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Testing for Bubbles in the Bitcoin Market

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Abstract

Intrigued by Bitcoin's exceptional value development and media attention the last years, we assess if there have been any speculative bubbles in the Bitcoin market and if it exists any bubble today. Our empirical analysis can be divided into three steps. First, it is conducted an econometric test on the existence and date stamping of bubbles in Bitcoin prices based on a new recursive test proposed by Phillips et al (2015) – the SADF and GSADF test. However, this statistical test derives a bubble conclusion from an explosive price behavior. This deviates from common definitions of bubbles within financial theories that a bubble exists if the value of an asset exceeds its fundamental value. Over the period 2010 – April 2018, we detected several of short-lived bubbles and a number of huge bubbles. Our empirical results indicate that there are found six huge bubbles during 2011-2018 lasting from 24 days – 123 days. Our statistical evidence suggests that there does not exist any bubbles in the Bitcoin market today. Second, we find that these bubbles may not incorporate information about rational expectation but rather of irrational exuberances, a finding consistent with the theory presented in the Google Trends, The RSI and the bubble model of “The Stages in a Bubble”. Third, we find that there are some reoccurring trends that are affecting the Bitcoin market investigating the date-stamping results. These are the incidents of the Mt. Gox and China's relation to Bitcoin as a legal currency.

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Preface

This master thesis was written as a completion of our Master of Science of Business Administration with specialization in Applied Finance. During these years at the University of Stavanger, we have increased our skills and knowledge within this field.

We would like to express our great appreciation to our supervisor Peter Molnár for his knowledge, commenting and being available till the very last. We would also like to thank Bård Misund for the help he provided when processing our data in the statistical software R. All remaining errors are solely ours.

1. Introduction

In the last decade, there has been an increased interest in the study of bubbles and crashes (Ardila, Sanadgol, Cauwels, & Sornette, 2017). Sometimes the economic consequences can be larger than others. A recent study according to Jordà, Schularick, and Taylor (2016) finds that equity bubbles are relatively benign compared to housing bubbles in which the latter concern with prompt credit grows. The financial world has witnessed several bubbles that have occurred over the last 15 years, where the succession of bubbles and bursts have resulted from consequences of massive debt expansion and deregulation (Ardila et al., 2017). This, among others, the postwar boom in 1954, the great stock price market crash in October 1987 and the Dot-com bubble bursting in 2000 (Gavurová, Kováč, Užík, & Schubert, 2018; Phillips et al., 2015). Another reason for the renewed interest in bubbles rests with the concern that the unprecedented monetary policies of the major banks (i.e European Central Bank, Federal Reserve) might create unintentionally new bubbles in the years to come (Ardila et al., 2017). In 2012 the European Central Bank found that cryptocurrencies did not threaten the financial stability. This, due to the cryptocurrencies' limited connection to the real economy, low volume traded and low interest among the public. ECB's statement was made due to a caveat that the growth of cryptocurrencies could, without any monitoring, potentially jeopardize the economy as they remain a potential source of financial instability (Corbet, Lucey, & Yarovaya, 2017; European Central Bank, 2012). Since the report release of ECB in 2012, the cryptocurrency market has evolved significantly with Bitcoin as the decidedly largest cryptocurrency.

Models of detecting bubbles have been studied by Phillips, Yu and Wu (2011). However, Phillips et al. (2015) build further on this methodology testing for multiple bubbles. Corbet et al. (2017) used this methodology in detecting bubbles in the Bitcoin and Ethereum market. Their empirical investigation finds periods of certain bubble behavior in both cryptocurrency markets. Cheung, Roca, and Jen-Je (2015) find results of explosive behavior in bubbles during the period 2011-2013, where the biggest bubbles collapsed due to the demise of Mt. Gox. Cheah and Fry (2015) concluded that Bitcoin prices are prone to speculative bubbles and that there exists no fundamental value in the cryptocurrency.

When date-stamping the Bitcoin bubbles, they seem to subject to explosive behavior (Phillips et al., 2015). However, Thies and Molnár (2018) conclude that the structural breaks in average returns and volatility of Bitcoin occur frequently. That is why we are interested in using the methodology of Phillips et al. (2015), which is a robust method to date-stamp bubbles when there are multiple episodes of exuberances. Bouri, Molnár, Azzi, Roubaud, and Hagfors (2017) find in their empirical research that Bitcoin is a poor hedge and is more suitable for diversification purposes only.

When it comes to clarification with regards to broad financial stability, it is important to pin down to whether Bitcoin's substantial increase in price is driven by underlying fundamentals, or whether there are speculative bubbles. Against this background, this thesis investigates if Bitcoin currently is in a bubble phase. Shiller (2017) suggests that Bitcoin behaves like an irrational bubble. We are therefore interested in whether Bitcoin is driven by rational expectations or irrational exuberances. First, we used the Phillips et al. methodology (2015) in testing for multiple bubbles and date-stamping them. Second, we investigated in the results from the date-stamping to see if these earlier events can reveal reoccurring trends that is affecting the Bitcoin price. We identified all these measurements by conducting the Google Trends, The Relative Price Index and a theoretical bubble analysis – The Stages in a Bubble.

The rest of the paper is organized as follows: Section 2 provides an overview of Bitcoin, its development and key features. Section 3 describes relevant theories and previous literature on bubbles. We then discuss the data gathered in section 4. The methodology is represented in section 5. Section 6 includes the analysis and discussion on our findings. Sections 7 concludes.

2. Background: Introduction to Bitcoin

In rapidly developing Internet era of digital currencies, we examine one of the largest phenomena in the financial markets. One of them is called Bitcoin. The Bitcoin was introduced in 2009 by a person under the pseudonymous name Satoshi Nakamoto which published an academic white paper consisting of eight pages: *Bitcoin: A Peer-to-Peer Electronic Cash System*, describing how to implement this electronic system based on the Bitcoin unit. Since Bitcoin is a decentralized virtual currency, it eliminates the need for trust in a central authority as it is managed by the open global network. One of the key distinguishing features is that Bitcoin serves as an alternative to standard fiat currencies (e.g. paper dollars, coins that the government has declared to be a legal tender). Another is that Bitcoin can be bought with lower transactions cost, lower inefficiency and a higher degree of anonymity (Nakamoto, 2009).

Bitcoin emerged after the 2008 financial crisis, where Satoshi Nakamoto's protocol was published shortly after the collapse of Lehman Brothers in September 2008. The crisis prompted central banks worldwide to take unprecedented action, including to run a more expansionary monetary policy. Huge amounts of money had been injected into the economies by quantitative easing and asset purchases¹ (Batten & Wagner, 2014). The low-interest rate led, firstly, to huge amounts of credit and money supply. Secondly, the government spending increased to mitigate the risk of further build-up financial imbalances but instead, put up an inflationary pressure on the economy. When financial crisis plunged countries into recession, many eastern European countries suffered. This led into crisis in the banking sector and therefore conducted an impaired thrust to government-controlled currencies.

Bitcoin was created on January 3, 2009. Several cryptocurrencies emerged in the following years such as Litecoin, Namecoin, Quackcoin, Peercoin, and Mastercoin, which serve in the same way as Bitcoin. Today, thousands of different cryptocurrencies has achieved significant market

¹ Quantitative easing is referred to extension in the Central Bank's bank sheet to increase liquidity, by purchasing assets from the Government or the market in order to stimulate the economy. See Batten & Wagner (2014) for further explanation

penetration. The value of Bitcoin has grown and fluctuated throughout its beginning, from trading at \$0.07 USD and today to be roughly \$11,500 USD.² Bitcoin reached its peak in December 2017 at a price of \$19,535.70 USD and it is still the highest price stamped (Figure 1).

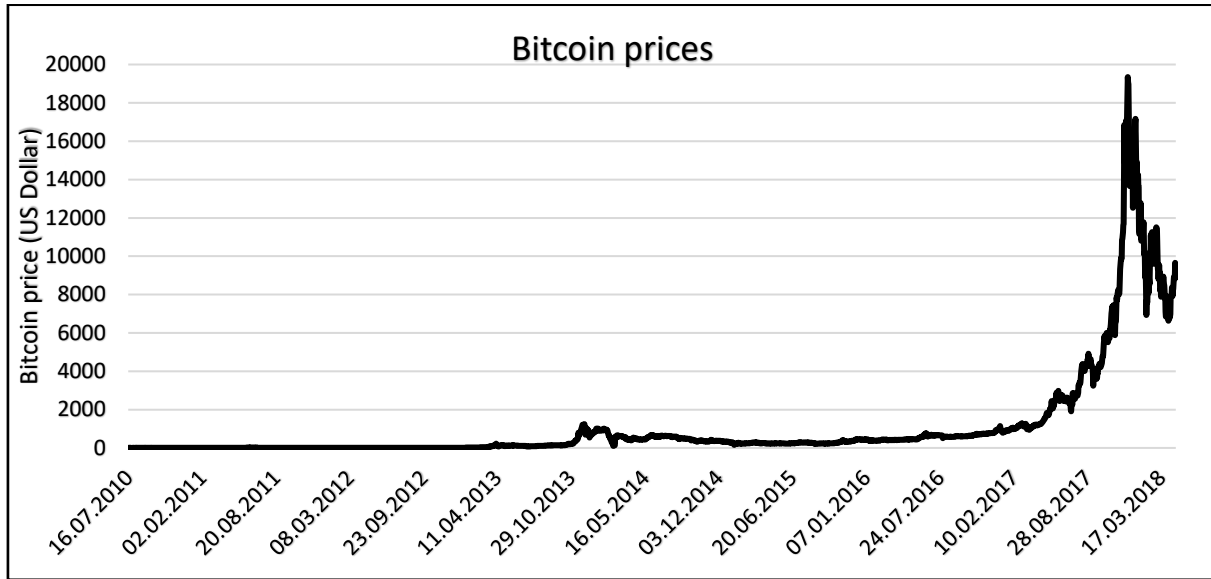


Figure 1: Bitcoin prices

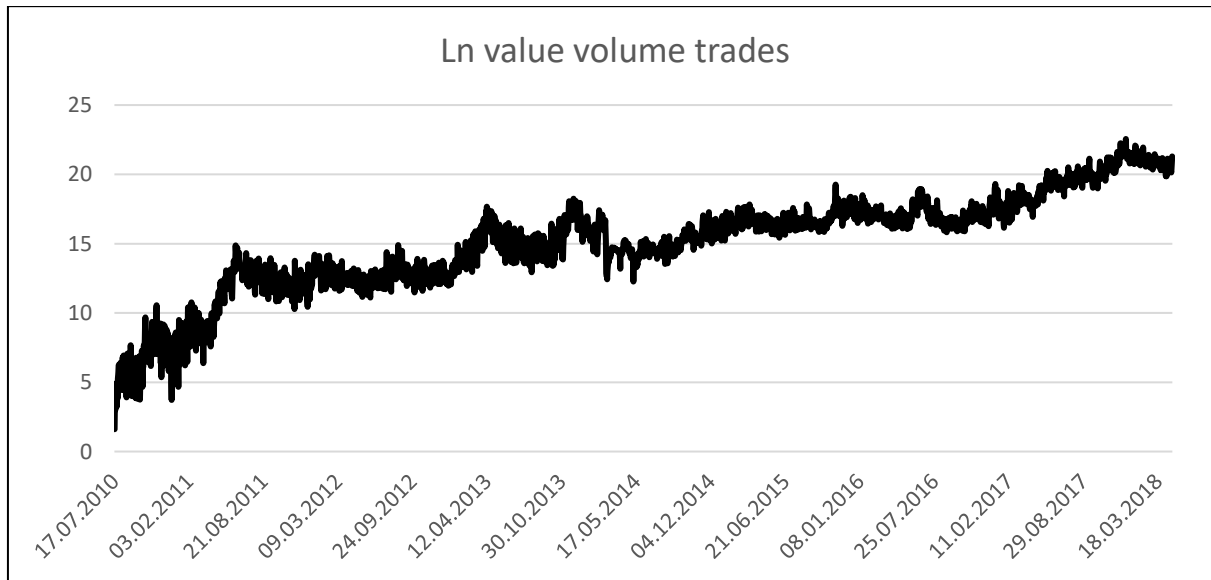


Figure 2: Bitcoin Traded volume (Ln value)

² Note: Financial information provided at coinmarketcap.com estimates price to \$11 534.90 as of March 5th, 2018.

