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En forklaring av Bitcoins prisbevegelser

Explaining Bitcoin's price fluctuations

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Abstract

The purpose of this study is to uncover factors that may help explain Bitcoin's price fluctuations. The price of the cryptocurrency Bitcoin is volatile and has increased from zero in 2009 to an all-time high of 1287USD in March 2017. To explain the price movements we have estimated two Autoregressive Distributed Lag models by using Ordinary Least Squares method. The data includes 279 weekly observations from 18.09.2011 to 05.02.2017. The dependent variable is the Bitcoin price and the analysis has examined nine independent variables. The results show that political incidents and statements ("shocks") are significant drivers of Bitcoin's price. This has, to our knowledge, not been examined in earlier research on Bitcoin and is thus the main contribution of this study. The volume of Bitcoin and Bitcoin's price has a significant, negative relationship. The interest of Bitcoin, measured by Google searches, has a positive, significant relationship with Bitcoin's price. The study does not find evidence for Bitcoin being a safe haven investment.

Sammendrag

Formålet med denne studien er å finne faktorer som kan hjelpe til med å forklare Bitcoins prisutvikling. Bitcoins pris er svært volatil og har økt fra null i 2009 til et toppunkt på 1287USD i mars 2017. For å forklare prisutviklingen har vi estimert to Autoregressive Distributed Lag modeller ved bruk av minste kvadraters metode. Datasettet inkluderer 279 ukentlige observasjoner fra 18.09.2011 til 05.02.2017. Den avhengige variabelen er Bitcoins pris og det inkluderes ni uavhengige variabler i analysen. Resultatene viser at politiske hendelser og uttalelser ("sjokk") er signifikante drivere av Bitcoins pris. Dette har, så vidt vi vet, ikke vært undersøkt i tidligere studier og er dermed det største bidraget i denne studien. Volumet av Bitcoin og Bitcoins pris har et signifikant, negativt forhold. Interesse i Bitcoin, målt ved Google-søk, har et positivt, signifikant forhold med Bitcoins pris. Studien finner ikke bevis for at Bitcoin er en "safe haven"-investering.

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1. Introduction

The purpose of this study is to explain Bitcoin's price fluctuations. The aim is to identify variables that may affect the Bitcoin price, as it has increased from zero in 2009 to an all-time high of 1287USD in March 2017 (USD/BITCOIN Exchange Rate, 2016). Bitcoin is a peer-to-peer cryptocurrency created in 2009 by Satoshi Nakamoto (Frequently Asked Questions, 2017). There has been a rising interest in cryptocurrencies over the last years, whereas Bitcoin is the most prominent one (Kristoufek, 2013). Bitcoin is unique because of its significant price development and volatility (Ciaian et al., 2016).

Bitcoin is a decentralized currency that is controlled by Bitcoin users and not a central authority. This makes Bitcoin stand out from the standard fiat currencies. Bitcoins are created in a process called "mining", where individuals are rewarded for their contribution. Mining Bitcoins can be compared to mining gold in a digital form. Other important roles of the miners are to process transactions and secure the network. The supply of Bitcoin is fixed at 21 million units, and because of this limit the mining gets more difficult over time (Frequently Asked Questions, 2017). It is expected that this limit will be reached by year 2140 (Bouoiyour and Selmi, 2014).

Bitcoin is still a new phenomenon in the financial world. We believe that it is important to understand this phenomenon better to know how to deal with it both as an investor and as a government. We think that not enough research exists on Bitcoin, despite its importance. Existing studies also have contradictory findings. The research question that will be examined in this study is: "How can Bitcoin's price fluctuations be explained?". Earlier studies have pointed out the importance of doing research on cryptocurrencies like Bitcoin. Technological innovations affect the financial market and the Internet has been one of the most prominent ones over the last decades (Matta et al., 2015). Polasik et al. (2015) say that the innovation behind Bitcoin will have a significant impact on e-commerce. Dyhrberg (2015) stresses that the creation of Bitcoin has caused a disruption in monetary markets, challenging participants to think differently about money. There has been a great interest in Bitcoin (Kristoufek, 2015), which underlines the importance of understanding the features behind this phenomenon deeper.

This article proceeds as following: Part 2 reviews earlier findings on classification of Bitcoin and variables that might affect Bitcoin's price, in addition to introducing a theoretical

foundation. Part 3 describes the data, the data collection process and the methodology. Part 4 presents the empirical findings. Part 5 discusses the results and presents some concluding remarks. References and the appendix can be found in parts 6 and 7.

2. Literature

2.1 Literature review

Bitcoin is difficult to classify as it has characteristics of currencies, stocks and assets. Dyhrberg (2015) found that Bitcoin has similarities to both gold and the dollar and that it may be classified as something between a currency and a commodity. Bitcoin differs from gold because of its limited supply and from currencies because of its decentralized nature. Yermack (2013) argues that Bitcoin behaves as a speculative investment more than a currency, and the study found a low correlation between Bitcoin and traditional exchange rates. Dwyer (2014) defines Bitcoin as an electronic currency, which is an asset that can be used for trade, and that the owner can show his holdings through a balance account. The United States government treats Bitcoin as property with regard to tax, and the German government classifies it as ”a unit of account” which can be used for tax and trading purposes (Van Alstyne, 2014).

