

Crypto-Currency Bubbles: An application of the Phillips-Shi–Yu (2013) methodology on Mt. Gox bitcoin prices

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Abstract

The creation of Bitcoin heralded the arrival of digital or crypto-currency and has been regarded as a phenomenon. Since its introduction, it has experienced a meteoric rise in price and rapid growth accompanied by huge volatility swings, and also attracted plenty of controversies which even involved law enforcement agencies. Hence, claims abound that bitcoin has been characterised by bubbles ready to burst any time (e.g. the recent collapse of Bitcoin’s biggest exchange, Mt Gox). This has earned plenty of coverage in the media but surprisingly not in the academic literature. We therefore fill this knowledge gap. We conduct an econometric investigation of the existence of bubbles in the bitcoin market based on a recently developed technique that is robust in detecting bubbles - that of Phillips, Shi and Yu (2013a). Over the period 2010-2014, we detected a number of short-lived bubbles; most importantly, we found three huge bubbles in the latter part of the period 2011-2013 lasting from 66 days to 106 days, with the last and biggest one being the one that ‘broke the camel’s back’ - the demise of the Mt Gox exchange.

Keywords: bitcoin, bubbles, crypto-currency

JEL codes: G01, G12, C01

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I. Introduction

Bitcoin heralded the coming of digital or crypto-currency. Its creation is attributed to a Japanese computer programmer using the pseudonym Satoshi Nakamoto. It is supposed to be a currency that overcomes the problems that beset existing currencies. Its supply is not at the whims of regulators; rather it is protected by an “uncrackable” computer algorithm that controls its supply which is set at a maximum of 21 million units. Mining of new bitcoins is done through computer algorithms. Its transactions are open to the public and supposed to be without transactions fees as these do not involve intermediaries (Lo and Wang, 2014). Given all these qualities of bitcoin, it has been hailed as the future of money. Since its introduction in 2009, its price has seen meteoric rise (see Figure 1). In December 2013, its price peaked at USD1,200 per unit after it climbed by about 700% in that year. The volume of bitcoin in circulation now stands at 12.7 million units and trading volume reached 85 million units in 2013 (see Figure 2) and actively traded against around 30 currencies (Biere et al., 2013). This success of bitcoin has in fact spawned the introduction of other digital currencies such as litecoin, namecoin, quackcoin, peercoin, anoncoin, zero coin, which operate on the same concept as bitcoin but with minor modifications. Thus, bitcoin, in this sense, has truly signalled the coming of the age of digital or crypto-currency.

In spite of its rapid growth, bitcoin has been mired in several controversies relating to accusations of its use in illegal business activities¹. There has been also reluctance by regulatory authorities in a number of countries to endorse it as a currency and in fact, lately, the Chinese government has explicitly banned financial institutions and businesses from

¹ For example, there has been allegations of bitcoin being used in drug-related activities facilitated by the e-commerce website, Silk Road, which has attracted an investigation by the FBI (The Economist, February 1, 2014)

using it.² Since its introduction, bitcoin has experienced a meteoric rise in its price. However, this has also been accompanied by huge volatility swings, as can be seen in Figure 1. This has therefore led to constant claims in the investment industry and the media of the bitcoin market being characterised by bubbles which could burst anytime. The recent collapse of the Mt Gox Exchange, the biggest bitcoin exchange, is now taken as evidence that there were indeed bubbles in the market and this has finally burst.

It is argued by some that by its very nature, bitcoin is destined to be characterised by bubbles (Grinberg, 2011). It is supposed to be a currency but it does not essentially perform the functions of a currency. Yes, it is a medium of exchange as it used by a number of businesses; however, it fails as a store of value and as a unit of account because of its volatility. It does not have any intrinsic value – it is simply anchored on a computer program. Thus, it simply derives its value from being a speculative commodity, and because of this, it is therefore bound to be characterised by bubbles.