The number of Bitcoins in circulation supply is approximately around 16.9 million, where the max supply will have a cap of total 21 million. Adapt to this, the total market cap of the Bitcoin economy is estimated to be around 195.1 billion USD (March 5th, 2018).

2.1 Key features of Bitcoin

Bitcoin is based on the blockchain technology and has no physical representation. The technical aspects of Bitcoin are explained for example in www.bitcoin.org.

Values sent between the accounts in the Bitcoin network must go through a “mining” process, where the miners use computers to create new bitcoins into circulation. To maintain the open-source protocol, the objective is to construct a new block to appear every 10-15 minutes on average. Simultaneously, the miners validate and secure transactions between the Bitcoin addresses and make sure that the public-key cryptography to Bitcoin belongs to the right owners and the same Bitcoin are unspent, thus prevent the double-spending problem (Brito & Castillo, 2013). Every bitcoin-related transaction goes through the Blockchain (also called the open ledger) and contains information of Bitcoin ownership and historical records of all the transactions that ever occurred in this network. Utilizing the ledger, any participants of the Bitcoin network is assigned with a wallet that has a unique address that makes up the private key. This private key is derived from a public key and the anonymity ensures that nobody knows who owns which address (Møller, 2014). As a resource-incentive for this computer process, miners get paid transaction fees and a bit of a newly created Bitcoin.

3. Theory

3.1 Defining a bubble

There are several different definitions and assumptions of what a “speculative bubble” is within the financial theory. Speculative bubbles can be categorized as either rational or irrational (Dale Richard, Johnson Johnnie E, & Tang, 2005). Below there are two different definitions of bubbles that are different but fundamentally quite similar.

“A bubble may be defined loosely as a sharp rise in price of an asset or a range of assets in a continuous process, with the initial rise generating expectations of further rises and attracting new buyers- generally speculators interested in profits from trading in the asset rather than its use of earning capacity. The rise is usually followed by a reversal of expectations and a sharp decline in price often resulting in financial crisis” (Kindleberger, 1991, p. 20)

“If the reason that the price is high today is only because investors believe that the selling price will be high tomorrow—when “fundamental” factors do not seem to justify such a price—then a bubble exists” (Stiglitz, 1990, p. 13).

The common definition is that bubble refers to asset prices when an asset’s price exceeds its market fundamental value. Hence, when the price of an asset equals the expected present discounted value of its dividend (Tirole, 1985).

3.1.1 Rational bubble

Rational bubbles must be infinite yet, much of the literature discusses bubbles that collapse within a finite period (Meltzer, 2002). Gürkaynak (2008) and Canterbury (1999) argues that it exists a rational bubble if investors are willing to pay more for the stock that they know is advocate because they expect to sell the asset at a higher price in the future. This assumes that all participants in the market have rational expectations and symmetric information, otherwise the participants will not have the same perception of the asset’s fundamental value. Another important assumption for an

existence of a rational bubble is when investors are rational and there are no arbitrage opportunities (Tirole, 1985).

3.1.2 Irrational Bubble

Irrational exuberance refers to a bubble where a price of an asset rising to unsustainable levels due to new technological or organizational structure to increase further, and followed by a collapse or even a crash (Meltzer, 2002). The main distinction between rational and irrational bubble theory is that irrational bubbles are driven by psychological factors within behavioral finance.

Shiller (2005) points out one psychological factor about herd behavior within the irrational exuberance. Herd-behavior can be defined as people who tend to act or think similarly after interacting with each other regularly. Even rational people are affected by herd behavior when taking into account the judgment of others, as long as they know that everyone else behaves in this herd-like behavior (Shiller, 2005).

Furthermore, he describes how the information cascade works, how the human mind is affected by communication. Shiller (2005) mentions “Human Information Processing and Word of Mouth” effect, meaning that conventional- and social media has contributed to superior ability to communicate and created an emotional drive to communicate effectively. When information floats easier and likely to be rapidly spreading conversation about a hot stock, prices are driven up (Shiller, 2005).

3.1.3 The stages in a bubble

Hyman Minsky was the first to propose a model of stages in a bubble, further supported by Kindleberger and Aliber (2011). Allen and Gale (2001) argue that bubbles have three distinct phases. The first phase is where the central bank issues lower interest rates and increasing credit expansion. Second, the asset prices collapse after a bubble bursts. Third, default on loans, where both investors and firms default on loans after the burst.

Rodrigue (Rodrigue, 2017) finds that bubbles (financial manias) behaves differently, but there are some phases that always have similarities.

3.1.3.1 Stealth

Only those who understand the new fundamentals realize an emerging opportunity for a substantial price movement invests for future appreciation. Money invested in the asset is called “smart money” which is the term for smart investors that trade in the same financial markets (Rodrigue, 2017; Shiller, 2005). However, in this phase is often quiet because their investments are at a risk since the outcome of the future is uncertain and unproven (Rodrigue, 2017). Those who invest in this phase are usually cautious and tend to allocate information better because of their wider understanding of the economic context. As the price gradually increases, investors understand that they have carried out an asset class that is now well grounded. The bubble starts with “displacement” or an altered shock to the system, which leads to an increase in opportunities and expectations. These shocks typically include a technological innovation (like the internet era of 1990’s and set the stage for the dot-com bubble), low-interest rates, and have to be sufficiently large enough to qualify as displacement (Kindleberger & Aliber, 2011).

3.1.3.2 Awareness

While the “smart money” is deeply anchored in its existing positions, many new investors want to gain significant future valuations. Those who bring additional money in this face according to Rodrigue (2017) are institutional investors, which is also in line with what Kindleberger and Aliber (2011) call the phase; expansion. Because of the emerging activity among new investors and media’s interference, prices get pushed higher.

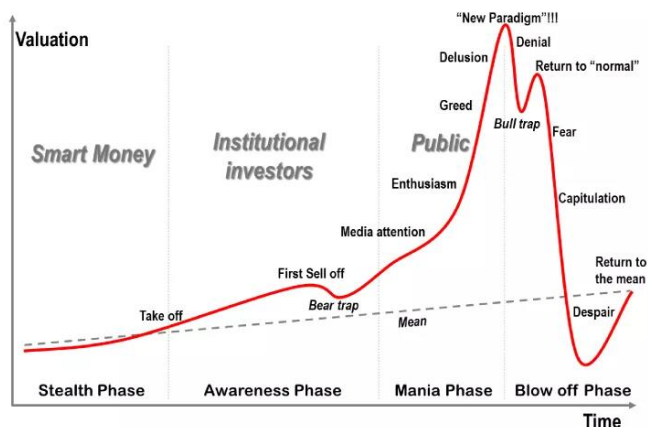


Figure 3: Stages in a Bubble (Rodrigue, 2017)

3.1.3.3 Mania

The high public attention towards this asset class drives to the “Mania” phase of the model. In accordance to Rodrigue (2017), the expectations about future appreciation become responsive for the public as they believe that the prices are going to rise even further. Thus, more investments are undertaken, and floods of money come in creating even greater expectations. This pushes up the price which is rising at a rapid speed. While everyone wants to accompany this ride of soaring levels, institutional investors, and “smart money” reduces the risk of a particularly bad outcome by quietly pulling out and selling their assets. However, Shiller (2005) states that there is no strong evidence that “smart money” investors make more money than institutional investors.

3.1.3.4 Blow-off

According to Rodrigue (2017) everyone realizes at the same time that this bubble is about to burst, and prices drastically start to return to their fundamental value. There will be a point in this phase where some will convince the public that this is just a temporary setback. As figure 3 exhibit, is it difficult to lean against the bubble when the fear first kicks in. Most investors and late comers (the general public) want to sell their assets and realize that they are left with holding depreciating assets, while “smart money” investors have pulled out a long time before this phase. However, this is the phase where they typically seize their opportunity and acquiring the asset at low prices (buy low, sell high).

(Tirole, 1985) states that a bubble can do a lot of harm, slowing down the economic growth for multiple generations. Not all bubble collapses are dire, but the collapse of an asset price bubble can create a bigger deal of economic disruption. Nonetheless, the evidence suggests that housing bubbles have more impact on the economy than the asset price bubbles (Jorda et al., 2016).

3.2 The Relative Price Index

J. Welles Wilder conducted a technical stock analysis indicator called The Relative Strength Index (RSI). It compares the fluctuations in recent gains and losses over a specific time period in a stock's prices. Thus, it is used to determine whether a stock is in an overbought or oversold position. The calculation method is as below:

$$RSI_t = 1 - \frac{1}{1 + RS} \quad (1)$$

Where

$$RS_t = \frac{\sum_{i=1}^n U_{t-i+1}}{n} / \frac{\sum_{i=1}^n D_{t-i+1}}{n} \quad (2)$$

and

$\sum_{i=1}^n U_{t-i+1}$ = sum of the price gains (in absolute value) in the n previous to t ;

$\sum_{i=1}^n D_{t-i+1}$ = sum of the price losses (in absolute value) in the n previous to t .

Overbought and oversold indicators are intended to reflect when prices have risen or fallen rapidly and thus are vulnerable to a reaction (Schwager & Etzkorn, 2016). The way to calculate the RSI is to find the daily return for each day for the entire time series. Then calculate the average gains and average losses, which makes up the relative strength (RS). From equation 1 and 2, the RSI can be derived by dividing the average gain and loss for the specific time period. The total changes in price losses are used as positive numbers (Kaufman, 2013).

The RSI, like all other technical indicators, is a leading or synchronized indicator, meaning that it can tell something about the future turning points. Therefore, is it traditionally used along with

other indicators. This RSI is more robust than the momentum (RS) because it uses all the value in the calculation period, instead of only the first and the last (Kaufman, 2013). The RSI momentum indicator identifies stocks by scaling all values between 0 to 100. Based on the standard interpretation of Wilder, RSI movement above 70 is considered overbought and a value below 30 suggests an oversold condition. Values in-between are considered as neutral. There is a temporary equilibrium in the market, indicating non-trend when the sum of gains equals to the sum of losses and the RSI is 50%.

