Chapter 1

Bubbles on Bitcoin Price: The Bitcoin Rush

Dominique Guegan^{*,†,§,¶} and Marius-Cristian Frunza^{†,‡,||}

^{*}*Paris-1 Panthéon-Sorbonne, 106 bd de l'Hopital, 75013, Paris, France*

[†]*Ural Federal University (UrFU), Ekaterinburg, Russia*

[‡]*LABEX ReFi, Paris, France*

[§]*University Ca'Foscari, Venezia, Italy*

[¶]*dominique.guegan@univ-paris1.fr*

^{||}*mfrunza@urfu.ru*

1. Introduction

In 2014, *Fortune* magazine published an igniting article on Jeffrey Robinson,¹ one of the world's biggest financial crime authors who tackled cryptocurrencies, in a harsh way especially Bitcoin. The article made a very pessimistic forecast for Bitcoin's legacy. The French journal *Marianne* was even more direct, qualifying Bitcoin as the new scam *à-la-mode* on the Internet.² Despite a negative and reluctant reception from part of the public, cryptocurrencies are without any doubt the main financial innovation since the credit derivatives. Many libertarian economists see this new "virtual" currency as the new Holy Grail of a 21st century global economy trapped in a long

¹Jeffrey Robinson argues that the Bitcoin movement will end in tears for the little guy. <http://fortune.com/2014/10/24/bitcoin-fraud-scam/>.

²Marianne, Bitcoin, The giant scam on Internet. http://www.marianne.net/Bitcoin-l-arnaque-geante-sur-internet_a231609.html.

recovery post-crisis scenario. Its advocates pledge for its advantages as sources of progress in the electronic economy and also for democratizing global trade and the access to currencies.

Bitcoin, by far the most popular, surfaced in 2013 (Figure 1) when its exchange rate with the US dollar rallied from almost nothing to 1,000 dollars for one Bitcoin, thereby leading most likely to the first virtual financial bubble.

Looking back at the history, it appears that alternative payment methods are not new and many solutions like PayPal, Apple Pay, and Google Wallet, which are still based on fiat currency, represent viable solutions mainly for e-commerce. Beyond these digital ways of using fiat money, new digital currencies have risen over the past two decades, cryptocurrencies being only a subcategory of digital currencies (Lee, 2015).

Attempts to create a distributed digital currency date from 1990 with DigiCash Inc., founded by David Chaum (Chaum *et al.*, 1990). DigiCash introduced eCash as probably the first cryptocurrency. Despite some initial popularity, eCash did not survive the 2000 Internet bubble (Frunza, 2015).

In 1971, when the Nixon administration liberated the US dollar from the Breton Woods' covenant, which implied a monetary mass backed by gold, many economists predicted the beginning of the country's economic decline. Nixon's idea that the dollar is backed by confidence remained one of America's fundamental doctrines. And yet investors had an appetite for a currency backed by gold and the opportunity came with the Internet era in early 2000, when digital gold currencies surfaced. Most of those second-generation digital currencies like iGolder, gbullion, and e-gold were in fact electronic money backed by one ounce of gold, which was stored for a fee. Their legacy was short as the companies that ran those currencies were either shut down by the Federal Government for various offenses or faded away due to heavy regulatory burdens (Frunza, 2015).

Figure 1: Bitcoin market price evolution. (a) Bitcoin–USD exchange rate reached the 1,000 dollars level toward the end of 2013 and 19,000 dollars in December 2017. (b) Bitcoin market capitalization in million US dollars is mainly driven by the exchange rate.

The main motivation, however, behind this study is to assess the sharp explosions in Bitcoin's price that occurred in 2014 and 2017. The econometric features and the price efficiency are channeling consistent facts on the economic nature of the Bitcoin in relation to other investments.

These aspects were explored by previous researches including MacDonell (2014) who used auto-regressive moving average functions to explain trading values, then applied log-periodic power law models in an attempt to predict crashes. Bouoiyour *et al.* (2016) used empirical mode decomposition and showed that despite the fact that Bitcoin is usually labeled as a purely speculative asset, it is extremely driven by long-term fundamentals (above 1 year). Dyhrberg (2016) tested the hedging capabilities of Bitcoin by applying the asymmetric GARCH methodology showing that Bitcoin can clearly be used as a hedge against stocks in the Financial Times Stock Exchange Index.

Another crucial issue related to the efficiency of the Bitcoin price is the role of speculation. Blau (2017) tested whether the unusual level of Bitcoin's volatility is attributable to speculative trading. Dwyer (2015) explained how the use of these technologies and limitations on the quantity produced can create an equilibrium in which a digital currency has a positive value and also summarizes the rise of 24/7 trading on computerized markets in Bitcoin in which there are no brokers or other agents.

This chapter enriches the literature related to Bitcoin's econometric features and explores these features. When looking at its statistical features, Bitcoin seems closer in nature to a commodity than to classic currency. The efficiency tests support this finding. The main results are focused on the presence and around the timing of bubbles in the Bitcoin–USD rates. The chapter is organized as follows: Section 2 discusses the nature of Bitcoin from a qualitative point of view, Section 3 explains the particularities of Bitcoin prices and explores the market efficiency test, Section 4 describes the methodology for bubble testing introduced by Phillips *et al.* (2013), Section 5 presents the results of bubbles tests and Section 6 concludes with a brief summary.