Several existing studies have focused on finding the drivers behind the Bitcoin price. The findings are somewhat inconsistent. Kristoufek (2015) says that because of the dynamic nature of Bitcoin and its rapid price fluctuations, it is logical that the drivers behind the price will vary over time. Bouoiyour et al. (2016) say that the rapid price movements in Bitcoin may be caused by attention from media and speculation in this new phenomenon. Ciaian et al. (2016) found that the Bitcoin price to a large extent is driven by supply and demand, and claim that standard economic currency models partly can explain changes in Bitcoin’s price. Kristoufek (2013), on the other hand, says that the price behavior cannot be explained through standard economic theory. This is justified by the fact that Bitcoin is a digital currency that is not driven by macroeconomic variables like the standard fiat currencies. An algorithm sets the supply of Bitcoin and the demand is driven by the investor's expected profit of buying and selling Bitcoins. There are no interest rates or other benefits of just holding a digital currency. Because of these features, Bitcoin has a more speculative nature, which is dominated by short-term investors.

Earlier studies have found that the Bitcoin price and volume are driven by what people assign to it and its popularity (Mai et al., 2015; Polasik et al., 2015; Matta et al., 2015). Preis et al. (2013) analyzed Google search queries for terms related to the financial market. The study found that the Google search volume reflected the current state of the stock market and that the search volume may predict future trends. Kristoufek (2013) says that the frequency of online searches on Bitcoin is a good proxy for measuring its interest and popularity, and most studies examining the interest in Bitcoin are following this path.

Kristoufek (2013) found a strong positive correlation between Bitcoin's price and the search frequency for Bitcoin on Google and Wikipedia. Increasing interest in Bitcoin leads to an increased demand, which drives Bitcoin's price up. Furthermore, the study finds the relationship to be bidirectional, meaning that the price also influences the interest. In a later study, Kristoufek (2015) found a strong but varying relationship between interest and Bitcoin. In periods with a strongly increasing Bitcoin price, interest had a positive impact on the price and the opposite during periods of declining price. Ciaian et al. (2016) found a positive relationship between Wikipedia searches and the price when Bitcoin was a relatively new phenomenon, but in the later years Wikipedia searches had no impact on Bitcoin's price. Garcia et al. (2014) examined the relationship between Google Trends, Twitter and the Bitcoin price and found a "social circle". When the price increased, the search volume rose, leading to higher numbers of tweets, which again would drive the price further up. The study also found a negative relation from Google search to Bitcoin's price, as a large increase in searches would lead to a price drop the following day. Kaminski (2014) found a moderate correlation between Twitter posts' emotional signal and Bitcoin's price. The findings were stronger for negative emotions and signals of uncertainty, which led to a lower Bitcoin price.

Hayes (2015) tried to identify a cost of production model for Bitcoin. The study focused on Bitcoin's technical factors such as the difficulty of mining, total number of coins available and competition in the network of producers. Factors that tend to reduce the Bitcoin production costs had a negative impact on the price. Examples of these factors are lower electricity prices worldwide, lower mining difficulty and higher mining efficiency. Factors making it more difficult to mine would increase the Bitcoin price (Hayes, 2015). Kristoufek (2015) discovered that an increase in Bitcoin's price would lead to more miners joining the network, but the effect was not strong over time. Bouoiyour and Selmi (2014) found technical factors – measured by the hash rate – to be a positive, albeit minor, driver of Bitcoin's price.

Some studies have looked into the possibility of Bitcoin being a safe haven investment. During the Cyprus banking crisis in 2012-2013, Bitcoin was used as a security investment (Kristoufek, 2015). After the United States presidential election of 2016, Bitcoin may have been used as a safe haven as its price increased (Bouoiyour and Selmi, 2017). Kristoufek (2015) examined the relationship between Bitcoin's price, the Financial Stress Index and the gold price, but did not find any evidence for Bitcoin being a safe haven investment. The study did find the gold price to be a minor driver of the Bitcoin price. Bouri et al. (2017a) examined whether Bitcoin can be used as a safe haven or not. The study could not find evidence for this, but findings showed that Bitcoin can serve as a significant diversifier and has some safe haven properties. A later study confirms this (Bouri et al., 2017b). Bouoiyour and Selmi (2014) found signs of Bitcoin being a safe haven investment. Global macro financial development, estimated through oil prices and exchange rates, have been found to have a short run, but not long run, impact on Bitcoin's price (Ciaian et al., 2016).

Some studies have looked into Bitcoin's vulnerability when it comes to cyber attacks. Ciaian et al. (2016) claim that Bitcoin is more vulnerable than traditional currencies and that news about cyber attacks may reduce Bitcoin's attractiveness to investors. Bolici and Rosa (2016) investigated the fall of the major Bitcoin trading platform Mt. Gox, which collapsed after a major security breach in 2014. The study states that despite the collapse, Bitcoin survived and consolidated its position. Van Alstyne (2014) says that Bitcoin is not in a worse position than traditional currencies regarding security breaches, as real banks also get robbed. Considering these findings and the difficulty of measuring cyber attacks' impact in a regression model, this study ignores the potential effect of security breaches on Bitcoin's price development.

Kristoufek (2015) says that news about the Chinese market and the Chinese government's reactions to Bitcoin are closely related to Bitcoin's price movements. The study examined whether the Chinese market influences the USD market, but could not find any evidence for this.

Earlier studies have not, as far as we know, examined the relationship between volume and Bitcoin's price development. This may be a limitation of earlier research, as Ciaian et al. (2016) found that the Bitcoin price may be driven by supply and demand. Another limitation is that no earlier studies, to our knowledge, have examined how news about political incidents

and statements regarding Bitcoin affects its price in terms of a regression analysis. Van Alstyne (2014) claims that political incidents regarding Bitcoin are the only critical threat to Bitcoin.

