and Economics*, [online] 10(1), pp.65-74. Available at: https://ro.uow.edu.au/eispapers/2381/.

Krätzig, M. and Lütkepohl, H. (2004). *Applied time series econometrics*. Cambridge: Cambridge Univ. Press.

Laidler, D. (1969). The Definition of Money: Theoretical and Empirical Problems. *Journal of Money, Credit and Banking*, [online] 1(3). Available at: https://www.jstor.org/stable/1991204 [Accessed 19 Jun. 2018].

Lee, T. and Tse, Y. (1996). Cointegration tests with conditional heteroskedasticity. *Journal of Econometrics*, [online] 73(2), pp.401-410. Available at: https://www.sciencedirect.com/science/article/pii/S0304407695017453

Ljung, G. and Box, G. (1978). On a Measure of Lack of Fit in Time Series Models. *Biometrika*, [online] 65(2), pp.297-303. Available at: https://www.jstor.org/stable/2335207.

Lunesu, I., Marchesi, M. and Matta, M. (2015). Bitcoin Spread Prediction Using Social And Web Search Media. [online] Available at: https://www.researchgate.net/publication/279917417_Bitcoin_Spread_Prediction_Using_Social_And_Web_Search_Media.

Maddala, G. (2001). *Introduction to econometrics*. 3rd ed.

Mai, F., Bai, Q., Shan, Z., Wang, X. and Chiang, R. (2015). *The Impacts of Social Media on Bitcoin Performance*. [pdf] Available at: https://abdn.pure.elsevier.com/en/publications/the-economics-of-bitcoins-news-supply-vs-demand-and-slumps.

McLeod, A. and Li, W. (1983). DIAGNOSTIC CHECKING ARMA TIME SERIES MODELS USING SQUARED-RESIDUAL AUTOCORRELATIONS. *Journal of Time Series Analysis*, [online] 4(4), pp.269-273. Available at: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1467-9892.1983.tb00373.x.

Merriam-webster.com. (2018). *Definition of CURRENCY*. [online] Available at: https://www.merriam-webster.com/dictionary/currency [Accessed 13 Jul. 2018]

Mullen, C. (2018). [online] Bloomberg.com. Available at: https://www.bloomberg.com/news/articles/2018-03-14/bitcoin-is-worthless-bubble-may-pop-soon-allianz-global-says.

Nakamoto, S. (2008). *Bitcoin: A Peer-to-Peer Electronic Cash System*. [ebook] Available at: https://bitcoin.org/bitcoin.pdf [Accessed 25 Jan. 2018].

Nghiem, L., Papworth, S., Lim, F. and Carrasco, L. (2016). Analysis of the Capacity of Google Trends to Measure Interest in Conservation Topics and the Role of Online News. *PLOS ONE*, [online] 11(3). Available at: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0152802.

Popper, N. (2018). *Coinbase: The Heart of the Bitcoin Frenzy*. [online] Nytimes.com. Available at: https://www.nytimes.com/2017/12/06/technology/coinbase-bitcoin.html.

Rissanen, J. (1978). Modeling by shortest data description. *Automatica*, [online] 14(5), pp.465-471. Available at: https://www.sciencedirect.com/science/article/pii/0005109878900055.

Schwarz, G. (1978). Estimating the Dimension of a Model. *The Annals of Statistics*, [online] 6(2), pp.461-464. Available at: https://www.jstor.org/stable/2958889.

Tappe, A. (2018). *Dollar unlikely to lose top reserve currency status soon*. [online] MarketWatch. Available at: https://www.marketwatch.com/story/dollar-unlikely-to-lose-top-reserve-currency-status-soon-2018-04-03 [Accessed 2 Jun. 2018].

TechCrunch. (2018). *China has banned ICOs*. [online] Available at: https://techcrunch.com/2017/09/04/chinas-central-bank-has-banned-icos/?_ga=2.8546613.1669500696.1526852118-1197754133.1508870639.

The Economist. (2018). *Who is Satoshi Nakamoto?*. [online] Available at: https://www.economist.com/the-economist-explains/2015/11/02/who-is-satoshi-nakamoto.