2. Bitcoin: Is Bitcoin a New Currency?

A first particularity of Bitcoin compared to other digital currencies is in the fact that it uses open source software, which is not owned by any one company, and there is no legal entity behind it (Lee, 2015). Nevertheless, a dedicated team that does the maintenance of the software does exist. The software that allows the interface with the Bitcoin universe can be downloaded freely, and the system runs through a decentralized and fully distributed peer-to-peer network.

This implies that all hardware terminals involved are connected to each other and each terminal can leave and rejoin the network at its convenience, and will later accept the information supplied by other terminals as the authoritative record. The basic idea in this way of functioning revolves around the concept of *blocks*, which incorporate the information about the previous validated transactions. In the world of physical currency, this would mean that the holder of a coin or a note would be able to trace all the previous owners of the money since its inception as well as all the transactions. The complete history of transactions is stored such that anyone can verify who the owner is of a particular group of coins. The blocks are aggregated in historical order in a blockchain. The number of transactions in a block is limited in size at 1,000,000 bytes to support quick propagation and reduce anomalies. The size of each transaction is determined by the number of inputs and outputs of that transaction. The transaction information is included in the body of a block. When a Bitcoin holder is connected to the system and reads the inputs from the blockchain, they have available the history of what happened previously in terms of transactions. The blockchain is thus like a general ledger, carrying the track of transactions, and is available to everybody at any given time.

Few studies including that of Burniske and White (2017) assessed Bitcoin's and generally cryptocurrencies's economic nature. When looking at the historical time series of Bitcoin–USD exchange rate, it can be easily observed that Bitcoin appreciated massively since 2013 as shown in Figure 1. The currency exhibits jump and regime-change,

due to a multitude of factors, like technology advances, new arrivals in the mining arena, and changes in the confidence for both crypto- and real currencies. At the dusk of the financial crisis, cryptocurrencies appeared as a solution in order to provide an alternative tool to the failing classic financial system. The increasing lack of confidence in the banking system that culminated with the Lehman default in September 2008, and the perspective of deposit holders of their losing economies, inflamed the speculation around cryptocurrencies. They are perceived by some as a *deus-ex-machina* able to deal with the current situation. Cryptocurrency bypasses not only the financial system but also the governmental authority related to the financial system. For these reasons, Bitcoin and the similar underlyings represent more than a simple currency.

Scholars seem to find consensus (Selgin, 2013) in considering Bitcoin and generally virtual currencies as a “synthetic” commodity because they share features with both commodity money and fiat money. Bitcoin offers its owner an alternative that carries value in the same way stamps or art objects do. Thus, Bitcoin is more like a digital commodity that has a circumstantial intrinsic value, related to investor propensity toward it. The only difference from commodities is that it does not carry any physical/real value (besides the value of the hardware used for mining). Bitcoin could be perceived as virtual good or service used for transactions as simple as electricity or gas that is used for functioning houses and industries. This argument, juxtaposed with the econometric features discussed further in Table 1, makes Bitcoin move a commodity than a currency.

Bitcoin also offers its owner a unique right to exert financial activities at the international level, without passing through the classic system. In this new-system, there are or there should be no issues related to the country of residence of the parties and the regulation specific to those jurisdictions. The new Matrix is libertarian and is equal in terms of rights to trade or transfer money despite the embargo or sanctions that a country, corporation or group of individuals could face. At this point, the *Matrix* has no *Mr. Smith* to deal with the less compliant miners. This point gives Bitcoin a

similar right-to-transfer-freely value in the same way that CO₂ or SO₂ allowances give their owners the right to pollute.

2.1. *Econometric models*

Statistics of the Bitcoin–USD rate (Table 1) underline that the returns exhibit strong kurtosis and high variance. Also, the time series show a positive significant asymmetry. The Jarque–Bera test indicates non-Gaussian features. In terms of distribution fit, the Normal Inverse Gaussian looks like the best candidate, as shown in Figure 2.

When looking at the annualized volatility of the Bitcoin–USD exchange rate exhibited in Figure 3, it appears that the cryptocurrency has more fluctuations than other forex markets. Even the US dollar to Russian ruble rate, since the Donbass crisis, has lower volatility levels (around 50%) than Bitcoin–USD. European CO₂ pollution rights and British power prices have volatility levels comparable to Bitcoin–USD rate, reinforcing the above-mentioned hypothesis about, Bitcoin’s nature.

The analysis of the persistence in returns with the autocorrelation function reveals a strong effect of volatility clustering (Figure 4), similar to what can be observed in many commodities markets from the energy complex.

Table 1: Descriptive statistics for the daily returns on Bitcoin–USD exchange rate.

Metric	Value
Mean	0.004289975
Maximum	0.6418539
Minimum	−0.4783052
Standard deviation	0.05841347
Skewness	1.485072
Kurtosis	21.60493
Jarque–Bera test	54327 (p -value = 0.00)

Notes: The series exhibit strong kurtosis and high variance. The Jarque–Bera test indicates non-Gaussian features (January 2010–February 2018).