In spite of these claims in the media and in the investment community of bitcoin being characterised by bubbles, surprisingly, no systematic study yet that has been conducted on this issue. There are a very few academic studies on bitcoin and most of these deal with legal and institutional issues (Biere et al., 2013). To our knowledge, there is only one academic study relating to the financial economics of bitcoin – the one by Biere et al. (2013). We therefore address this knowledge gap. In this paper, we investigate the existence of bubbles (e.g. explosive behaviours) in the bitcoin market based on recently developed econometric

² For most of the time, since its inception, at best, a number of governmental regulatory authorities have just turned a blind eye on bitcoin. However, some governments have started to “crack the whip” on bitcoin. For instance, the French government has explicitly warned against the use of bitcoin (<http://m.theglobeandmail.com/report-on-business/economy/economy-lab/bursting-the-bitcoin-bubble/article16327155/?service=mobile>). Starting in December 2013, the Chinese regulatory authorities have also explicitly banned financial institutions and business from using bitcoin (April 14, 2014). India has also done the same as China although probably to a lesser extent (<http://www.businessspectator.com.au/article/2013/12/31/currency/bursting-bitcoins-bubble>)

techniques, particularly that of Phillips, Shi and Yu (2013a; hereafter, PSY).³ Our results confirm claims of the existence and burst of bubbles in the bitcoin market. Over the period 2010-2014, we detected a number of short-lived bubbles but most importantly, we found three huge bubbles in the latter part of the period (2011-2013) lasting from 66 days to 106 days, with the last one and also the biggest one occurring during the period November 2013 – February 2014. Our results confirm that the last bubble, indeed, burst, and thus, may have been the fatal one that ‘broke the camel’s back’ - the collapse of the Mt Gox exchange.

II. Bubbles: Definition, Detection and Existence in Asset Markets

Definition and Detection

There is no agreement as regards the definition of bubbles.⁴ One may take the asset-pricing approach which defines bubbles as the part of the market price which exceeds or undershoots an asset’s fundamental value (Diba and Grossman, 1988a; West, 1987; Van Norden, 1996; and Wu, 1997). Detecting the existence of bubbles therefore entails determining first the fundamental value of an asset. In its most generic form, the fundamental value of an asset is the present value of the payoffs taking into account all available relevant information (Taipalu, 2012). There exist a number of financial economics theories that provide explanations as to what determine the fundamental value of an asset (see Taipalu, 2012). However, bitcoin is hard to value as it does not have any clearly identifiable cash flows. It is not even clear what its nature is. There is no agreement as to whether it is a currency or commodity or both (Lo and Wang, 2014). It has no intrinsic value and its value simply depends mostly on its speculative value. It has been argued that bitcoins are simply claims

³ Plenty of theories also exist as to why bubbles exist (see, for example, Griffin et al, 2011, and Taipalus, 2012). However, this paper does not intend to test these theories. Our goal is mainly to detect whether bubbles existed in the bitcoin market.

⁴ In fact, they can vary by discipline. See Waites and Von Maravic (2010) for a discussion of this issue.

on numbers.⁵ Its speculative value is based on the spin of technological mystery – the crypto nature of bitcoin, and the mining of these supposed to be magical crypto numbers. There are even claims that it is a Ponzi-scheme.⁶ Hence, despite the fact that the asset-pricing approach is quite well-developed in the literature, this approach will be difficult to implement in relation to the examination of bubbles in the bitcoin market.⁷

Alternative approaches that avoid modelling the fundamental value are available in the literature. They include the sigmoid curve approach (Foster and Wild, 1999), the Markov-switching process approach (Hall, Psaradakis and Sola, 1999) and the mildly explosive process approach (PSY, 2013a, 2013b, 2014). The sigmoid (or logistic) curve approach employs a curve-fitting strategy to identify the dynamics of an economic variable of interest (see, for example, Foster and Wild, 1999). Sigmoid (or logistic) curve is used because it can exhibit some typical phases that are commonly observed in the evolution of bubbles. These phases include expansion phase, inflexion phase, and saturation phase. Denote the variable of interest as Y_t . The expansion phase is usually characterized in terms of positive growth ($dY/dt > 0$) while the inflexion phase and the saturation phase are characterized in terms of close to zero and negative growth, respectively. The evolution of Y_t may be captured by the following equation:

$$\frac{dY}{dt} = \frac{bY}{1 - (\frac{Y}{c} - a)}$$

where a , b and c are the parameters to estimate and control the shape of sigmoid curve. The idea of this approach is to identify the beginning date of the saturation phase by which a bubble is expected to burst. However, Jarne, Sanchez-Choliz and Fatas-Villafranca (2007) point out two shortcomings associated with the standard sigmoid curve approach. First, the

⁵ <https://medium.com/future-of-currency/945260c2c193>

⁶ <https://medium.com/future-of-currency/945260c2c193>.