Our research will focus on several elements inspired by the mentioned studies. The majority of earlier studies have focused on popularity and interest, which will be included as a variable in this study. As we also include technical factors and the possibility of Bitcoin being a safe haven investment this study is most similar to Kristoufek (2015) of the studies mentioned above. In addition, this study will examine the relationship between volume and Bitcoin's price, as well as political incidents' impact on the price.

2.2 Theoretical foundation

The signaling theory has been applied to diverse areas as finance, management and anthropology to explain the social phenomenon of how people react to various signals. In this study, the signaling theory will be introduced as a theoretical foundation in order to explain Bitcoin's price fluctuations. Bitcoin is a social phenomenon where the price is driven by what people assign to it (Mai et al., 2015). The signaling theory is based on the assumption of information asymmetry in the market, meaning that both public and private information exists. People make their decisions based on public information (Connelly et al., 2011).

Spence (1973) introduced the signaling theory addressing this phenomenon by examining signaling in the job market. Later, signaling has been used to understand a wide range of situations. For example, the signaling theory has been used to explain the manager's financing and dividend decisions and how these decisions signal the quality of the firm (Connelly et al., 2011). Allen and Faulhaber (1988) examined the effect of signaling by underpricing in the initial public offering (IPO) market. Grullon and Ikenberry (2000) say that share repurchases may be explained by the managers' intention to signal to the market that the firm may be underpriced. In the signaling theory, the signalers are insiders in an organization and the receivers are outsiders (Connelly et al., 2011).

Connelly et al. (2011) encourage extending the use of the signaling theory to other areas. This study will extend the use of signaling theory to the world of cryptocurrencies. Our application of the theory will be similar to the applications where the managers' decisions work as a signal for the outsiders. In Bitcoin's case, there is no organization with insiders and outsiders.

Other parties, like governments sending signals about Bitcoin, will work as insiders, and investors interpreting these signals will be outsiders.

3. Research design

3.1 Data selection

This study is based on 279 observations from one dependent and nine independent variables. All variables are weekly observations collected from 18.09.2011 to 05.02.2017.

The dependent variable is the Bitcoin price in USD. The weekly price observations are collected on Sundays, as Sundays are the only possible day from which to retrieve weekly data. We are using the closing price to get the spot closest to Mondays, as some of our variables are obtained on Mondays. The data is downloaded from Quandl using Bitstamp's prices. Bitstamp is the second biggest Bitcoin trading platform, as it was not possible to obtain data for the entire period required from the biggest platform, Bitfinex (Rosenfeld, 2015). The differences between the prices on Bitstamp and Bitfinex are insignificant and we thus consider Bitstamp as a reliable source.

As the literature review shows, Bitcoin may be classified as something between a currency, a speculative asset and a commodity (Dyhrberg, 2015; Yermack, 2013). Based on earlier studies we find it relevant to include gold price and volatility indices as variables in the analysis. Changes in these variables may be seen as a measure of the worldwide economy. Originally, this study included stock price as a variable in addition to volatility and gold price. Running a model with these three variables gave multicollinearity problems, which made it necessary to omit either volatility or the stock price. As volatility contains more information about the market and gives a better indication of variations in the worldwide economy, we chose to omit the stock price, which solved the problem of multicollinearity.

We have used Standard & Poor's 500 (S&P) to compute the gold price and volatility. S&P is one of the most used indices by investors and is considered to be one of the best representations of the US financial market (A Guide To The S&P 500, 2017). We are using S&P GSCI Gold Spot for gold prices and S&P Low Volatility for volatility. Because there are no data available on Sundays for these variables, we retrieved the Monday values.

Changes in the oil price are often regarded as an indication on how the world economy is faring and seen as a trigger for recession and inflation (Barrell and Pomerantz, 2004). Ciaian et al. (2016) found the price to have a short run impact on the Bitcoin price. We have therefore chosen to include Crude Oil (spot cushing) as a variable in the analysis, obtained from Thomson Reuters through Datastream. The oil price, gold price and volatility variables will together give an impression on whether Bitcoin may be a safe haven investment or not.

Technical factors may also have an impact on Bitcoin's price (Hayes, 2015; Kristoufek, 2015; Bouoiyour and Selmi, 2014). The hash rate tells how many calculations the Bitcoin network can run per second, and is therefore a good measure of the mining speed. With a higher hash rate the mining is more efficient and the miner's expected profit increases with this efficiency (How to Calculate Mining Profitability, 2017). The hash rate data are Sunday observations downloaded from Quandl.

The study includes volume as an explanatory variable. This is done because we believe that increased volume may affect Bitcoin's price considering traditional supply and demand theory. The data is Sunday observations obtained from Quandl, and the observations show the volume in BTC.

Earlier studies found a tight relation between interest in Bitcoin and movements in Bitcoin's price, where interest is measured by online searches (Kristoufek, 2013; Kristoufek, 2015; Ciaian et al., 2016; Garcia et al., 2014). Preis et al. (2013) found that Google search volume may predict future trends in the financial market. We have obtained data on Sundays directly from Google by contacting them to measure the interest in Bitcoin. The data tells how frequently people search for the word "Bitcoin" on Google.com. The numbers are normalized and thus shown with values from 0 to 100, where 100 is the point with the highest search frequency. The data is also corrected for trends (Trends Help, 2017).