An alternative method to estimate the trend signals in the RSI, is to set the signal levels to 80 and 20 or even 90 to 10. These extreme high and low levels occur less frequently but filter out the noise and indicate stronger momentum. Sometimes the market is captured by a risen streak where the prices and the sum of D_t assumes zero value, RS_t will go to infinity and RSI_t to 100%. This situation is extreme and the market signaling that it is completely overbought and is prone to a reversal (Macedo, Godinho, & Alves, 2017).

Traditional interpretation usage of the RSI is using a default time for comparing up and down periods that range over a period of 14 trading days. However, the default setting for the RSI can be set to longer trading days. Kaufman (2013) states that if the calculation period is too short, then the RSI will remain outside the 70 and 30 zone for extended periods rather than signaling an immediate turn in the trend. Prices that continue higher for the chosen trading days' interval, will lead the RSI to go sideways. To avoid this, traders can either increase or reduce the time interval, and at the same time increase or lower the signal levels. The longer trading days, the fewer numbers of trading signals will be generated. But, the RSI yields a greater level of reliability. However, when the trading days for calculation is small, these indicators can be highly unstable as they jump from frequent overbought signal to corresponding frequent oversold ones (Kaufman, 2013). The idea is therefore to pick the frequency of trades that are needed to find the precisely immediate turn in the momentum.

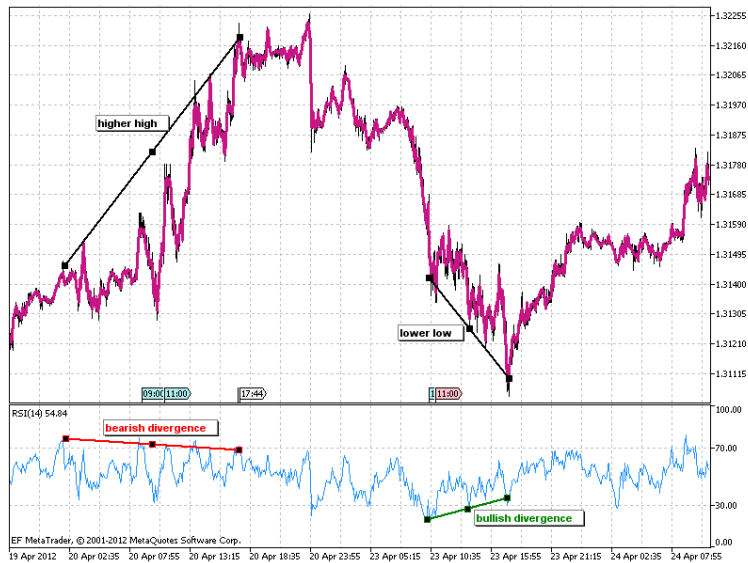


Figure 4: Illustration of bearish and bullish divergences (Euro-Finance, 2018)

The RSI is also used to spot divergences. A divergence is when the RSI and the price action move in the opposite direction indicating loss or gain momentum in the trend. Wilder describes two types of divergences, bearish and bullish. Bearish divergence (also called negative divergence) happens when the price increases and the RSI is falling. Thus, indicate a weakening momentum. Contradictory, a bullish divergence (positive divergence) happens when the asset decreases in price, while the RSI starts to climb (Kaufman, 2013). It warns the price could soon correct higher since the momentum is increasing. Wilder believes that divergences can last a long time and helps confirm other signals and let traders know when a trend may almost be over.

4 Data

In this paper, the data samples are collected from various sources. Bitcoin prices and volume are obtained from yahoo finance, in both daily and weekly values. The sample size reaches from July 16th, 2010 to April 24th, 2018 and gives a total of 2841 daily observations. All prices and returns are denoted in US dollars. Bitcoin first started trading January 9th, 2009 but in the first time period a significant number of data points were observed missing, we therefore chose to exclude them from our analysis. Complete statistic overview of bitcoin prices and return is listed in table 1. The daily dataset with 2841 observation is used as our foundation in the calculation of the (Phillips et al., 2015) methodology in date-stamping bubbles.

Bitcoin	price	Volume (per day)	Daily log return
Mean	1115.53	126008464.52	0.0043
Min	0.0589	5.00	-0.3359
Max	19345.49	6245731508.00	1.4744
Standard deviation	2672.71	416602057.35	0.07
Skewness	3.69	5.61	2.90
Kurtosis	14.35	43.23	87.49

Table 1: Bitcoin statistics

Bitcoin prices and return are calculated for both linear values and in natural logarithmic values (ln). Ln form is used to normalize the measurement of the variable into a comparable metric. Figure 5 displays the ln value of bitcoin prices, indicating there is an upward sloping trend with up and down fluctuations.

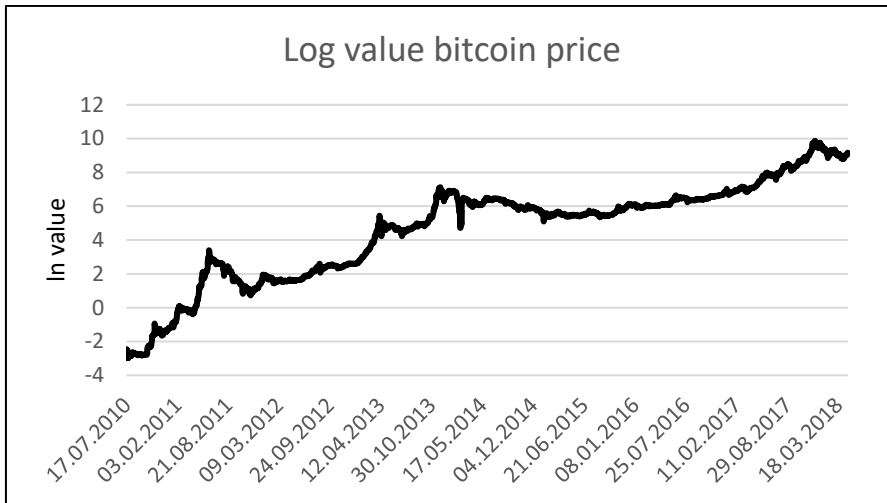


Figure 5: USD Bitcoin prices in ln scale

Kristoufek (2013) conducted an empirical investigation of the relationship between the Bitcoin price and media of the public interest by measure the effects of Bitcoin -related terms on Google Trends with the price in Bitcoin. Including this investigation in our analysis may help reveal information about whether the relationship between the public has influenced the rapid growth in the Bitcoin price.

The data retrieved from Google Trends on the search frequency of the term “Bitcoin” are gathered in both weekly and monthly values. The total sample size is obtained from 24 March 2013 to 18 March 2018, giving 261 weekly observations. In this analysis, the normal state of the values is used for different graphical displays. While the ln value of the trends output is used in the correlation calculations. How the values from google trend search works are that it ranges from 0 to 100, where a value of 100 indicates the highest point of popularity and a score of 0 means the term did not have enough data points for this period (Google, 2018). In figure 6 is the Bitcoin search term from google trends, and the ln values displayed.

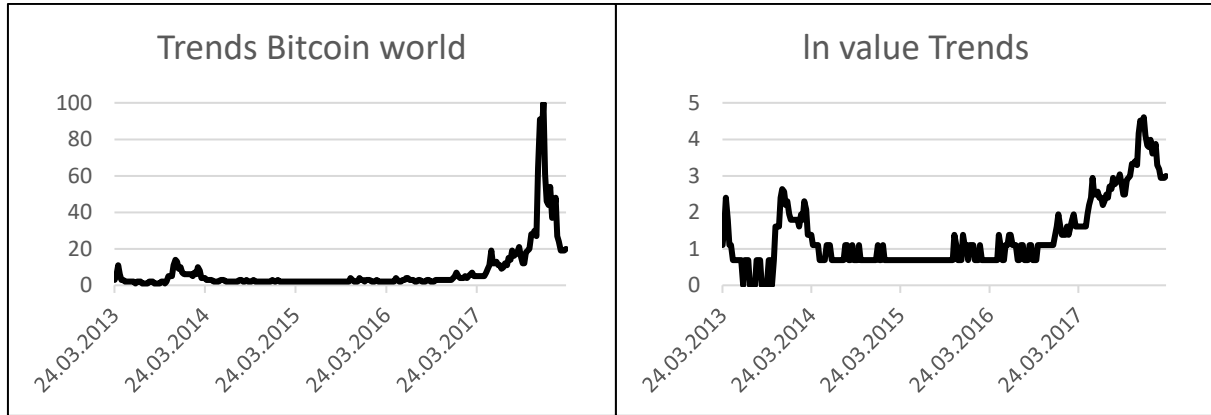


Figure 6: Google Trends Searches (Bitcoin)

5 Methodology

Stationary and Non-Stationary Time Series - The Phillips et al. methodology

One of the first to use supremum ADF (SADF) in detecting bubbles and collapses with help of unit roots was Phillips, Wu and Yu(2011). Phillips et al (2015) developed on this previous work when allowing for a flexible window.

We use a rolling window test by (Phillips et al., 2015) which the test relies on the repeated estimation of the ADF model and obtain as the supremum value of the ADF algorithm sequence. This rolling window test is used for detecting bubbles. The supremum ADF (SADF) and the generalized supremum ADF (GSADF) test, are followed by the original work of (Dickey & Fuller, 1981) the extended augmented Dickey-Fuller (ADF) unit root test.

Both SADF and GSADF tests show whether a time series follows a unit root test, but the GSADF test is a rolling window regression unit root test with double-sup selection criteria (Phillips et al., 2015). When the sample period includes one or more episodes of exuberance and collapse, the SADF test suffers from revealing the existence of bubbles. That is why the of GSADF is employed to overcome this weakness due to detecting the presence of a bubble when the sample period includes more than one bubble. The SADF test uses fixed initialization window. Meanwhile, GSADF test is proceeded with a range of flexible windows, where instead of the fixing starting point of the recursion on the first observation, it extends the sample coverage by changing the starting and end point. Therefore, becoming a right-sided double recursive test for a unit root (Phillips et al., 2015). Following similar approaches taken in Corbet et al. (2017), we test for bubbles over a flexible time window.

A common starting point for the analysis of detecting bubbles in Bitcoin is the asset price equation with a bubble term B_t introduced, formally defined as:

$$P_t = \sum_{I=0}^{\infty} \left(\frac{1}{1+r_f} \right)^I E_t(U_{t+1}) + B_t \quad (3)$$

P_t = represents the price of Bitcoin.

r_f is the risk-free interest rate.

U_t denoting unobservable fundamentals

$P_t^f = P_t - B_t$ represents the market fundamental, where B_t is in the process that increases on average (satisfy the sub-martingale).

There exist a rational bubble and the term $E_t(U_{t+1})$ is not zero if the investor believes that the selling price will be higher than the discounted value of dividends. Hence, this bubble term can be defined as a rational bubble, in the sense that it is entirely consistent with rational expectation (see section about ration bubbles).