⁷ For a survey of this approach, see Gurkaynak (2008).

growth rates of sigmoid curve never increase, even though the expansion (saturation) phase is expected to exhibit an increasing (decreasing) growth rate. Second, the symmetry properties of the sigmoid curve imply that the period of expansion phase must be equal to that of saturation phase, even though the empirical data always suggests otherwise. In addition, it is also not clear as to how the sigmoid curve should be used in the presence of multiple bubbles.

Hall, Psaradakis, and Sola (1999) propose to use a Markov-switching process (i.e., Markov chain) to capture the change from a non-bubble regime to a bubble regime. Within this framework, the existence of a bubble is consistent with one of the regimes that is characterized by the presence of an explosive autoregressive root and a Markov-switching augmented Dickey-Fuller unit root (MSADF) test can be used to detect if an explosive autoregressive root exists. This approach also allows for multiple bubbles. The problem with this approach is that it is difficult to distinguish between a regime with high volatility and a regime with an explosive autoregressive root and the estimation results are sensitive to (mis)specifications of the MSADF test (Shi, 2013).

PSY (2013a) argue that bubble expansion can be viewed as mildly *explosive* behaviour (i.e., autoregressive root $\theta = 1 + gT^{-m}$ with $g > 0$ and $m \in [0, 1)$). They develop a new bubble test to distinguish sub-martingale (exuberant or mildly explosive) behaviour from martingale behaviour soon after the change in behaviour occurs. According to Phillips (2012, p3), “bubbles differ from trends because the general tendency during an upswing contrasts with the general tendency during collapse. During an upswing we have sub-martingale behaviour where the conditional expectation is a price rise tomorrow whereas, during a collapse, the conditional expectation is a price fall, giving super-martingale behaviour.” This test has been

successfully applied in detecting bubbles in stock market and foreign exchange market (See next section for details).

Bubbles in Asset and Currency Markets

Bubbles seem to be a natural phenomenon in markets particularly in asset markets. Bubbles, crashes and crises have occurred in different financial markets at all stages of development: developed financial systems as well as emerging economies and developing financial markets (Brunnermeier and Oehmke, 2012, see Section 2, p. 7). Bubbles have been known to occur in different markets dating all the way back to hundreds of years ago. Historically, there are three famous bubbles which occurred in the first half of the 1600s and 1700s - the Tulipmania, Mississippi Bubble and South Sea Bubble which are considered as classic cases (Taipalus, 2012 and Kindleberger, 2000). In the Tulipmania bubble, investors became so enamoured with tulips which resulted in the price of this commodity to rise steadily over a period of time until its collapse in 1637. In the case of the other two bubbles, investors poured money into monopolies which investors came to believe as money machines, driving the values of these companies to very high levels but only to find out later that these companies were severely overvalued beyond their fundamentals which then led to their demise in 1720. Additional detail on these episodes can be found in Kindleberger (2000), Shiller (2000), Allen and Gale (2007), and Reinhart and Rogoff (2009).

In the 1920s, the US experienced a stock market boom particularly during the period 1927-29 which was followed by the great stock market crash of 1929 and the ensuing Great Depression. According to White (2009), this stock market boom and bust was actually accompanied by the same situation in the real estate market. The 1970s and 1980s also witnessed bubbles in the international credit markets particularly in relation to sovereign

debts of South American countries (Sturzenegger and Zettelmeyer 2006). In the early 1990s, bubbles also occurred in the credit markets as well as in the real estate markets of Scandinavian countries (Englund, 1999 and Jonung, Kiander, and Vartia, 2009). The decade starting with the year 2000 immediately witnessed the occurrence of a bubble associated with internet companies whose stock values had greatly risen starting in the latter part of the 1990s but burst in March 2000 wiping around US\$7 trillion of stock market value (Malkiel 2010). The most recent one was the real estate bubble in the US which burst in 2008 and led to the global financial crisis (see Malkiel 2010 and Pavlidis, et al, 2013).

As regards the regulated currency market, there is evidence from the literature of the existence of bubbles. For example, Bettendorf and Chen (2013), using the PSY methodology, found explosive behaviour in the sterling-dollar exchange rate in the early 1980s which they attribute to the relative prices of exchange traded goods. Meese (1986) and West (1987) also detected the existence of bubbles with regards to the US dollar-deutschemark exchange rate.