Kristoufek (2015) says that large movements in Bitcoin's price are closely connected to events in the Chinese market. We believe that political incidents and statements regarding Bitcoin in general are affecting Bitcoin's price, and not only events in China. We have collected a number of political events that may affect Bitcoin's price and will treat these as dummy variables in the analysis. The events are found through 99Bitcoins.com and HistoryofBitcoin.org and then located to the closest observation number (e.g. an event

occurring on a Wednesday will be located to the last Monday's observation). In this study, there are one dummy for events expected to have a positive impact on Bitcoin's price ("positive shocks") and one dummy for events expected to have a negative impact ("negative shocks"). In the data, 1 is used as value for periods where events are occurring and 0 when there are no events. Examples of the events included are news about legal hearings considering Bitcoin in the United States and China, tax decisions regarding Bitcoin in the United States and EU, shutdown of the Silk Road and the Cyprus banking crisis.

Table 1: Description of the variables

The study's variables with reference

Variable	Description	Reference
Bitcoin	Bitcoin price in USD, Bitstamp	Quandl
Volume	Volume BTC	Quandl
Google	Google Search	Google Trends
Volatility	S&P 500 Low Volatility index	Datastream
Gold	S&P GSCI Gold Spot index	Datastream
Oil	Crude Oil spot, Thomson Reuters	Datastream
Hash	Hash rate	Quandl
Stock	S&P 500 index	Datastream
Neg.Shock	Dummy, negative political incidents	99bitcoins.com, historyofbitcoin.org
Pos.Shock	Dummy, positive political incidents	99bitcoins.com, historyofbitcoin.org

3.2 Descriptive statistics

Figures 1-4 show time series of the weekly observed Bitcoin Price and the variables used to measure for safe haven; volatility, gold price and oil price. Table 2 describes the statistics of the variables.

Figure 1: Bitcoin price in USD, Bitstamp

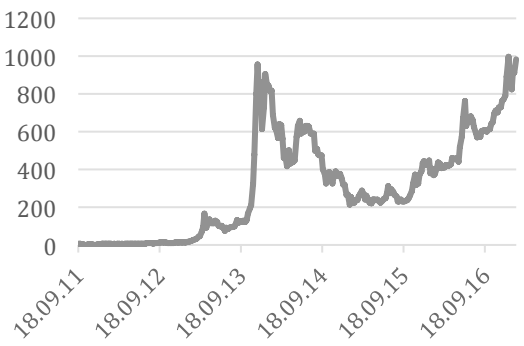


Figure 2: S&P 500 Low Volatility index

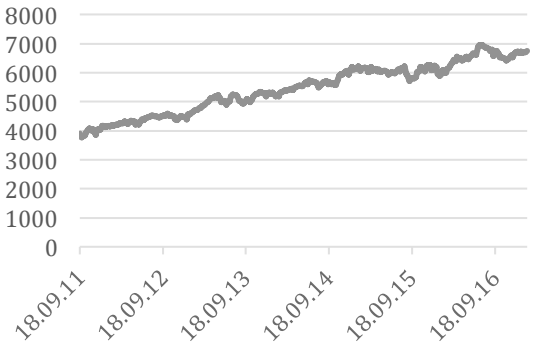


Figure 3: S&P GSCI Gold Spot index

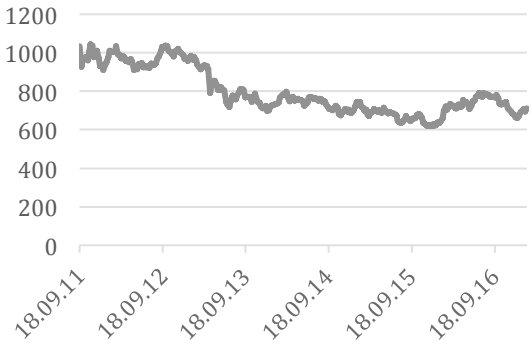


Figure 4: Crude Oil spot, Thomson Reuters

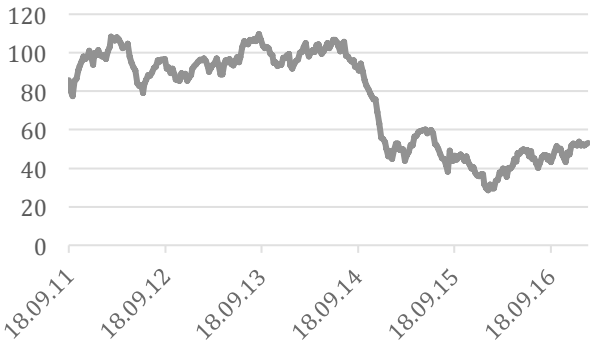


Table 2: Descriptive statistics

The descriptive statistics are based on 279 weekly observations collected from 18.09.2011 to 05.02.2017

Variables	Mean	Std.Dev.	Min	Max
Bitcoin	306.393	268.178	0	997.75
Volume	174015.3	211000.9	39199	3204551
Google	16.918	15.023	2	100
Volatility	5454.763	852.855	3769.05	6949.14
Gold	796.121	120.791	619.12	1043.07
Oil	75.877	25.283	28.47	109.62
Hash	441440.1	690578	6.758	3750587
Stock	1797.384	313.727	1131.4	2297.42

3.3 Econometric method

This study aims to find a relationship between the dependent variable, the Bitcoin price, and several independent variables. These relationships may give a better insight in Bitcoin's price fluctuations. To capture both short-term and long-term effects, we have chosen to estimate Autoregressive Distributed Lag models (ARDL). By using ARDL, the models include lags that may show how the different variables in earlier periods affect Bitcoin's price.