From equation 3, the bubble term satisfies:

$$E_t(B_{t+1}) = (1+r_f)B_t \quad (4)$$

The equation 4 represents the equilibrium price and eliminates arbitrage opportunities. When the degree of non-stationary of the asset price is decided by the dividends of Bitcoin, the component B_t is 0 and there is no bubble detected. Hence, B_t is independent of the expected dividends. If the non-stationary of the dividends has a true relationship with the non-stationary of the stock prices, then the stock prices and the dividends are cointegrated. A cointegrating relationship between these variables is inconsistent with rational bubbles.

The SADF and GSADF test on bubbles is based on the price-dividend ratio, but the difference is at the flexible window setting. The GSADF is obtained by first changing the rolling window by a forward recursive progress. Then this progress becomes the SADF statistic. Under the null hypothesis, this process is a unit root. More specifically: $H_0: \theta = 1$ and the alternative hypothesis

is $H_1: \theta > 1$ (explosive root). Equation (5) is allowed for a martingale null and has a non-dominating drift (i.e. asymptotically negligible) that makes it suitable for testing bubbles. which gives the following model for the null hypothesis:

$$y_t = dT^{-\eta} + \theta Y_{t-1} + \varepsilon_t, \varepsilon_t \sim iid(0, \sigma^2), \theta = 1 \quad (5)$$

Where the d is a constant, T is the sample size, and the n parameter is the localizing coefficient that controls the magnitude of the intercept and drift as $T \rightarrow \infty$. If $n > 0$, the drift is small relative to a deterministic trend. When $n > 0.5$, the drift is small compared to the stochastic trend, and when $n < 0.5$, the y_t output is similar to the Brownian motion with a drift. However, the objective of this thesis is to detect bubble and focuses on the case of $n > 0.5$.

The rolling window (SADF) style regression is now applied to the test. Assumption implies that rolling window regression samples starts from r_1^{th} sliding to the end of the r_2^{th} sample. We have: $r_2 = r_1 + r_w$, where $r_w > 0$ is the window size. This empirical regression can be written as:

$$\Delta y_t = \hat{\alpha}_{f_1, f_2} + \hat{\beta}_{f_1, f_2} \cdot y_{t-1} + \sum_{i=1}^k \hat{\psi}_{f_1, f_2}^i \Delta y_{t-1} + \hat{\varepsilon}_t \quad (6)$$

$k = \text{lag order}$

$ADF_{r_1}^{r_2}$ = The ADF statistic (t-ratio) and is the measurement of the ADF statistic for a sample that runs from 0 to r_2 .

To make up the rolling window regression to detect bubbles, the window size r_w expands from r_0 (the biggest widow fraction in the recursion) to 1. By fixing the window size starting point at 0, the endpoint of each sample (r_2) equals to r_w and changes from r_0 to 1. Again, this test is proposed by (Phillips et al, 2015) and based on the forward recursive regression, namely:

$$SADF(r_0) = \sup_{r_2 \in [r_0, 1]} \{ADF_0^{f_2}\} \quad (7)$$

Now the GSADF can be modified from the repeated ADF test regression. Since the GSADF statistic is the largest ADF statistic in this double recursion of r_1 and r_2 , it can be denoted as:

$$SADF(r_0) = \sup_{r_2 \in [r_0, 1], r_1 \in [0, r_2 - r_0]} \{ADF_{f_1}^{f_2}\} \quad (8)$$

(Corbet et al., 2017) uses the following date-stamping strategy to identify when a bubble occurs and collapses, where the bubble phase in the overall trajectory is denoted by $\tau = [T_r]$. (Diba & Grossman, 1988) studied the pseudo-stationary behavior, which connects the ADF test since the data ($I_{[T_r]}$) may include one or more collapsing bubble episodes (Corbet et al., 2017). To counteract this weakness in multiple breaks of exuberance, (Phillips et al., 2015) proposes the backward supreme ADF test on $I_{[T_r]}$ to enhance the impression of the identifications from the sample. The function of this model is to expand sample sequences where the end point of each samples is fixed at r_2 and the start point varies from 0 to $r_2 - r_0$. This flexibility of varying points in the window sample results in substantial power gain over the SADF test, which can be defined as:

$$GSADF_{f_2}(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} \{ADF_{f_1}^{f_2}\} \quad (9)$$

(Phillips et al., 2015) adds one important requirement for a bubble to exist. Its duration must exceed a slowly varying quantity such that $L_T = \log(T)$. This implementation can exclude short lived blips in the fitted autoregressive coefficient and can be adjusted to be added in the data frequency (Phillips et al., 2015). Since the data estimates are delivered in the crossing time formulas, they can be written as follow:

$$\hat{r}_e = \inf_{r_2 \in [r_0, 1]} \{r_2 : ADF_{r_2} > cv_{f_2}^{\beta T}\} \quad (10)$$

$$\hat{r}_f = \inf_{r_2 \in [r_e + \delta \log(T)/T, 1]} \{r_2 : ADF_{r_2} < cv_{f_2}^{\beta T}\} \quad (11)$$

$cv_{f_2}^{\beta_T} = 100(1 - \beta_T)\%$ critical value of the ADF statistic based on $[Tr_2]$ observations. Tr_2 = based on the backwards supreme ADF statistic $BSADF_{f_2}(r_0)$ $\beta_T \rightarrow 0$ as $T \rightarrow \infty$, where the significance level β_T depends on the sample size T . $\delta \log(T)$ = the minimal duration of a period that must exceed to be classified as a bubble, where δ = frequency-dependent parameter.

Following the date-stamping strategy, we can determine whether there are existence of bubbles or collapses. The start date of a bubble is defined as the first observation on which the backward GSADF statistic is greater than the critical value of the backward GSADF. Conversely, the end date of a bubble is defined as the first observation after that start date $((T\hat{r}_e) + \delta \log(T))$ on which the GSADF statistic goes below the critical value. The start and end date are calculated as follow:

$$\hat{r}_e = \inf_{r_2 \in [r_0, 1]} \{r_2: BSADF_{r_2}(r_0) > cv_{f_2}^{\beta_T}\} \quad (12)$$

$$\hat{r}_f = \inf_{r_2 \in [r_e + \delta \log(T)/T, 1]} \{r_2: BSADF_{r_2}(r_0) < cv_{f_2}^{\beta_T}\} \quad (13)$$

The SADF test is conducted repeatedly of the ADF test $r_2 \in [r_0, 1]$ and the GSADF test based on the repeated implementation of the backward supreme ADF test. (Corbet et al., 2017; Phillips et al., 2015). They can now be respectively written as:

$$SADF(r_0) = \sup_{r_1 \in [r_0, 1]} (ADF_{f_2}) \quad (14)$$

$$GSADF(r_0) = \sup_{r_1 \in [r_0, 1]} (BSADF_{f_2}(r_0)) \quad (15)$$

The new date-stamping method (SADF) may be used as an ex-ante real-time dating procedure, whereas the GSADF test is an ex post statistic used for analyzing bubble behavior given the data set (Corbet et al., 2017)³

³ See (Phillips et al, 2015) for an exhaustively explanation of the asymptotic properties of the ADF and SADF and the process for identifying one bubble, multiple bubbles, and no bubbles.

6 Analysis and Results

6.1 Analysis of The SAFD and GSADF

To empirically investigate the long-run relationship and dynamics among economic variables, we employ the SADF test and the GSADF test to date-stamp the bubble periods in the Bitcoin market. The SADF does not identify bubbles through the whole endogenous subsample determination. It clearly fails to detect bubbles when the full sample is utilized but succeeds when the sample is truncated to exclude some of the collapsing episodes. Comparing these two tests, the GSADF test cover more subsamples of the data. This empirical result suggests that the moving sample GSADF test outperforms the SADF test in terms of detecting explosive behavior when there are multiple series of exuberance and collapses within the simulated trajectory. The graph in Appendix 9.2 evidently shows fewer date-stamping periods for the SADF than for the GSADF. Regarding this, we analyze the bubbles found in the GSADF test. The whole date-stamping results obtain through SADF and GSADF testing approaches are reported in Appendix 9.1 to 9.6.

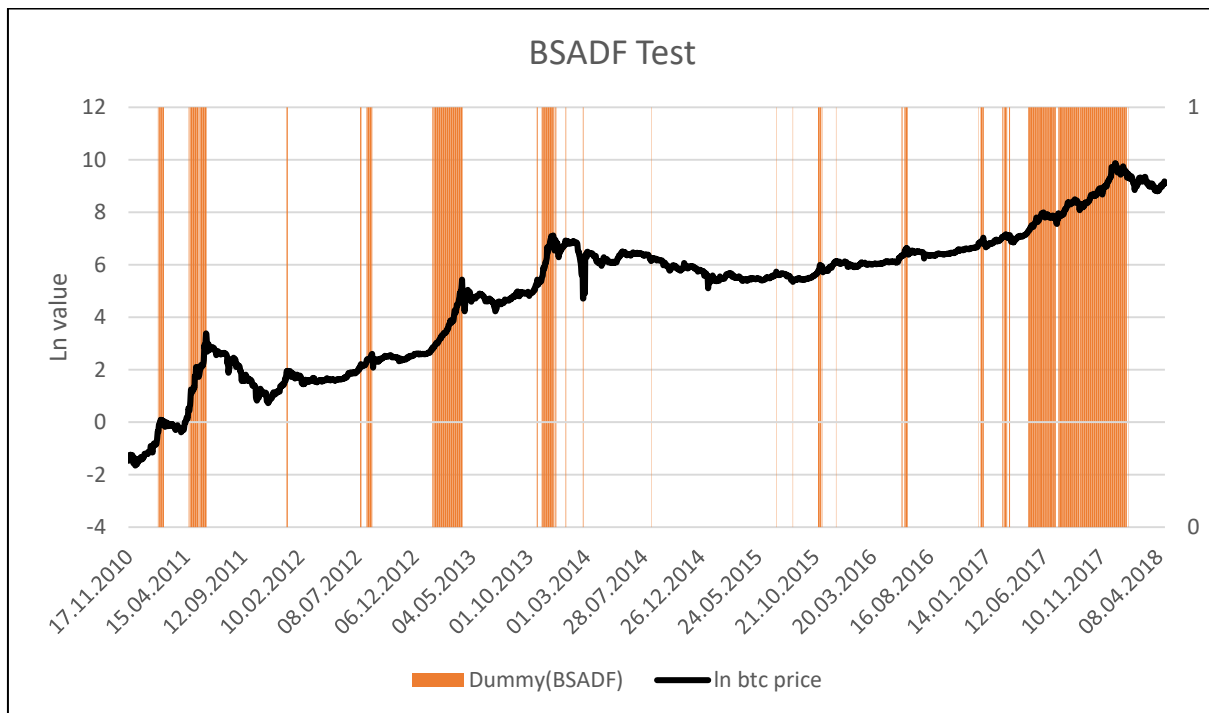


Figure 7: BSADF test (Bitcoin displayed in \ln values)

Note: This graphical illustration exhibits the Bitcoin prices from 2010-2018, overlaid on a series of dummy variables. These variables take the value of 1 when the ratio of (calculated BSADF(GSADF) test / simulated critical value -1) exceeds 0.