It should be pointed out that those studies that document the existence of bubbles argue that bubbles are caused by such factors as lax regulations or a breakdown in regulations (Sornette, 2003, and Herrera and 2003; Shiller, 2000; Vogel, 2010); growth prospects (Shiller 2000; Pastor and Veronesi 2004; Vogel 2010), inadequate market infrastructure that hinders the efficient flow of information (Taipalus, 2012), and overtrading (Vogel, 2010; Kindleberger, 2000; Heaton and Lucas, 2000).

Hence, it appears that bubbles in regulated markets come about due to such reasons as laxity in regulations, overtrading and overestimated growth prospects. These seem to be the same

factors driving the bitcoin market. As mentioned, bitcoin is a currency that does not have intrinsic value but simply relies on the trust of participants in a computer program that is supposed to be uncrackable, with a limited supply and operates in a mainly unregulated market. Thus, we expect that the bitcoin market will be characterised by bubbles.

III. Methodology

In this section, we briefly outline the testing procedure and dating algorithm proposed in PSY (2013a). This procedure is designed to detect stochastic explosive behaviour of a given time series because such explosive behaviour is usually deemed as a key feature of a bubble. This procedure may be also viewed as a response to the critique of Evans (1991) on standard unit root procedures which fail to detect bubbles in the presence of multiple bubbles and/or collapsing bubbles because inclusion of collapsing time period(s) make a time series appear mean-reverting. The PSY (2013a) procedure is a straightforward extension of the standard augmented Dickey-Fuller (ADF) test, which is a unit root test in a time series sample T , to a setting where multiple bubbles are allowed. However, there are four key distinguishing features of this procedure. First, instead of running the ADF test over the full sample, this procedure relies on the idea of repeatedly running the ADF test on subsamples of the data in a recursive fashion because recursive estimation is well-known for its ability to utilizing data efficiently. Second, as sliding windows are known for their ability to detect sudden or abrupt changes, this procedure is also used with adaptive sliding (or rolling) windows. Third, to minimize the impact of collapsing time period(s), the test is estimated backward (i.e., from T to zero) rather than forward (i.e., from time zero to T). Finally, this procedure can be used as a warning alert system to tell if there is a bubble on an ex ante basis.

First, we specify the following model for the null hypothesis:

$$y_t = \mu_y + \theta y_{t-1} + \varepsilon_t, \varepsilon_t \sim iid(0, \sigma^2) \quad (1)$$

where $\mu_y = \alpha T^{-\pi}$ and π is a parameter that controls the magnitude of drift. PSY (2013a) argues that this specification is particularly suitable for testing bubbles because the drift term is non-dominating (i.e., asymptotically negligible). In particular, if $\pi > 0$, the drift is small relative to a linear trend; if $\pi > 0.5$, the drift is small compared to the stochastic trend; if $\pi = 0.5$ and $T \rightarrow \infty$, then the (standardized) y_t behaves very much like a Brownian motion with drift. Recall our objective is to detect explosive bubble(s), it is noteworthy that under the null this process is a unit root (i.e., $H_0: \theta = 1$), while the alternative hypothesis is specified as an explosive root (i.e., $H_1: \theta > 1$). This also implies that right-tailed (rather than left-tailed) unit root tests should be used in this setting. Second, we apply the augmented Dickey-Fuller (ADF) test repeatedly to the data for a rolling window of width n , where $n \in (r_0, T)$ and r_0 is the smallest window size. In particular, the following rolling regression is estimated by OLS for the window:

$$y_t = \mu_y + \theta y_{t-1} + \sum_{j=1}^J \Delta y_{t-j} + \varepsilon_t \quad (2)$$

where J is the lag order. Observations in y_t are n most recent values from times $t - n + 1$ to t . OLS estimates are computed for sliding windows of width n with r_1 and r_2 being the window start point and end point, respectively. In other words, the window size n is just $r_2 - r_1 + 1$. The ADF t-test statistic for the window size n is:

$$ADF_{r_1, r_2} = \frac{\theta_{r_1, r_2}}{se(\theta_{r_1, r_2})} \quad (3)$$

The standard ADF test is a special case with $n = T$. Given a fixed window size n and a fixed window end point r_2 , we can vary the starting point r_1 and generate $[r_2 - n + 1]$ ADF statistics. Generalized Supremum ADF (GSADF) statistic is defined as the largest ADF statistic out of these ADF statistics. Now by varying r_2 from n to T , a series of $[T - n + 1]$ GSADF statistics can be generated. PSY (2013b) derives the asymptotic distribution of GSADF statistic and shows that it is identical to the case where the regression model includes an intercept term and the null hypothesis is a unit root processes without drift. Note that the limit distribution of GSADF statistic depends on the smallest window size r_0 . In practice, we have to choose r_0 in such a way that r_0 must be large enough to allow for feasible initial estimation and r_0 must be small enough to be able to detect a bubble, i.e., it should be smaller than the distance separating any two bubbles. Following PSY (2013a), we set r_0 to approximately 2% of the data (i.e., 20).