When using time series data, non-stationary variables may lead to spurious regression. Spurious regression can make unrelated variables appear to have a significant relationship, which makes the model unreliable. To deal with the problems related to non-stationarity we have used differencing, meaning that we transform all our variables to first differences. A time trend variable is added to account for any common trends in the variables, as this may cause spurious results (Wooldridge, 2015). To check for non-stationarity, we run an

Augmented Dickey Fuller test (ADF). To find the optimal lag length, Modified Akaike Information Criterion (MAIC) is used. MAIC is by many considered to be the test that gives the best estimate of the lag length (Enders, 2009). The results show that all variables except the hash rate are stationary at first difference. The hash rate has a structural break, which is a weakness of ADF. Vogelsang and Perron (1998) say that the ADF test does not take structural breaks into account, and therefore a test allowing structural breaks should be applied. The Zivot Andrews test (ZA) allows structural breaks. By running ZA, the hash rate becomes stationary at first difference.

After doing the mentioned actions and tests, the ARDL models are estimated. The models are run with lags for the independent variables, and the best models are chosen according to goodness of fit measures. The goodness of fit measures applied are Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Both AIC and BIC are non-standardized and are used to compare the quality of one model relative to another model. AIC is said to have a theoretical advantage over BIC, and thus we will emphasize AIC more than BIC (Enders, 2009).

Table 3: Results of the Augmented Dickey Fuller test

Lag length for the ADF test were selected using MAIC (modified Akaike information criterion). ***, **, * indicate statistical significance at the 0.01, 0.05 and 0.10 level, respectively

Variables	Level	First difference
lnBitcoin	-1.757	-4.059***
lnHash	-1.368	-2.664
lnVolume	-2.548	-5.617***
lnGoogle	-2.447	-6.081***
lnStock	-2.689	-6.172***
lnVolatility	-2.329	-5.754***
lnGold	-2.181	-4.953***
lnOil	-1.992	-4.497***

3.4 Model Estimation

To estimate the coefficients in the ARDL model, we have used Ordinary Least Squares (OLS). We have estimated two models. The first model includes all our variables. The second model only includes the variables that seem to be significant in model 1 and is therefore

expected to have a significant impact on the Bitcoin price. The following models are estimated:

Model 1:

$$\Delta lnBitcoin_t = \alpha + \sum_{p=1}^{n} \beta 1\ \Delta lnBitcoin_{t-p} + \sum_{p=1}^{n} \beta 2\ \Delta lnVolume_{t-p} + \sum_{p=2}^{n} \beta 3\ \Delta lnGoogle_{\ t-p} + \sum_{p=1}^{n} \beta 4\ \Delta lnVolatility_{t-p} + \sum_{p=1}^{n} \beta 5\ \Delta lnGold_{t-p} + \sum_{p=1}^{n} \beta 6\ \Delta lnOil_{t-p} + \sum_{p=1}^{n} \beta 7\ \Delta lnHash_{t-p} + \beta 8\ Neg.Shock + \beta 9\ Pos.Shock + Trend + \varepsilon_t \quad (1)$$

Model 2:

$$\Delta \mathrm{lnBitcoin}_t = \alpha + \sum_{p=1}^{n} \beta 1\ \Delta \mathrm{lnBitcoin}_{t-p} + \sum_{p=1}^{n} \beta 2\ \Delta \mathrm{lnVolume}_{t-p} + \sum_{p=2}^{n} \beta 3\ \Delta \mathrm{lnGoogle}_{\ t-p} + \beta 4\ \mathrm{Neg.\ Shock} + \beta 5\ \mathrm{Pos.\ Shock} + \mathrm{Trend} + \varepsilon_t \quad (2)$$

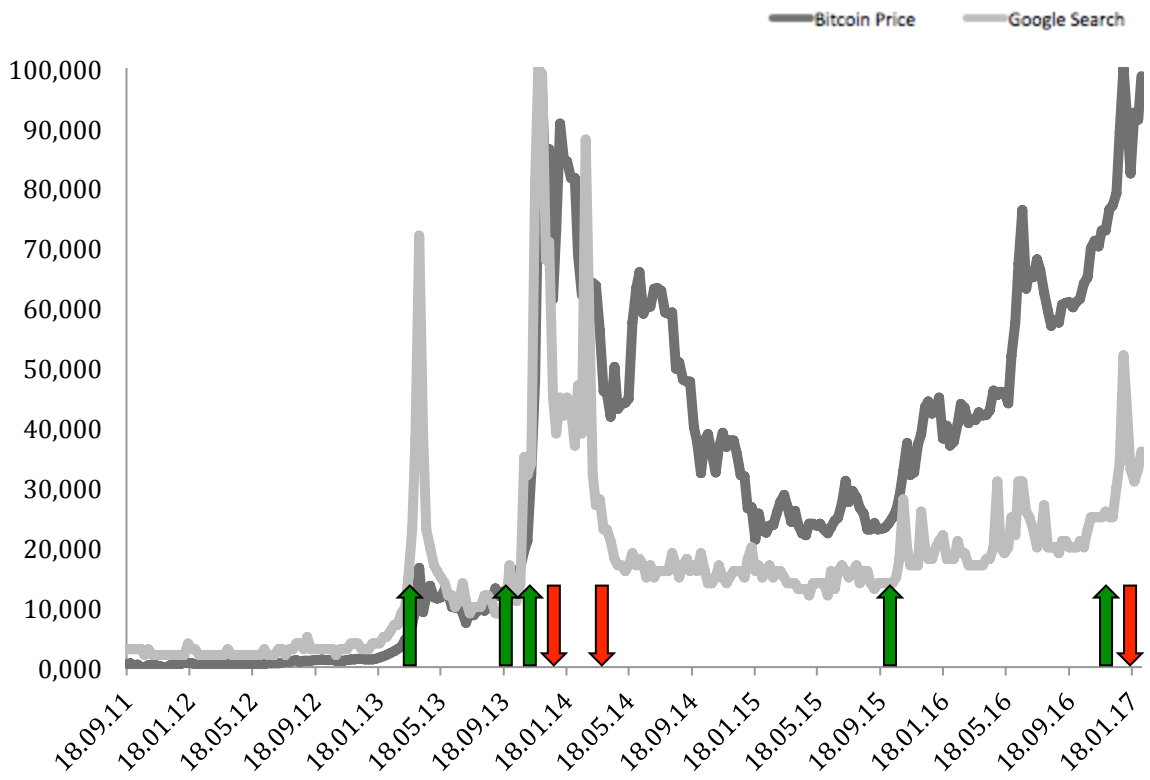
OLS has several assumptions that need to be fulfilled to have a reliable model. To ensure quality and reliability in our model, we have run several tests. According to the central limit theorem, we assume the data to be normally distributed, as the data has 279 observations. OLS assumes no multicollinearity. In cases of multicollinearity, the estimate of an independent variable's impact on the dependent one may be less precise. The variables in our models are tested by Variance Inflation Factors (VIF) to reveal multicollinearity. A solution to multicollinearity problems is to omit certain explanatory variables that may be correlated to one another. In our data, we detected multicollinearity and thus omitted the variable stock price to remove the problem. After the correction, the VIF test gave values around 1 for all variables, which indicates no multicollinearity (Brooks, 2008).