In figure 7, the orange data-stamp line refers to a dummy variable that captures when and how long a bubble exists for. The dummy variable takes the value of 0 if there is no bubble, it takes the value of 1 when there is a bubble. However, the dummy variables are calculated on the test for the price alone. Most of the bubbles in this analysis are short-lived because they only persist for 1-4 days. It is certainly that Bitcoin is being subject to a different duration for each bubble, as it ranges from 1 day only to up to 123 days. Adding the total duration, Bitcoin consisted in a bubble for 507 days according to the GSADF test. On the other hand, the SADF test showed only a total of 363 days where Bitcoin was in a bubble. This is not unsurprisingly as the SADF has a discriminatory power of separating the bubbles. Moreover, there are some periods the GSADF test has detected a bubble and where a new bubble has started only 3 days after. As one clarification, they are analyzed as one due to the small gap between the dates.

Looking at the Bitcoin price development from the beginning, we can observe several exponential bubbles throughout the history. We find particularly six bubbles that persisted for longer periods from Appendix 9.6, the first one originates in 2011 on April 25th and collapses May 18th. However, the next big bubble (seen as one big bubble with the first one) which starts only a few days after the burst, specifically from May 21st and burst June 8th. It is difficult to say why these bubbles occur in the first place, but with the hindsight of earlier events may help to pin down some incidents that may have led to these bubbles to collapse. Mt. Gox, the biggest exchange for trading Bitcoin may have triggered the first bubble to burst. In June 2011, approximately \$8.75 million in Bitcoin was hacked and stolen, resulting in Bitcoin price crashing from \$17.51 to \$0.01⁴ (Karpeles, 2011).

The second bubble occurred in 2013 on January 25th and collapsed April 9th and lasted for 76 days. Despite this setback in 2011, Mt. Gox had established itself in 2013 as the largest Bitcoin exchange in the world as they handled much as 70 percent of all Bitcoin transactions⁵ (Southurst, 2014). As shown in Fig 7, the price increased by 876.33 percent during the second bubble. Contrarily, the collapse seemingly had to do with the incident in which all trading at MT. Gox was suspended during April 11th, 2013 to April 12th, 2013 for temporarily pausing Bitcoin withdrawals. As a result,

⁴ <https://bitcointalk.org/index.php?topic=24727.0>

⁵ <https://www.coindesk.com/mt-gox-halts-bitcoin-withdrawals-price-drop/>

Bitcoin prices run down to pre-rally levels, before rising again only some days later. From November 4th until December 6th the price increased, building a new bubble that persisted for 33 days and yields a total of 277.24 percent increase in price. Also, another factor for the increased price can be recognized as China's surge in demand and investment for Bitcoin ⁶ (Wood, 2013). Although increasing price, this bubble burst one day after the Public Bank of China (PBOC) – the largest BTC exchange - announced that it would stop accepting payments in Chinese currency. They also stated that Bitcoin should not be used as a legal currency and enacted a partial ban on 5th of December⁴.

By looking at the graph in figure 7, it is found that the negative return at -57.34 percent in Bitcoin price is related to Mt. Gox decision to suspend all Bitcoin withdrawals on February 7th, 2014. After putting an abrupt halt to withdrawals, the exchange stopped all trading and closed its website on 24 February 2014, confirms with the rapid decrease in Bitcoin prices. Only a few days later, Mt. Gox filed for bankruptcy. Moreover, there are not found any big bubbles during the rest of 2014.

The next three bubbles are found between 2017 and 2018. With regards to this analysis, we analyze them connected as they can be merged into one big bubble because of the small gap amid the dates. Specifically, the first bubble occurs May 5th until July 12th, second bubble from July 19th to September 12th, and the third from September 14th to 2018 January 15th. The dummy variable takes a value of 0 the September 12th, indicating no bubble. One explanation for that can be connected with China's decision banning IPO⁷ (Chen & Lee, 2017). Despite Bitcoin price barrier at \$1000 in early January 2017, we observe time-periods when the price was above \$2000 and \$3000 where this methodology denoted this growth to not be a bubble. It is therefore reasonable to conclude that Bitcoin had the characteristic being in a bubble phase during this period. Results from GSADF test shows the bursting of Bitcoin bubble happens first in January 16th, 2018.

⁶ <https://www.nbcnews.com/businessmain/bitcoin-tops-1-200-does-its-fate-rest-chinas-hands-2D11673316>

⁴ <https://techcrunch.com/2013/12/18/bitcoin-drops-50-overnight-as-chinas-biggest-btc-exchange-stops-deposits-in-chinese-yuan/>

⁷ <https://www.bloomberg.com/news/articles/2017-09-04/china-central-bank-says-initial-coin-offerings-are-illegal>

We denoted bubbles to be large if it had a duration of at least 24 days. Looking at the complete specter of the Bitcoin bubbles occurred from its origination, it seems like some bubbles that lasted for 8 to 14 days are rather small at first sight. It can therefore be discussed whether these are big bubbles. There are specifically two cases where bubbles lasted for 8 to 14 days and results from the data and price ratio dividend indicate to be great values. The bubble occurred in 2015 from 29th of October to 5th of November displays the increase in price from \$226 to \$282 in 8 days, yielding a return of approximately 26 percent. The second bubble, in 2011 started on the 4th of February and lasted for 14 days, giving Bitcoin a return of over 50 percent. Hence, the data (se Appendix 9.6) also suggest substantial growth in price. However, there are some cases that the GSADF have suggested bubbles to last for 8 to 14 days where it has not been substantial growth. Therefore, it is suggested that these are small bubbles. For the specific cases described are suggested to be big bubbles, even they seem small compared to the extreme growth of the bubble from 2017 to 2018.

To underpin existences of bubbles and collapses, we implement theory of bubbles from “Stages in a Bubble”. The bubbles in 2011 constitute scantier signals of bubble. Such that they are concentrated in 2013 and from early 2017 to early 2018. The first stage of bubble in May 2018 to end of month, can be explained by the uncertainty around Bitcoin. Thus, only those who have insight in the market invests with the smart money. During this period, Japan declares Bitcoin as a legal tender that contributes the speculative component to booming. Period from end-May to around end-June is captured by the awareness phase followed by a small bear trap (Figure 3). According to Shiller (2005), speculative bubbles are signified by emerging social epidemic following the principles of irrational exuberances of social psychology, information channels and mass news media. Therefore, the relationship between mass media coverage and emerging activity of new users of Bitcoin pushed the price higher. At this point, price in Bitcoin was \$2500-3000. Continuing with the mania phase, theoretical expectations are consistent with more investments being undertaken. In which, we observe the massive investment among public in period late July to mid-December. In October 13th Bitcoin price smashed through \$5000 level to an all-time high⁸ (Kollewe, 2017). Price increased to sustainable levels becoming over \$19.000 as a result of Bitcoin

⁸ <https://www.theguardian.com/technology/2017/oct/12/bitcoin-price-5000-cryptocurrency-gold-bubble>

market reacting to media news and word-to-mouth effect. From this level, theory states that this bubble goes from being rational to irrational when its driven by psychological factors. Hence, prices are driven by delusion of a new paradigm is about to happen and everyone wants to invest (Rodrigue, 2017). This is also in line with that the public are affected by this herd-like behavior as Shiller (2005) stated. Cheah and Fry (2015) conclude that fundamental value of Bitcoin is zero. Thus, this result reflects wider academic concerns about Bitcoin's long-term viability. The collapse of the bubble happens after a blow-off phase, which takes place in mid-December 2017. Bitcoin slowly drifts downwards from \$19.000 to \$14.000 and somewhat Rodrigue (2017) calls the denial phase, before the capitulation in mid-January 2018.

Bitcoin has currently not returned its mean, but statistical evidence of GSADF test suggests that there is no bubble after this period, and we are no longer in a bubble phase. As earlier mentioned, the research of Cheah and Fry (Cheah & Fry, 2015) find empirical evidence that Bitcoin has a fundamental zero fundamental value. Firstly, if an asset according to bubble theories has zero fundamental value, there exist bubbles. Secondly, if the bubble component of Bitcoin contains substantial prices (Dowd, 2014). These results, therefore, reflect concerns that Bitcoin is a vulnerability to speculative bubbles.

6.2 The Relative Price Index

Table 2 represents the result of buy and sell signal based on an oversold/overbought RSI 7-days, 14-days and 28-days strategy. As mention earlier, this stock analysis is robust in terms of in use with other indicators. We studied 2841 cases where RSI for 7-days, 14-days, and 28-days either crossed the 30 limit and the 70 limit.

		Above 70	Under 30	Above 80	Under 20
RSI 7	Nr. of signals	970	488	628	231
	Total	2841	2841	2841	2841
	percent	34.1 %	17.2 %	22.1 %	8.1 %
RSI 28	Nr of signals	606	100	228	11
	Total	2841	2841	2841	2841
	percent	21.3 %	3.5 %	8.0 %	0.4 %
RSI 14	Nr of signals	769	267	411	75
	Total	2841	2841	2841	2841
	percent	27.1 %	9.4 %	14.5 %	2.6 %

Table 2: RSI outputs

6.2.1 14-days Interpretation of the RSI

Results from the 14-days strategy identified a total of 769 cases where RSI broke above the 70 limit, precipitate a selling signal. This, RSI indicator for the entire period has suggested Bitcoin to have been in an overbought position approximately 27 percent of the time. The impact of the RSI of Bitcoin trend is likely to become overbought than oversold. On the other hand, results showed 262 cases of RSI 14-days crossed below the 30 limit. Hence, Bitcoin was only 9.40 percent in an oversold position, underpinning that movements in Bitcoin price have been in a bull market period longer than in a bear market period. With the reference line adjusted to 80, we had cases with 411 signals being overbought. Meanwhile, 75 cases of a signal being oversold at the 20 limit. Compared with the SADF and GSADF, there are periods where RSI seems to miss some days between where it is detected bubbles. Also, RSI suggests overbought levels where the SADF and GSADF test do not exhibit bubbles.