Verhage, J. and Katz, L. (2018). *Jack Dorsey Is All In on Bitcoin as the Currency of the Future*. [online] Bloomberg.com. Available at:

https://www.bloomberg.com/news/articles/2018-05-16/square-s-dorsey-is-all-in-on-bitcoin-as-currency-of-the-future.

Worldcoinindex.com. (2018). *Bitcoin price | index, chart and news | WorldCoinIndex*. [online] Available at: https://www.worldcoinindex.com/coin/bitcoin [Accessed 8 Aug. 2018].

Yermack, D. (2015). Is Bitcoin a Real Currency?. *The handbook of Digital currencies*. [online] Available at: https://www.sciencedirect.com/science/article/pii/B9780128021170000023 [Accessed 7 Jul. 2018]

Appendix

1 What is Blockchain and Bitcoin?[64]

To be able to understand better how Bitcoin can function in the financial world, and what it is, it is important with knowledge about its functionality. The framework which bitcoin is built upon is known as blockchain.

1.1 What is Blockchain?

Blockchain acts as an open decentralized database making it possible for Bitcoin to function in the way it does. A blockchain does not have to be a decentralized technology, but in the context of Bitcoin it makes no sense to talk about a centralized version of blockchain technology. If one component should be pointed out as the most important in the Bitcoin eco-system, it is the fact that it is decentralized. The technology behind the Blockchain is nothing new, the only thing new is how these technologies are running together;

1. An open decentralized ledger
2. Cryptography
3. Incentives to keep the Blockchain running
(Coindesk)

These three components, with its underlying parts, will be presented and explained. Then all will all be concluded in a section where it will be explained how these interact to create the bitcoin network.

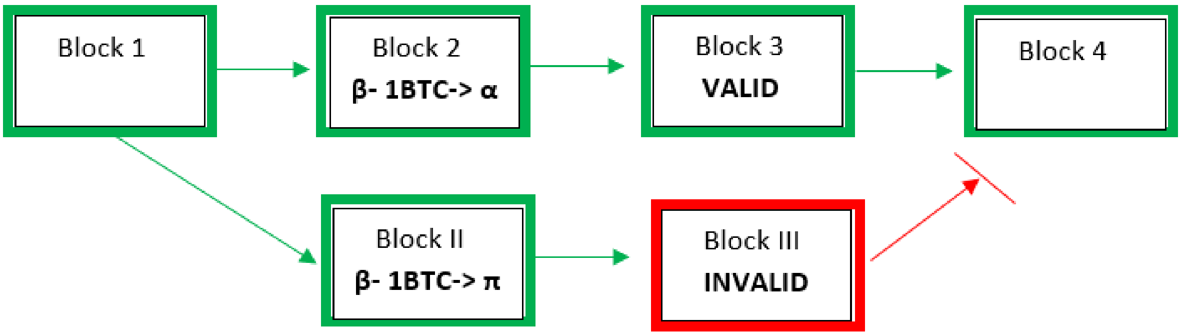
1.1.2 Decentralization

An open decentralized database can be thought of as an open ledger where all transaction of a given firm is available for the world to see. It is built upon peer-to-peer, which is a distributed application which delegates workloads across agents in the network. The decentralization of the blockchain makes it possible to perform and authenticate

[64] This section is written out of knowledge acquired over time, and by using KHAN academy. https://www.youtube.com/playlist?list=PL73q2zDIiGK_O5OYdK5vxcezzC0zu_3OS

transactions without tempering from a third party. This openness is something new in the world of finance, as this makes any intervention to manipulate or try to control the blockchain perfectly visible for any agent in the network. The decentralization makes it easy to authenticate that all transactions are correct, as there are someone always watching to make sure the blockchain does not get corrupted. The masses of the decentralization is its greatest asset. As more and more agents put computational power into the blockchain network- the more secure it gets.