Autocorrelation is often a serious problem with time series data, meaning that the error terms from different time periods in the model may be correlated. OLS estimation is based on the assumption of no autocorrelation because it may lead to an unreliable model and wrong conclusions. The Durbin-Watson (DW) test is run to detect any possible autocorrelation problems in the models. With DW values of 2,114 and 2,088 there is no autocorrelation

detected in the models. No heteroscedasticity is another assumption of OLS, as heteroscedasticity may lead to an unreliable model with wrong conclusions. To reduce problems regarding heteroscedasticity, all the variables are log transformed. In addition to this, we have used robust estimation for the standard errors, which corrects problems with autocorrelation and heteroscedasticity (Wooldridge, 2015). The residual plots of our models show white noise and this confirms that we have no problem regarding heteroscedasticity (see Appendix Figure 1A and 2A).

4. Empirical results

Figure 5: Bitcoin price, Google Trends and Shocks



How Google search volume and the Bitcoin price move together over the period 18.09.2011 to 05.02.2017. The green arrows show positive shocks and the red arrows show negative shocks.

Table 4: Results of ARDL, model 1 and 2

***, **, * indicate statistical significance at the 0.01, 0.05 and 0.10 level, respectively

	ARDL 1		ARDL 2	
Variables	Coefficients	T-statistics	Coefficients	T-statistics
$\Delta lnBitcoin_{t-1}$	-0.050	-0.53	-0.088	-0.77
$\Delta lnVolume_{t}$	-0.042**	-2.09	-0.043**	-2.16
$\Delta lnVolume_{t-1}$	-0.012	-0.82	-0.011	-0.71
$\Delta lnGoogle_{t}$	0.163***	3.09	0.176***	2.99
$\Delta lnGoogle_{t-1}$	0.107**	2.14	0.100**	1.97
$\Delta lnGoogle_{t-2}$	0.132**	2.58	0.133**	2.46
$\Delta lnVolatility_{t}$	0.342	0.83		
$\Delta lnVolatility_{t-1}$	0.574	1.31		
$\Delta lnGold_{t}$	0.724	1.35		
$\Delta lnGold_{t-1}$	-0.523	-1.57		
$\Delta lnOil_{t}$	0.014	0.11		
$\Delta lnOil_{t-1}$	0.2099*	1.82		
$\Delta lnHash_{t}$	0.053	1.05		
$\Delta lnHash_{t-1}$	-0.006	-0.11		
Neg.Shock	-0.104**	-2.52	-0.106***	-3.51
Pos.Shock	0.099*	1.69	0.104	1.61
Observations	279		279	
Adjusted R^2	0.186		0.171	
AIC	-416.803		-419.266	
BIC	-351.441		-382.954	
Ramsey RESET, p-value	0.027		0.063	
Durbin-Watson	2.114		2.088	
Augmented Dickey Fuller, residual p-value	0.000		0.000	

4.1 Model 1

Figure 5 indicates a positive relationship between Google's search volume and the Bitcoin price. This is confirmed by the analysis. The first difference of Google search is significant at a 1% level and both lag lengths are significant at a 5% level. The short-term effect of Google search on Bitcoin's price is 0,163%. When Google's search volume increases by 1%, Bitcoin's price is expected to increase by 0,163%, ceteris paribus. When including the two lags, the total short-term effect of Google search will give an expected increase of 0,402% in case of 1% increase in Google's search volume, ceteris paribus. The total long-term effect of Google search on Bitcoin's price is 0,424%, ceteris paribus. In this case, two lags indicates approximately two weeks.

The dummy variable for positive shocks is significant at a 10% level. When there is a positive shock, the Bitcoin price is expected to increase by 0,099% in average, ceteris paribus. The dummy variable for negative shocks is significant at a 5% level and shows that when negative shocks occur, the Bitcoin price is expected to decrease by 0,104% in average.

The analysis reveals a negative relationship between volume and the Bitcoin price. The first difference of volume is significant at a 5% level. The short-term effect shows that when the volume increases by 1%, the Bitcoin Price is expected to decrease by 0,042%, ceteris paribus. The total short-term effect is -0,054% and the total long-term effect is -0,057%, ceteris paribus.