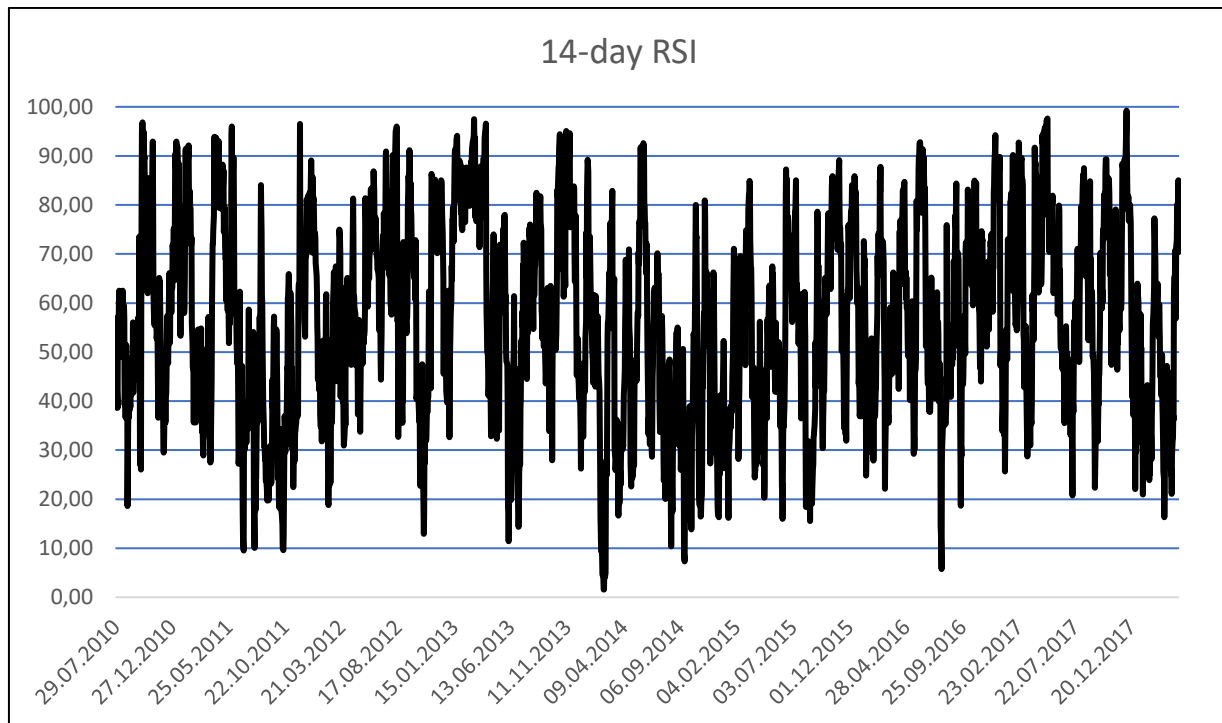


Figure 8: 14-days RSI graphical display

6.2.2 28-days Interpretation of the RSI

When the default setting for the RSI is changed to 28 days, the results display 606 cases where Bitcoin crosses above the 70 limit, which is approximately 21 percent of the time. There are 100 cases of Bitcoin crosses below the 30 limit, meaning that Bitcoin is only overbought 3.52 percent during the whole calculation period. Looking at cases when the signal levels are moved to 80 and 20, the respective numbers of signals are 228 and 11. These results reveal Bitcoin movements that are in a downtrend with overbought RSI 8.03 percent of the time and oversold RSI 2.64 percent of the time. Again, longer trading days will have more impact on RSI in which they generate a higher degree of reliability. In this case of 28-days RSI, the numbers of signals are reduced accordingly compared to the standard interpretation of RSI of 14 days.

6.2.3 7-days Interpretation of the RSI

The testing period for the 14-days RSI and the 28-days RSI is from 2010 to 2018. These results are based on that the number of signals has increased to 970 for the above 70 limit. For the cases, numbers of signal are 488 for the under 30 limit. Of the 2841 cases, RSI for 7 days suggests Bitcoin

to be in an overbought situation 34.14 percent of the time, while it suggest Bitcoin to be in an oversold condition for only 17.18 percent of the time. Moreover, the results show that Bitcoin is less in overbought and oversold conditions when comparing with the 80 and limit, with respective cases of 682 signals above the 80 limit and 231 cases for under the 20 limit. For every case that is analyzed, Bitcoin behaves to be partly in a bubble period for longer than not being in a bubble.

6.2.4 Interpretation of the SAFD, GSADF and The RSI

From the output days of predicted bubble phases, there is a moderate correlation between the RSI, SADF and GSADF test outputs. The results are consistent in that RSI 14-days is above the 70 limit in almost every situation it is detected bubbles. The correlation coefficient between the RSI and the SADF and GSADF is 0.389 for the 70 limit and 0.408 for the 80 limit. Meaning that for roughly 40% of the time they yield the same dates indicated in a bubble phase. Moving on to the 28-days RSI the correlation coefficient displays 0.515 for above the 70 limit and 0.486 for the 80 limit. The 7-days RSI exhibit a correlation coefficient of 0.284 for the 70 limit and 0.275 for the 80 limit. Thus, the correlation for the traditional 14-days RSI interpretation is somewhat lower than the correlation for the 28-days RSI but higher than 7-days RSI. The respective correlation can be read from the table 3.

	Correlation (70 limit vs GSADF)		Correlation (80 limit vs GSADF)	
		Significance		Significance
RSI 7	0.284	0.0000	0.275	0.0000
RSI 14	0.389	0.0000	0.408	0.0000
RSI 28	0.515	0.0000	0.486	0.0000

Table 3: Correlation Rsi(days) vs GSADF test(days)

However, the weakness in RSI seems to appear when the SADF test and GSADF test reveals the existence of a bubble that lasts for more than 24 days. There is also weakness in the correlation when the bubbles only persist for 1-2 days where the RSI does not show overbought situations. This regards to the 14-days, 28 days and 7 days RSI for the 70 and 80 limit. Meanwhile, the smaller bubbles detected from the SADF and GSADF are consistent in that RSI 14-days is crossing the 70 limit in almost every case. Furthermore, the relationship between the tests reveals that the RSI signals for 14 days show overbought conditions where the SADF and GSADF do not show any

periods of bubbles. The RSI suggest greater periods of oversold situations in 2011 and 2013 and somewhat scantier oversold situations in 2018 for the 14-days RSI.

Comparing these analyses, we tested the correlation between the ADF and the RSI in the same period. The results do not seem to show any clear patterns, and therefore we cannot conclude that they are perfectly correlated, but results show that there are some bubbles from the SADF and GSADF test that are correlated with RSI.

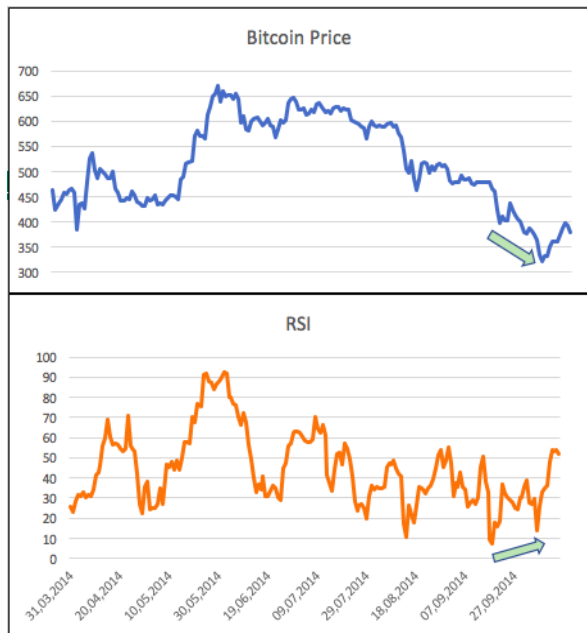


Figure 9: Bullish Divergence

Note: The graph displays a bullish divergence when the price decreases and the RSI increase in the same period.

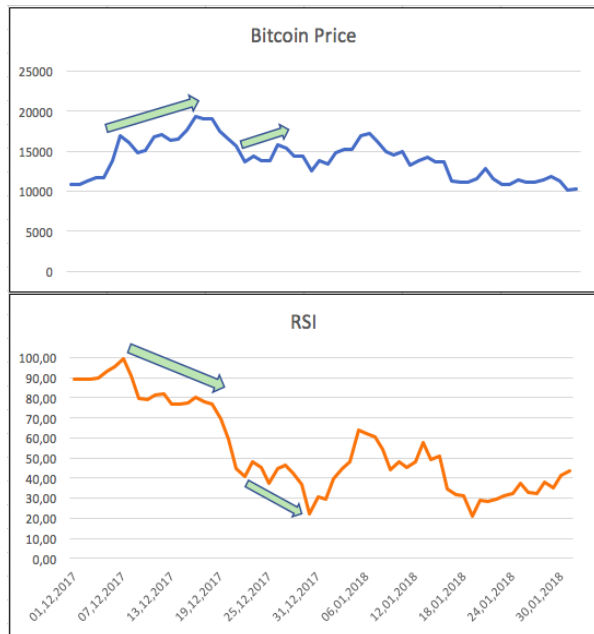


Figure 10: Bearish Divergence

Note: The graph displays a bearish divergence when the price increases and the RSI decrease in the same period.

Furthermore, we looked at divergences on the RSI indicator. Results display a strong bearish divergence formed beginning to mid- December 2017 showing the inverse relationship between price and Bitcoin and the RSI indicator. The subsequent breakdown beginning of January 2018 confirmed weakening momentum. During the period in September 2014, RSI formed lower lows for the bullish divergence. Thus, the Bitcoin price confirms the strong momentum as seen from the figure 9. Sometimes the RSI shows lower heights and bearish divergences, where it gives a warning of a short-term pullback, but there has not been any major trend reversal. Even divergences in these cases confirm the momentum, can it be pointed out that divergences can be misleading and are not always great trading signals. However, the analysis seems not to find any misleading divergences in the RSI for Bitcoin.

6.3 Google Trend Searches

Now, moving on to examine the correlation between Bitcoin's attractiveness among public and its price. Bitcoin has shown extreme volatility and returns throughout its history from 2011. We have looked at both rational and irrational bubble theory. Hence, the question of what type a bubble Bitcoin is remaining. Thus, we proceed to perform this sentiment analysis by assessing the general

public interest by comparing search queries for Bitcoin with Bitcoin price to see whether Bitcoin is driven by rational investment decisions or not.

Time	Data points	Place	Correlation	Significance
Last 5 years	Weekly	Norway	0.775	0.0000
Last 5 years	Weekly	World	0.892	0.0000
Last 12 months	Weekly	Norway	0.871	0.0000
Last 12 months	Weekly	World	0.921	0.0000

Table 4: Correlation output LN value Google trends VS Bitcoin Price

Table 4 shows the correlation coefficient of Google trends value vs bitcoin prices in logarithmic values. The correlation is calculated for the past 12 months and 5 years, in Norway and for the world. The Correlation differs from 0.775 to 0.921 and is all significant at a 0.001 level. In figure 11 is the graphical display of the correlation for 5 years weekly data points trending for the world.