Each entry in the decentralized blockchain is called a block, and the blockchain is achieved by combining all blocks together. Every block in the Blockchain contains information about all previous transactions in the network. Every Block in the Blockchain must contain a timestamp, the transaction history, info about current block and a digital signature. The timestamping of a transactions is important. If an agent in the network tries to double spend its Bitcoins the Blockchain will split.



In the above simplification of a transaction Blockchain we see that β wants to transfer 1 BTC to α, but simultaneously try to transfer the same Bitcoin to π. The timestamp on the transaction will then decide which transaction was done first, and so is valid. This secures that at any time in the network- it is the single longest chain of blocks that is the valid Blockchain.

1.1.3 Cryptography

Bitcoin is a cryptocurrency built on blockchain. Blockchain is built upon cryptography. Every block in the Blockchain is created through a process called *Mining*. A block is created when a *proof-of-work* is solved. A proof-of-work is a solution to a complex puzzle, which is solved by using computational power to solve puzzle[65] by trial and error. This process requires not only a lot of computational power- but also significant use of electricity. The computational power of every agent in the mining-network is put together into this effort, which often accounts to a trillion try and fail attempts. The proof-of-work protocol is designed in a way that a new block is to be mined approximately every ten minutes. The network adjusts the difficulty of the proof-of-work as to be close to ten minutes on average.

While blockchain being a fully transparent network, there are still anonymity. Every agent in the Bitcoin network use a digital signature while operating in the network. These signatures are used for signing and authenticating blocks. The difference from a traditional signature as we know it is that the digital signature depends on the underlying message in the transaction. When signing a transaction in the Bitcoin Blockchain, both the *private key* and the *public key* are used. There are nothing saying that the real identity of the agent must be attached to the private key, this private key only points to the wallet where the Bitcoins are stored.

1.1.4 Incentives

For miners to be willing to put computational power and bear the cost of electricity needed for mining blocks there must be some incentive, and here to incentive is bitcoins. For every block created there is a set amount of Bitcoin given to the node which were the first to solve the proof-of-work. At the time of writing[66] the reward is 12,5BTC, which is close to $100,000. This reward is halved every 210,000 blocks mined, which currently are set to be reached in May 2020. The solver of the proof-of-work is also rewarded all transaction fees by the transaction authenticated by the creation of the new block.

1.1.5 What is Bitcoin

The combination of technologies explained above gave rise and made possible the creation of a virtual currency based on mathematical cryptographic, known as Bitcoin. As it is built upon the decentralized Blockchain it has no centralized unity, and the trusted third-party has been replaced by the cryptographical mathematics. To own Bitcoin all that is needed is an

[65] This «puzzle» is a HASH-function which must be solved
[66] 24.05.18

internet connection to buy Bitcoins, and a wallet[67] to authenticate ownership of the Bitcoins. Satoshi (2008) proposed Bitcoin as the optimal solution to what he saw as a bank system which were failing to fulfill its purpose. “Bitcoin: A peer-to-peer electronic cash system” were sent out to a mailing list which were made up of fellow cryptography enthusiasts. The complete transparency in the Bitcoin system were seen as the complete opposite as to how banks and governments handles their transactions and finances. But an decentralized currency also comes with some drawbacks, as it has the risk of one agent taking control over the whole network- if it where to amass 51% of the computational which is present in the Blockchain. (Coindesk)

2. Multivariate information criteria

$$\text{SC} = \log\left|\widehat{\Omega}\right| + k\log(T)T^{-1} \tag{A.5.1}$$

$$\text{HQ} = \log\left|\widehat{\Omega}\right| + 2k\log(\log(T))T^{-1} \tag{A.5.2}$$

$$\text{AIC} = \log\left|\widehat{\Omega}\right| + 2kT^{-1} \tag{A.5.3}$$

3. Descriptive statistics, daily and weekly log series

Daily log series	Mean	SD	Skewness	Kurtosis	Min	Max
Bitcoin ($ / BTC)	6,31	1,21	0,74	0,71	3,29	9,85
S&P500	7,63	0,14	0,03	-0,3	7,31	7,96
$ / Euro	0,18	0,09	0,35	-1,41	0,04	0,33
$ / £	0,38	0,99	-0,33	-1,16	0,2	0,54
1 Y Tr. Yield (US)	-1,13	0,98	0,17	-1,4	-2,51	0,67
Observations 1305						