To identify when a bubble occurs and collapses, the following date-stamping strategy is used. 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 statistic obtained from Monte Carlo simulations while the end date of a bubble is defined as the first observation after that start date on which the GSADF statistic goes below the critical value. Similar definitions can be used for subsequent bubbles if there are more than one bubble in the data.

IV. Data

The variable of interest is daily bitcoin prices collected from the bitcoincharts.com website for the most actively traded bitcoins (i.e., MT.GOX) over the period 17July2010 to

18Feb2014. They are all denominated in the US dollar. There are 1307 daily observations in the sample period. To avoid the problem of thin-trading in some markets, only the (log of) weighted prices are used. A graphical representation of the data is depicted in Figure 3.

Table 1 reports the summary statistics of the variable. Panel A of Table 1 shows the overall summary statistics while Panel B depicts the autocorrelation plot. The mean is 2.1598 and the standard deviation is 2.4711, suggesting that the bitcoin price variable is somewhat over-dispersed. However, no significant departure from normality is found as both skewness and kurtosis are -0.1526 and 2.6203, respectively. Figure 3 seems to suggest that there is an upward trend with ups and downs with bitcoin prices in log scale. As shown in Panel B, the time series of the bitcoin price is highly persistent because its autocorrelation is close to one (i.e., 0.9971) and statistically significantly different from zero at lags 1 to 20. Thus, it is important to determine whether this trend is deterministic or stochastic. To this end, we use the augmented Dickey-Full test. The results on the augmented Dickey-Fuller test basically show that the time series are non-stationary in most cases (see Table 2). For example, if we allow for a trend in the underlying data-generating process, the ADF test clearly indicates that the variable is non-stationary so is the case where there is no drift term specified in the data-generating process. In the case where a drift is allowed, the null hypothesis that there is a unit root cannot be rejected with lag =1 and 2. The null is only rejected if the lag is either zero or three. However, as argued in PSY (2013a), the possibility that a bubble that bursts off in the sample period will render the variable *pseudo-stationary* if the period after the burst is also included in the ADF test. That is why we need to employ some tests like GSADF test that do not suffer from this limitation and the results are reported in the next section.

V. Empirical results

Figure 4 presents the GSADF test statistic together with its critical values at 90%, 95%, and 99% over the sample period. The GSADF test statistic, represented by the solid line, clearly shows that it exceeds its corresponding 99% critical value (denoted by the dotted line) 33 times over the sample period, suggesting that 33 episodes of bubbles are identified. Data-stamp line (denoted by the solid dark line) refers to a dummy variable that captures when and how long a bubble exists for. The dummy variable takes the value of negative six if there is no bubble; it takes the value of negative five if there is a bubble. The duration of a bubble is captured by the length of the line staying at negative three. The duration of the bubbles ranges from 1 day only to 106 days. Most of the bubbles are short-lived because they just last for a few days only. But there were three big bubbles that persisted for quite a long period of time. The start date and the end date of the first big bubble are 24April2011 and 3July2011 respectively, covering 66 days in between while the start date and the end date of the second big bubble are 27Jan2013 and 15Apr2013 respectively with a life span of 79 days. The third (and the longest) bubble has a history of 106 days, covering the period from 5Nov2013 to 18Feb2014 (i.e., the end of the sample period).

It may be very difficult to figure out how these bubbles started in the first place. But with the benefit of hindsight, it is possible to pin down some incidents that may have led to these bubbles to burst. For example, an event in June 2011 in which about \$8.75 million in bitcoin was stolen from the Mt. Gox exchange through an online attack using stolen passwords and which resulted in the bitcoin price crashing from \$17.51 to \$0.01 on the Mt. Gox exchange, may have triggered the first big bubble to burst.⁸ The collapse of the second bubble may have to do with the incident in which trading at Mt Gox was suspended from 11 April 2013 until

⁸ Karpeles(30 June 2011).