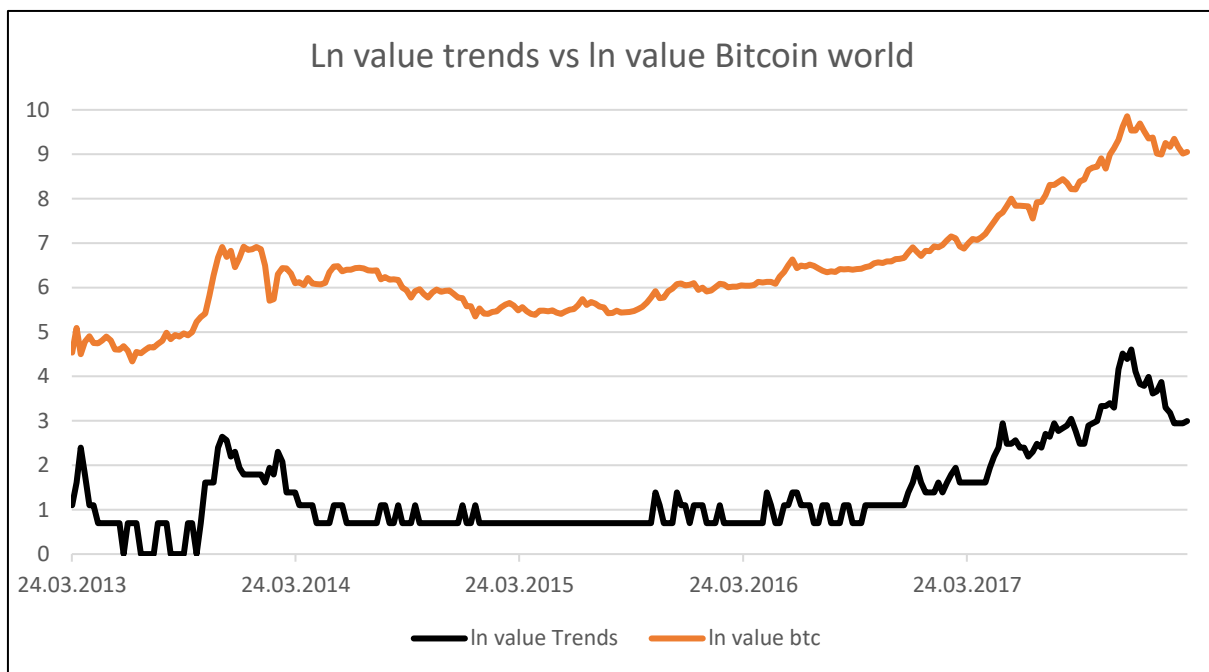


Figure 11: Bitcoin VS Google trends

The interpretation of the development in Bitcoin-related search terms and price in Bitcoin are highly correlated in all the cases. From table 4 we observe a somewhat higher correlation when we look at the search term on a world scale contrary to only Norway. Next is the higher correlation in

for the shorter 12 months window, both from Norway and the entire world. By examining the graph in figure 11 it is observed that both graphs take on a more similar upward trending slope than in the previous years. Explaining why the 12 months correlating is somewhat higher. In line with what Kristoufek (2013) found in his empirical results, we find a significant correlation between Bitcoin price and Google Trends. This further supports that Bitcoin trading is not derived from rational investment decisions, but from psychological sentiments which is consistent with Shiller's irrational exuberance theory. Indicating this bubble to be of the irrational kind.

7 Conclusion

This paper investigates whether there have been multiple bubbles in the Bitcoin market and if Bitcoin is currently in a bubble phase, using the relatively new recursive test of Phillips et. al (Phillips et al., 2015). Our approach was first to check where the GSADF test had date-stamped multiple bubbles. This study concerns the period from 2010 to April 2018.

Our empirical results based on the GSADF test statistic does not reject the null hypothesis for this period, indicating that there is not any current bubble in the Bitcoin market. The GSADF test date-stamped multiple bubbles the Bitcoin in several periods. Over the period 2010 – 2018, we detected several of short-lived bubbles and a number of huge bubbles. These results are consistent with the findings in Corbet et al., 2017 up until their date-stamping of the Bitcoin bubble in November 2017. Our empirical results indicate that there are found six huge bubbles during 2011-2018 lasting from 24 days – 123 days. We find that these bubbles may not incorporate information about rational expectation theory but rather irrational exuberance, a finding consistent with the theory presented in the Google Trends, The RSI and the bubble model of “The Stages in a Bubble”. On the other hand, the methodology of Phillips et al. (2015) suggest that these bubbles pertain to explosive behavior. Moreover, the results exhibit that there are some reoccurring trends that are affecting the Bitcoin market when investigating the date-stamping results. The Bitcoin bubble, like other bubbles, is expected at some point to burst. In this case of Bitcoin bubbles, there was no shortage of incidents that created the conditions for this to happen. During 2011-2014, the repeated incidents of Mt. Gox had an impact on Bitcoin bubbles bursting. This however, does not correspond to irrational exuberances but indicate more a technical issue. Another reoccurring trend concern first, that PBOC in 2013 informs that Bitcoin should not be used as a legal currency and enacted a partial ban. Second, that China deems initial coin offerings illegal and that all mainland-based cryptocurrency exchanges to shut down. These latter incidents correspond to irrational exuberances. To conclude this section of whether Bitcoin is driven by rational expectation or irrational exuberances, we find that bubbles date-stamped from the GSADF test seems to be driven by rational expectations in the beginning before evolving into irrational exuberances. Hence, without any exceptions, the results in this thesis confirm our study in the Bitcoin market to be driven by irrational exuberances.

Limitations and Further Research

Our analysis identifies limitations of the RSI when comparing it with the GSADF test. As discussed in section 6.2, testing the RSI correlation with the respective model yield somewhat positive correlation between all the cases measured. The RSI model fits especially well when the GSADF detects bubbles and the RSI show overbought conditions. Contrarily, the model show somewhat weakness in overbought conditions when the GSADF in some periods rejects the null and show no evidence of bubbles. Another limitation concerns the economic theories on bubbles existence on why they are difficult to apply. Due the ambiguous of whether Bitcoin is a commodity or a currency, or even both. Thus, this is a promising area of future empirical applications might want to take up.

8 References

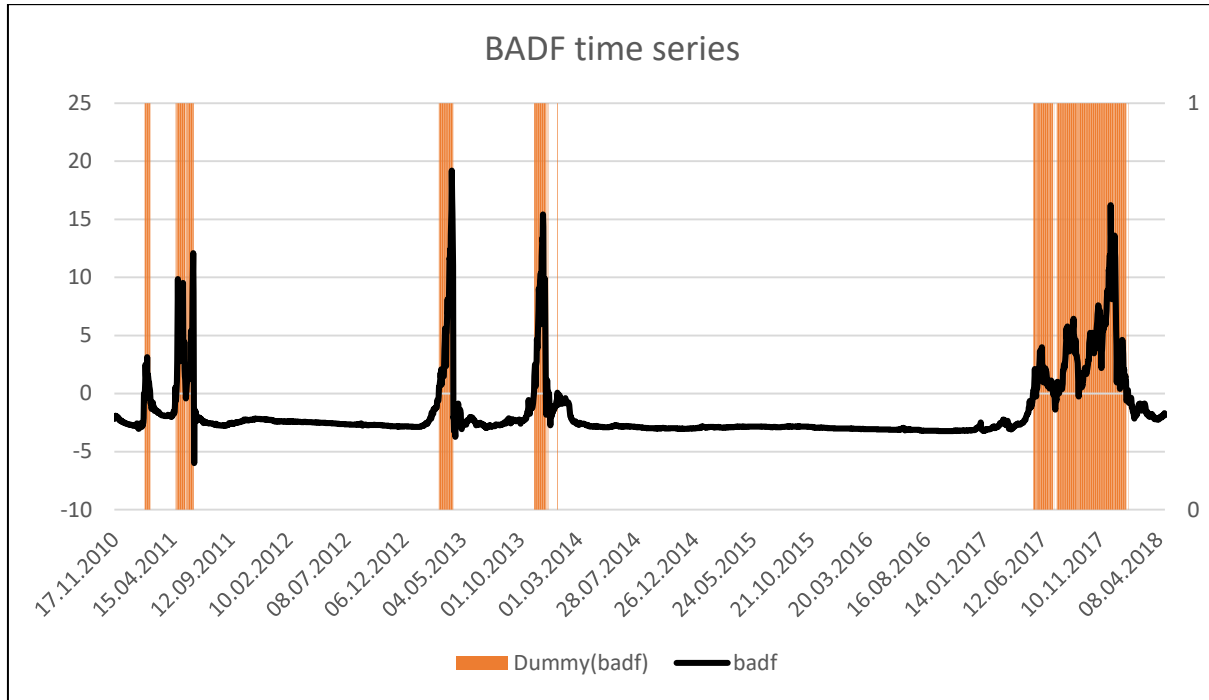
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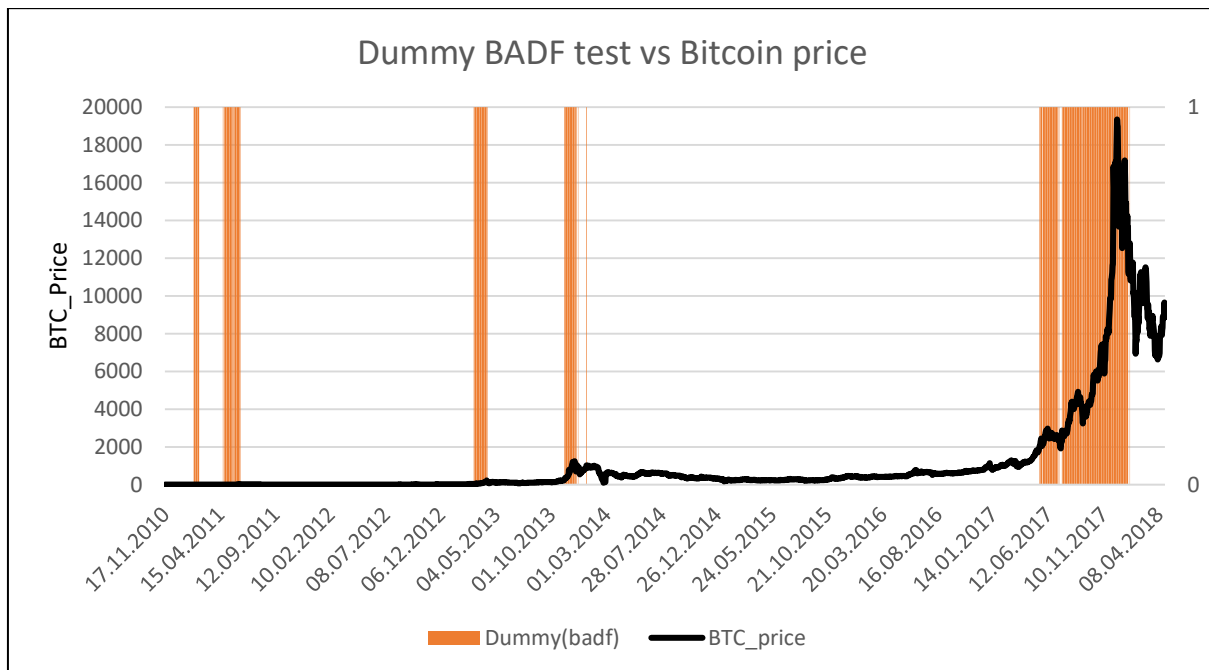
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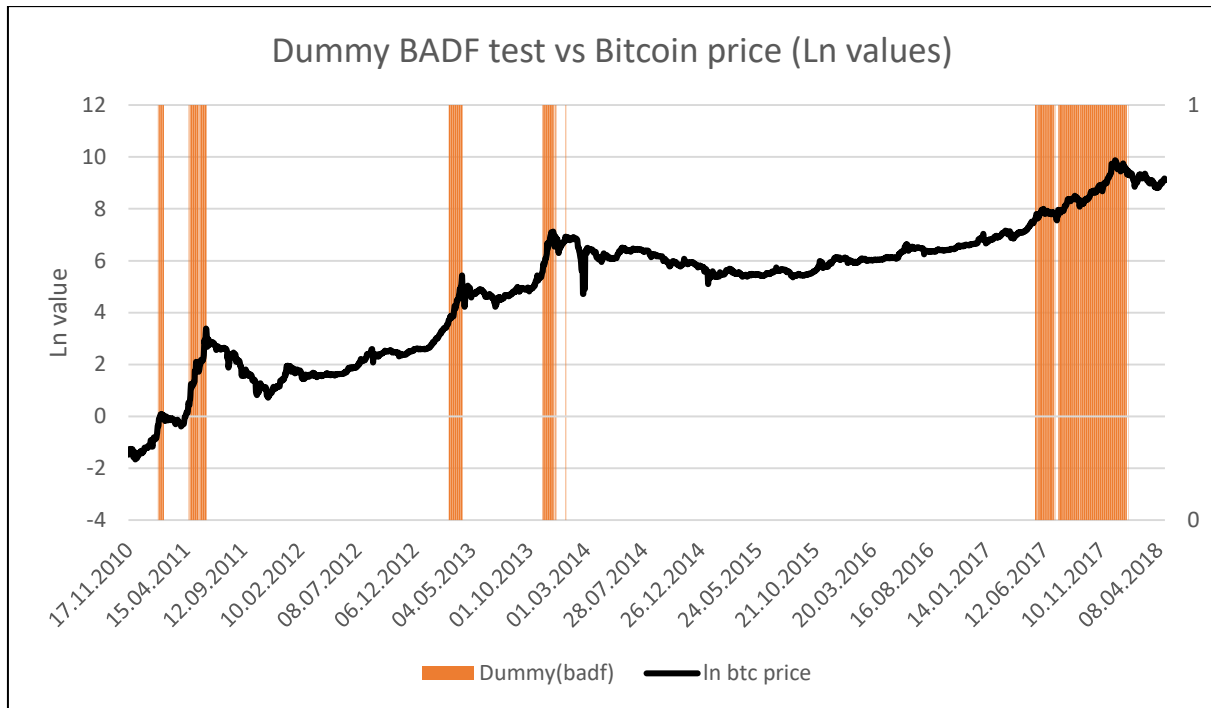
9 Appendix