Weekly log series						
Bitcoin ($ / BTC)	6,31	1,21	0,74	0,71	3,38	9,72
Trends	1,34	0,95	1,33	1,31	0	4,61
S&P500	7,63	0,14	0,03	-0,3	7,32	7,95
$ / Euro	0,18	0,09	0,35	-1,41	0,04	0,33
$ / £	0,38	0,99	-0,33	-1,16	0,2	0,54
1 Y Tr. Yield (US)	-1,13	0,98	0,17	-1,4	-2,51	0,67
Observations 261						

4. Post diagnostic test results

[67] The bitcoins are stored in the Blockchain. But the private- and public keys which shows you own the Bitcoins are stored in the wallet so ownership can be authenticated.

GARCH post estimation diagnostic testing

Daily return variables	Q-Statistics on Squared Standardized Residuals				ARCH LM-test (F-statistics)		
	Q(5)	Q(10)	Q(20)	Q(40)	1-2	1-5	1-10
Bitcoin	1,46	5,06	10,26	73,19	0,30	0,29	0,50
S&P500	2,04	5,83	8,01	12,86	0,65	0,42	0,57
Dollar to Euro	3,64	8,70	19,29	38,35	0,42	0,74	0,83
Dollar to Pound	7,66	10,58	12,80	24,64	0,88	1,48	1,04
Risk free rate	3,27	6,42	56,29***	124,21***	0,37	0,63	0,67

Weekly return variables	Q-Statistics on Squared Standardized Residuals				ARCH LM-test (F-statistics)		
	Q(5)	Q(10)	Q(20)	Q(40)	1-2	1-5	1-10
Bitcoin (IGARCH)	6,31	9,76	13,96	53,27	1,39	1,01	0,85
Bitcoin (GJR)	5,08	9,33	12,73	45,69	0,53	0,87	0,92
S&P500	2,19	12,49	22,44	34,59	0,15	0,49	1,58
Dollar to Euro	3,26	19,48*	22,45	31,93	0,58	0,68	1,94
Dollar to Pound	-	-	-	-	-	-	-
Risk free rate	6,77	9,45	16,93	42,51	0,85	1,42	0,97
Google Trends	2,07	6,61	10,52	25,16	0,23	0,43	0,56

In the table above we have gathered the post estimation diagnostic tests, that is the test results from the two tests on the different estimated GARCH(1,1) models for each variable. The test results suggest that for all variables, the GARCH errors have been accounted for in the respective models. We also see that there still exists serial correlation in the 20 and 40 lagged squared standardised residuals of the daily risk free rate return that is not removed by the GJR-model proposed for this variable. Though this model could have been better specified, it is not vital to the comparison of the volatility processes across the different variables, therefore, we let this model remain as it is. The weekly dollar to pound return is not included in the table, because none of the conditional variance parameters were significant.

5. Code for data extraction (Python 3)

```
import time
import os
from random import randint
import pandas as pd
from pytrends.request import TrendReq
pytrends = TrendReq()


# This script downloads a series of CSV files from Google Trends. A file path must be specified:
path = "data"
```

Specify the filename of a CSV with a list of keywords in the variable, keyordcsv. The CSV should be one column, with header equal to Keywords (case sensitive).

keywordcsv = "keywords.csv"

keywords = pd.read_csv(keywordcsv)

Downloads and Calculate Slope:

```
for index, row in keywords.iterrows():
    print("Downloading Keyword #" + str(index))
    pytrends.build_payload(kw_list=[row[0]], cat=0, timeframe='now 7-d', geo='World', gprop='')
    time.sleep(randint(5, 10))
    csvname = path + os.sep + "weekly_" + row[0] + ".csv"
    trenddata = pytrends.interest_over_time()
    trenddata.to_csv(csvname)
```