The first difference of the oil price is not significant, while the lag of the variable is significant at a 10% level. If the oil price increases by 1%, the expected change in Bitcoin's price the following week is 0,21%, ceteris paribus. The other safe haven variables, volatility and gold price, are not significant. Neither the hash rate nor the lag of the Bitcoin price is significant.

4.2 Model 2

The relationship between Google's search volume and the Bitcoin price in model 2 is similar to the relationship in model 1. Google search has the same significant levels as in model 1. The short-term effect of Google search on Bitcoin's price is 0,176% and by including two lags, the total short-term effect is 0,409%. The total long-term effect is 0,448%, ceteris

paribus. Thus, the impact of Google search on Bitcoin is somewhat stronger in model 2 than in model 1.

The significance levels of the dummy variables for shocks have changed. The dummy variable for negative shocks is now significant at a 1% level. When negative shocks occur, the Bitcoin price is expected to decrease by 0,106% in average, ceteris paribus, up from 0,104% in model 1. The dummy variable for positive shocks is no longer significant at a 10% level, as its significance level has changed to 11%. In case of a positive shock, the Bitcoin price is expected to increase by 0,104% in average, ceteris paribus, up from 0,099%

The Volume of Bitcoin is still significant at a 5% level. The effect has increased marginally from -0,042% to -0,043%.

4.3 Assessment of the models

Overall, model 1 and model 2 explain respectively 18,6% and 17,1% of the variance in Bitcoin's price. This is measured by adjusted R-square. Considering Bitcoin being a phenomenon that is hard to both understand and explain, we consider this as an acceptable level. When we compare the goodness of fit measures, model 1 has AIC and BIC values of -416,803 and -351,441, while model 2 has values of -419,266 and -382,954. Model 2 has higher absolute values for both of the goodness of fit measures and is therefore considered a better model than model 1. A Ramsey RESET test is run to see if the models are misspecified (Brooks, 2008). The result for model 1 shows a p-value of 0,0271, indicating that the model may be misspecified. The p-value for model 2 is 0,0626, which indicates that the model is not misspecified at a 5% level. To check if the residuals are stationary, we run the ADF test. For both the models we get a p-value of 0.000, which indicates that the residuals are stationary. Overall, the tests indicate that model 2 is better than model 1. A weakness of our models is that they do not detect the direction of the relationships and thus we cannot say anything about causality in the revealed relationships.

5. Discussion and conclusion

5.1 Discussion

The purpose of the study has been to explain Bitcoin's price fluctuations. We have aimed to create a better understanding of the fluctuations by finding which variables that may affect

Bitcoin's price by estimating two ARDL models. Part 4 shows that Bitcoin's price has a significant relationship to the variables Google search, volume, positive shocks and negative shocks. There are no significant findings indicating that Bitcoin is a safe haven investment.

The positive relationship between the Bitcoin price and online searches is consistent with the findings of Kristoufek (2013; 2015) and Ciaian et al. (2016). Mai et al. (2015) say that Bitcoin's price is driven by what people assign to Bitcoin, and it is thus no surprise that there is a relationship between the price and the interest. On the other hand, Garcia et al. (2014) found a negative relation from online searches to Bitcoin's price. Our analysis does not detect the direction of the relationship between Google search and the Bitcoin price, and thus we cannot compare our results to this study. The results of this study can be related to general findings in the financial market, as Preis et al. (2013) found a positive relationship between Google search and trends in the financial market.

To our knowledge, no other studies have examined the relationship between volume and the Bitcoin price like it is done in this study. The negative relationship between volume and Bitcoin's price may be explained by standard supply and demand theory. When volume increases, Bitcoin's price is pushed down because the demand is satisfied. When the volume of Bitcoins offered to the market decreases, Bitcoin's price is driven up by the demand. This is consistent with the findings of Ciaian et al. (2016) saying that Bitcoin's price development partly is driven by supply and demand forces and thus can be explained by standard economic theory. Kristoufek (2013) says that the price development cannot be explained by standard economic theory. Our study does not strongly contradict this as the variable volume barely has an effect on the Bitcoin price, ceteris paribus, despite being significant.

The analysis shows that political incidents and statements regarding Bitcoin affect Bitcoin's price when the news is announced. When media publishes news about political incidents and statements regarding Bitcoin, it affects the price movements. As expected, negative shocks push the price down and opposite for positive shocks. The dummy for negative shocks is significant at a higher level than positive shocks. This may be explained by that people react stronger to negative news than positive ones. Kaminski (2014) found that negative emotions and signals of uncertainty had a stronger effect on Bitcoin's price than positive emotions when analyzing Twitter posts' impact on the price. The relationship between the shocks and Bitcoin's price may only go one way, and therefore news about political incidents and

statements appear to be drivers of the Bitcoin price. Kristoufek (2015) says that news about the Chinese government's reactions to Bitcoin might affect Bitcoin's price, which is consistent with our findings. Our results also confirm Van Alstyne's (2014) assertion about political incidents regarding Bitcoin being a critical threat to its price and existence. To our knowledge, no other studies have examined the relationship between political incidents and statements regarding Bitcoin in general and Bitcoin's price. After the observation period of this study, several major political incidents regarding Bitcoin have occurred and we recommend further research to include these events.