12 April 2013 for a "market cool-down", sparking a sharp sell-off. As a result of this, the value of a single bitcoin fell to a low of \$55.59 after the resumption of trading. Mt. Gox's decision to suspend all bitcoin withdrawals on 7 February 2014 and to shut down its trading activities on 25 February 2014, led to the burst of the third bubble. There have been claims that the decision of the Chinese government in March 2013 to ban the use of bitcoin by financial institutions and business may have been the last straw that broke the camel's – Mt Gox exchange – back (The Economist, April 14, 2014).

VI. Conclusion

Bitcoin heralded the introduction of digital currency and was therefore touted as the future of money. It was created for the purpose of overcoming the shortcomings of the existing currencies, particularly on the promise that its creation and supply will not be at the whim of regulators, and one that is based on transparency. The protection of its supply comes from a supposed to be uncrackable algorithm. Based on these promises, the value of the currency rose dramatically since its introduction in 2009, reaching a high of USD1,200 per unit in 2013 and in that year, its price in fact rose by about 700%. Furthermore, its meteoric price rise has been accompanied by huge volatilities which have led to claims by investors and in the media that bitcoin is a commodity that has been experiencing bubbles which could therefore burst anytime. The collapse of one of its major exchanges, the Mt Gox Exchange, has been taken as evidence of the bursting of the bubble. In spite of the high profile and extensive media coverage of this issue in the media, there has been no academic study that has investigated this issue.

In this study, we conduct an econometric investigation of the existence of bubbles in the bitcoin market based on a recently developed technique of Phillips, Shi and Yu (2013a) that

has been shown to robustly detect bubbles. This technique is designed to detect stochastic explosive behaviour of a given time series since such explosive feature is commonly shared by all bubbles. Over the period 2010-2014, we detected a number of short-lived bubbles but most importantly, we found three huge bubbles in the latter part of the period (2011-2013) lasting from 66 days to 106 days. The bursting of these bubbles also seems to coincide with certain major events that occurred in the bitcoin market.

Our study therefore confirms what investors, financial journalists and other participants in the bitcoin market have been saying – that bitcoin has been in a bubble over its relatively short existence. Our results give credence to the claim that the latest bubble and the biggest one had indeed burst and this may have been responsible for the demise of bitcoin's biggest exchange – Mt Gox.

A number of anecdotal explanations abound as to why there have been bubbles in the bitcoin market. As mentioned earlier, it is claimed that because of its very nature, bitcoin will develop bubbles as it is simply a speculative commodity, and not a currency or commodity with intrinsic value. It lives on the hopes and trusts of investors on that “uncrackable computer algorithm”. In fact, it has been shown that “miners” of bitcoins do hoard the coins rather than use them for transactions (the number of transactions is relatively small relative to the bitcoin market capitalisation). Bubbles, of course, are expected to burst, and in the case of bitcoin, there was no shortage of incidents that created the conditions for this to happen – the theft of a huge amount of bitcoin, and the decision of the Chinese regulators to ban the use of bitcoin by financial institutions and currency market which is claimed to be the straw that broke the Camel's back (the demise of Mt Gox).

Likewise, a number of financial economic theories exist as to why bubbles develop. However, as stated previously, these theories are difficult to apply. Bitcoin is difficult to value as its nature is not even clear – is it a commodity, currency or both? It does not have any explicit cash flow. Thus, in this paper, we did not attempt to go into this. This is something that, perhaps, future researchers might want to take up. There is need for more studies on digital currencies, particularly that there is now a proliferation of other digital currencies, although still much smaller than bitcoin, such as litecoin, peercoin, namecoin, quackcoin, etc.

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Table 1:

Panel A: Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
bitcoin	1307	2.1598	2.4711	-2.9957	7.0983	-.1526	2.6203

Panel B: Autocorrelation plot

LAG	AC	PAC	Q	Prob>Q	-1	0	1	-1	0	1
					[Autocorrelation]	[Partial Autocor]				
1	0.9971	0.9988	1302.5	0.0000						
2	0.9943	-0.2186	2598.5	0.0000						
3	0.9916	0.0433	3888.5	0.0000						
4	0.9888	0.0919	5172.2	0.0000						
5	0.9858	-0.0966	6449.3	0.0000						
6	0.9826	-0.0446	7719	0.0000						
7	0.9793	-0.0558	8981.2	0.0000						
8	0.9759	0.0557	10236	0.0000						
9	0.9726	0.0383	11482	0.0000						
10	0.9691	-0.0450	12721	0.0000						
11	0.9657	-0.0834	13952	0.0000						
12	0.9621	-0.0623	15175	0.0000						
13	0.9586	-0.0147	16390	0.0000						
14	0.9550	-0.0400	17597	0.0000						
15	0.9512	-0.0307	18795	0.0000						
16	0.9475	0.0080	19985	0.0000						
17	0.9437	-0.0130	21166	0.0000						
18	0.9400	-0.0384	22339	0.0000						
19	0.9362	0.0434	23503	0.0000						
20	0.9324	-0.0265	24659	0.0000						