9.1 Graphical display SADF test time series statistics



9.2 Graphical display Bitcoin price vs dummy SADF test

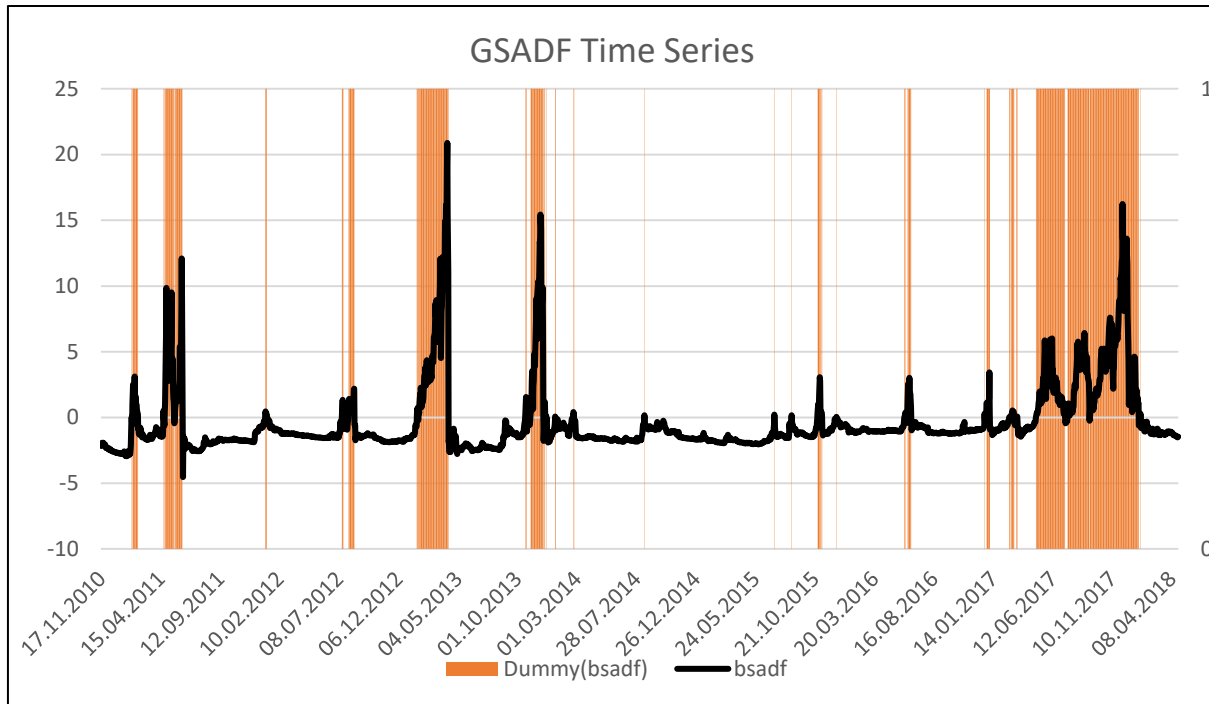




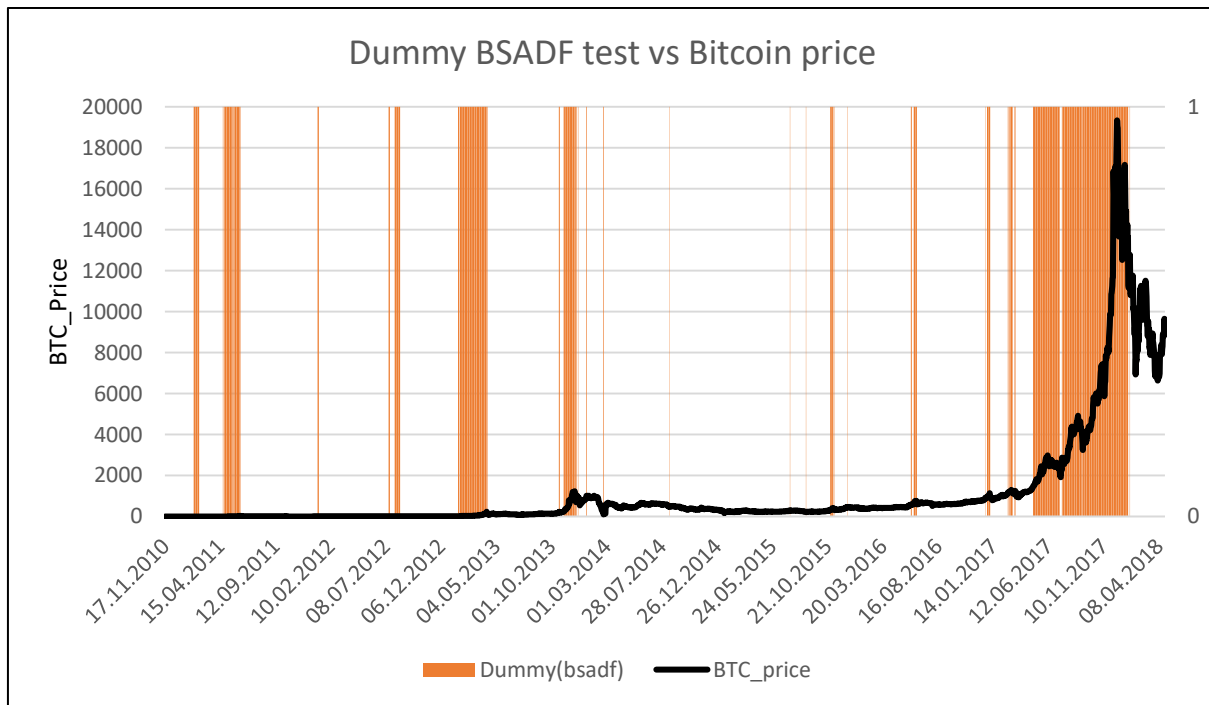
9.3 Date-stamps from SADF test

No	Start date	End date	No of days	Return
1	02.02.2011	02.02.2011	1	2.29 %
2	04.02.2011	17.02.2011	14	50.72 %
3	22.04.2011	22.04.2011	1	20.57 %
4	25.04.2011	18.05.2011	24	336.54 %
5	21.05.2011	08.06.2011	19	372.55 %
6	05.03.2013	09.04.2013	37	356.43 %
7	06.11.2013	06.12.2013	31	236.26 %
8	09.12.2013	10.12.2013	2	12.49 %
9	13.12.2013	13.12.2013	1	4.09 %
10	05.01.2014	06.01.2014	2	9.51 %
11	19.05.2017	25.05.2017	7	14.42 %
12	27.05.2017	08.07.2017	43	22.36 %
13	11.07.2017	11.07.2017	1	3.39 %
14	19.07.2017	12.09.2017	56	69.56 %
15	14.09.2017	15.01.2018	123	320.34 %
16	20.01.2018	20.01.2018	1	10.95 %
Total days			363	

9.4 Graphical display BSADF test time series statistics



9.5 Graphical display Bitcoin price vs dummy BSADF test



9.6 Date-stamps from BSADF test

No	Start date	End date	No of days	Return
1	02.02.2011	02.02.2011	1	2.29 %
2	04.02.2011	17.02.2011	14	50.72 %
3	22.04.2011	22.04.2011	1	20.57 %
4	25.04.2011	18.05.2011	24	336.54 %
5	21.05.2011	08.06.2011	19	372.55 %
6	05.01.2012	08.01.2012	4	27.65 %
7	15.07.2012	18.07.2012	4	16.40 %
8	01.08.2012	15.08.2012	15	41.36 %
9	21.01.2013	23.01.2013	3	11.46 %
10	25.01.2013	09.04.2013	76	876.33 %
11	21.10.2013	23.10.2013	3	7.37 %
12	04.11.2013	06.12.2013	33	277.24 %
13	09.12.2013	10.12.2013	2	12.49 %
14	13.12.2013	13.12.2013	1	4.09 %
15	05.01.2014	06.01.2014	2	9.51 %
16	20.02.2014	21.02.2014	2	-57.34 %
17	17.08.2014	17.08.2014	1	-4.80 %
18	11.07.2015	11.07.2015	1	6.33 %
19	23.08.2015	23.08.2015	1	-6.76 %
20	29.10.2015	05.11.2015	8	26.08 %
21	07.11.2015	07.11.2015	1	4.13 %
22	09.11.2015	09.11.2015	1	2.33 %
23	15.12.2015	15.12.2015	1	4.67 %
24	03.06.2016	05.06.2016	3	2.92 %
25	11.06.2016	19.06.2016	9	24.07 %
26	23.12.2016	23.12.2016	1	6.63 %
27	28.12.2016	05.01.2017	9	6.87 %
28	23.02.2017	24.02.2017	2	5.00 %
29	27.02.2017	07.03.2017	9	5.22 %

30	13.03.2017	15.03.2017	3	2.31 %
31	01.05.2017	12.07.2017	73	66.86 %
32	19.07.2017	12.09.2017	56	69.56 %
33	14.09.2017	15.01.2018	123	320.34 %
34	20.01.2018	20.01.2018	1	10.95 %
Total days			507	