Signaling has been used to explain a wide range of situations in the financial market and Connelly et al. (2011) encourage extending the use of the theory. We believe that the signaling theory may help us to understand Bitcoin's price fluctuations better. In the traditional signaling theory, the signalers are insiders in the organization and the receivers are outsiders (Connelly et al., 2011). This is not applicable for Bitcoin and therefore we have applied the theory in a different way. For example, the Chinese government may have the role as the signaler, while investors are outsiders. When the Chinese government warned investors and announced an investigation of the major Bitcoin exchange platforms in China in January 2017, investors may have interpreted this as a signal indicating that China is likely to ban Bitcoin in the future and thus they are reluctant to invest in Bitcoin. When the United States Senate Committee had a hearing regarding the legitimacy of Bitcoin in November 2013, they worked as a signaler and the investors (receivers) interpreted this in a positive way, leading to a rising Bitcoin price. The theoretical foundation behind signaling may explain why the positive and negative shocks have a significant impact on Bitcoin's price development.

Kristoufek (2015) found gold prices to be a minor driver of Bitcoin's price, which is inconsistent with our findings saying that there is no significant relationship between the gold price and Bitcoin's price. Ciaian et al. (2016) found oil prices to have a short run impact on Bitcoin's price. Our analysis found that last week's changes in the oil price may impact the Bitcoin price. In this study, the variables gold price, oil price and volatility are used as an indication of whether Bitcoin is a safe haven investment or not. Only one of the variables is significant at a 10% level, while the gold price and volatility are not significant. Hence, we cannot prove Bitcoin to be a safe haven investment. This is consistent with the findings of Kristoufek (2015). Bouoiyour and Selmi (2014), on the other hand, found signs of Bitcoin

being a safe haven investment, and Bouri et al. (2017a) found that Bitcoin has some safe haven properties.

Earlier studies have found a relationship between technical factors and Bitcoin's price (Hayes, 2015; Kristoufek, 2015; Bouoiyour and Selmi, 2014). This study measures technical factors by the hash rate. The analysis did not find a significant relationship between Bitcoin's price and the hash rate, and we can thus not conclude that technical factors affect Bitcoin's price.

5.2 Concluding remarks

The purpose of this study has been to explain the fluctuations in Bitcoin's price by estimating two ARDL models. The study shows that it is difficult to find the drivers behind the price. However, some variables may help understand the underlying forces behind the price fluctuations. The volume of Bitcoin has a significant, negative relationship with Bitcoin's price. Interest in Bitcoin and the price fluctuations are tightly connected, as there is a significant, positive relationship between Google search and Bitcoin's price. This study's main contribution to the research on Bitcoin is how political incidents and statements ("shocks") are drivers of the price, as no earlier studies have examined this to our knowledge. When media publishes news about an incident regarding Bitcoin, the market reacts and the price is pushed up or down, depending the nature of the news. We cannot prove Bitcoin to be a safe haven investment, nor that technical factors have an impact on the price. These findings should be taken into account in future research on Bitcoin and may also help investors and governments to understand Bitcoin better.

5.3 Limitations and further research

A limitation in this study is that we do not investigate the direction of the relationship between the variables. The findings can be improved by including causality. A new contribution to the research of Bitcoin is the findings regarding political shocks. After the sample period of this study, several political incidents and statements regarding Bitcoin have been announced. Further research should thus include these events as it may give a stronger result. Further research may also include other types of news regarding Bitcoin as dummy variables to give a deeper insight. For example news about security breaches can be included. Further research should also emphasize how volume and supply and demand forces affect Bitcoin's price.

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7. Appendix

Table A1: Results of the Augmented Dickey Fuller test, residuals

Statistics and critical values for the ADF test of the residuals in model 1 and 2

	Statistics	1% critical value	5% critical value	10% critical value	P-value
Model 1					
Z(t)	-6.055	-3.458	-2.879	-2.570	0.000
Model 2					
Z(t)	-4.377	-3.459	-2.879	-2.570	0.000

Table A2: Results of the Ramsey RESET test

Statistics and critical values for the Ramsey RESET test of model 1 and 2

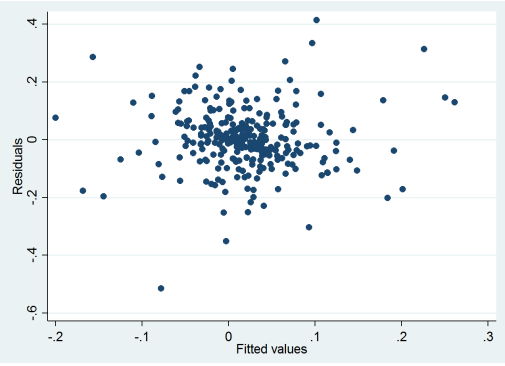
	Statistics	1% critical value	5% critical value	10% critical value	P-value
Model 1					
F-test	3.11	3.858	2.640	2.105	0.027
Model 2					
F-test	2.47	3.856	2.639	2.104	0.063

Table A3: Results of the Durbin-Watson test

Statistics and critical values for the DW test of model 1 and 2

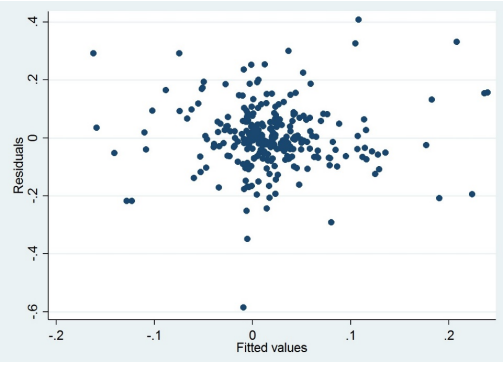
	Statistics	dL	dU
Model 1			
DW	2.114	1.677	1.934
Model 2			
DW	2.088	1.738	1.871

Figure A1: Residual plot, model 1



Residual versus fitted plot, model 1

Figure A2: Residual plot, model 2



Residual versus fitted plot, model 2