Panel C: Augmented Dickey-Fuller test for unit root

Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value	Number of obs.	Underlying DPS	Lags
1.144	-2.580	-1.950	-1.620	1305	No constant	0
0.841	-2.580	-1.950	-1.620	1303	No constant	1
0.994	-2.580	-1.950	-1.620	1301	No constant	2
1.078	-2.580	-1.950	-1.620	1299	No constant	3
-1.647	-3.430	-2.860	-2.570	1305	trend	0
-1.680	-3.960	-3.410	-3.120	1303	trend	1
-1.505	-3.960	-3.410	-3.120	1301	trend	2
-1.424	-3.960	-3.410	-3.120	1299	trend	3
-1.647	-2.329	-1.646	-1.282	1305	drift	0
-1.277	-2.329	-1.646	-1.282	1303	drift	1
-1.154	-2.329	-1.646	-1.282	1301	drift	2
-1.316	-2.329	-1.646	-1.282	1299	drift	3

Figure 1: Mt. Gox USD bitcoin prices over the period 17July2010 to 18Feb2014

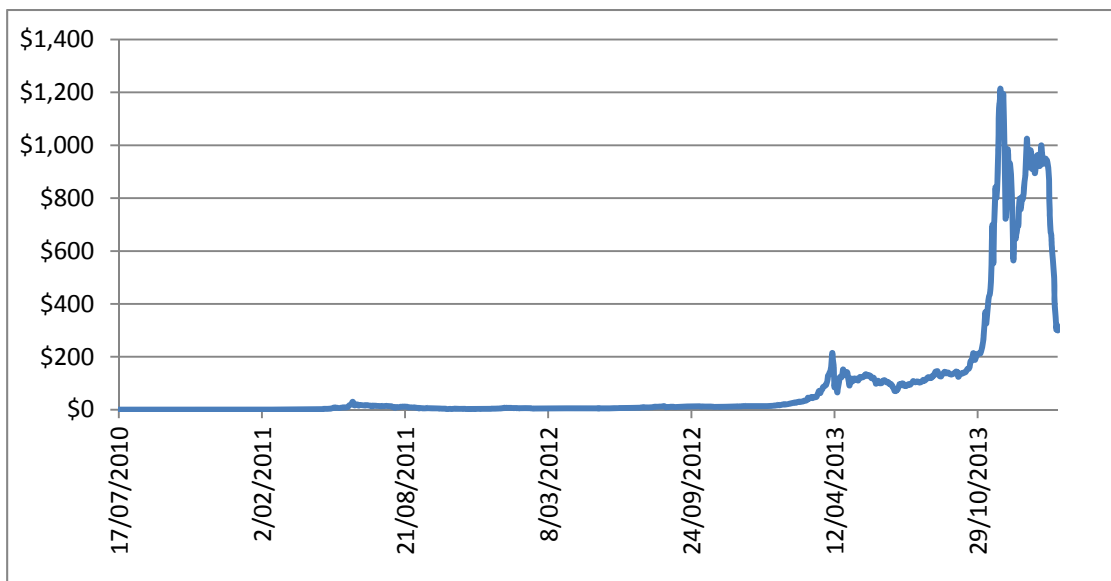


Figure 2: Mt. Gox USD bitcoin trading volume over the sample period

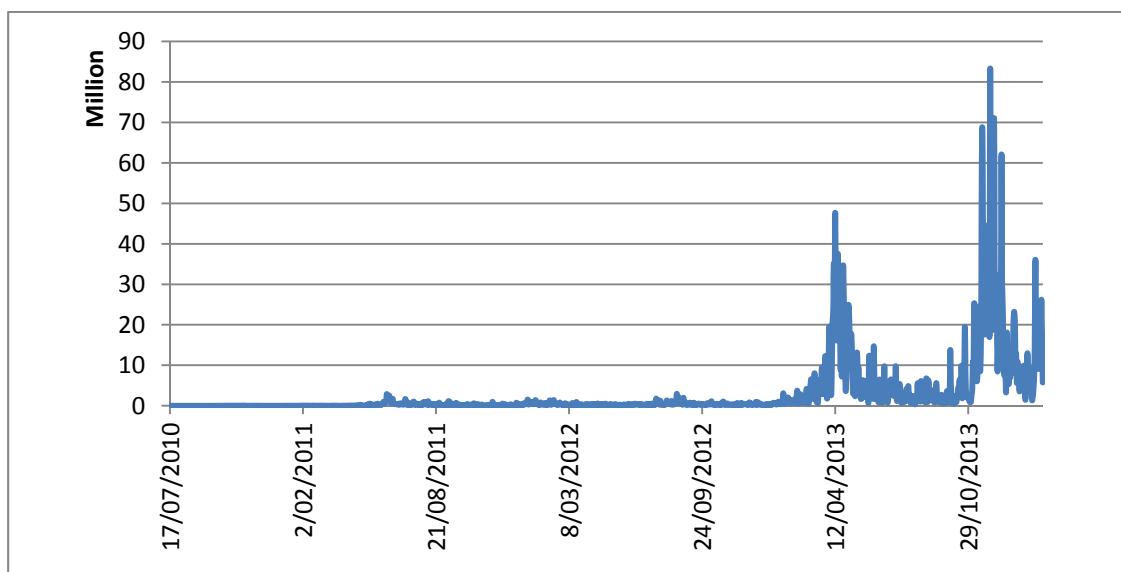


Figure 3: Mt. Gox USD bitcoin prices in log scale over the sample period

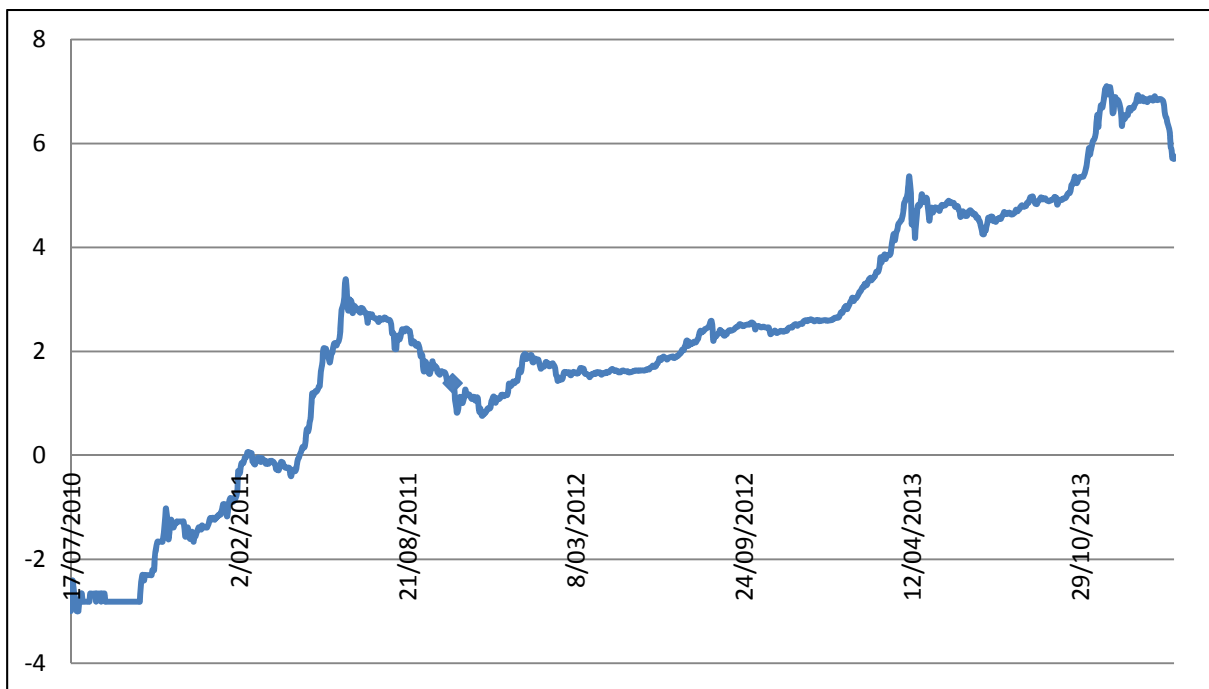


Figure 4: The GSADF test result on the log of Mt. Gox bitcoin price series over the sample period