Figure 2: Distribution fitting for the Bitcoins–USD daily returns. (a) Histogram of the fit for the Normal Inverse Gaussian compared to the Gaussian distribution. (b) QQ plot for the observed returns against the NIG fit.

Table 2 shows the results of fitting GARCH models with various innovations to the daily returns of the Bitcoin–USD rate. The best fit in terms of Bayesian Information criteria (BIC) corresponds to the GARCH model with NIG innovations, thereby underlining the fat-tails effects.

A deposit holder in a specific currency bears in mind many of the aspects related to this very basic investment. First, the perspective of the currency and of the underlying economy, second the interest rate, and last but not the least the creditworthiness of the banks taking the deposit if the bank is located in the currency domestic country. The strengthening of the American dollar during 2014 compared to the European currency is a very good example to underline the first point. Since the Eurozone crisis, the American economy observed a faster and stronger recovery relative to the European Union and many analysts forecasted the US dollar going toward, parity with the Euro. Thus, based on this appreciation one could expect to see deposit flight toward the US currency.

Figure 3: Volatility of the Bitcoin-USD exchange rate: Benchmark with other underlyings.

In the case of a cryptocurrency, it would be very difficult or almost impossible to make any judgments regarding the economy that backs the currency. In fact the only reasoning would be linked to the degree of confidence merchants have toward that particular currency. Interest rates are another argument for holding deposits in fiat currency, but in the case of cryptocurrencies, the interest rate seems to be a very complex topic. Currently, a Bitcoin account holder does not receive interest in the same way a Yen deposit holder does.

The point of the deposit guarantee scheme which is proposed for almost all developed countries for deposits lower than 100,000 dollars (euros) is out of scope in the case of the cryptocurrencies, at least until banks will adopt one of them.

Figure 4: Autocorrelation in the Bitcoin-USD rates. (a) ACF for the daily returns. (b) ACF for the squared daily returns.

So the question relative to the true nature of Bitcoin (or other virtual/cryptocurrencies) is crucial before entering into further discussions about the Bitcoin-USD rates. Looking at its pure econometric features, it can be observed that Bitcoin is as different from a classic currency as can be.

The presence of persistence in returns, clustering in volatility, and fat tails in Bitcoin-USD exchange rate underline the fact that

Table 2: GARCH fit parameters.

Parameter	GARCH			GARCH-NIG			GARCH-STD		
	Value	Std	<i>p</i> -value	Value	Std	<i>p</i> -value	Value	Std	<i>p</i> -value
ω	0.000068	0.000037	0.066	0.000052	0.000023	0.025	0.000047	0.000022	0.03
α	0.158890	0.027404	0.00	0.196502	0.023891	0.00	0.198569	0.022786	0.00
β	0.838407	0.027757	0.00	0.802498	0.032198	0.00	0.800431	0.032863	0.00
ν							3.111196	0.119759	0.00
ζ				0.185832	0.033286	0.00			
ξ				0.324860	0.040720	0.00			
LL	4688.52			5241.528			5195.99		
BIC	−3.4186			−3.8171			−3.7867		

Notes: Successful fitting of GARCH model to the daily returns of Bitcoin–USD rate underlines the existence of clustering in volatility. GARCH(1,1) model with Normal Inverse Gaussian innovation provides the best results.

Bitcoin should be regarded differently from others currencies. From its features, Bitcoin has a lot in common with commodities, with sudden disruptions in the supply demand equilibrium. A first similarity would be with commodities from the energy complex (electricity, gas, emissions). Jumps and spikes in energy (electricity) prices are explained by the fact that small increases in demand can inflate the price rapidly and vice versa. Oversupplies can push prices very low if there is no need for that commodity. As revealed in Figure 1, the Bitcoin–USD rate exploded in 2013 and once again in 2017. This would be very uncommon for a real currency even in a fast growing emerging economy. The shock observed over 2014 and 2018, when Bitcoin lost almost 50% of its value to the US dollar, would have catastrophic consequences if it would happen for a real currency. Nevertheless, in the commodities world these kinds of variations are very frequent as regime changes in price equilibrium operate often.

2.2. *Bitcoin and market efficiency*

As the Bitcoin becomes more popular and the flows grow in volume and frequency, the question on market efficiency rises naturally. The EUR–USD exchange is one of the most liquid markets across the globe and given its features it could be a good candidate for market efficiency. In the case of Bitcoin, the dialectic is different from what one can experience in the classic markets. A Bitcoin deposit owner is generally a Bitcoin generator if he is also involved in the mining process. The mining process induces a lot of particularities that impact the market efficiency. In a classic efficient market, all investors have homogeneous access to information and the ability to buy and sell a fraction of the available stock. If classic currency faces high and sudden depreciation, the central bank can try to address the issues by buying back currencies or altering the interest rates. Obviously, in the case of the cryptocurrency these aspects are not applicable. The concept of mining that currencies create an asymmetry among “investors” is due to the fact that not all miners have access to the same mining tools, in terms of computation speed.

Thus, some have more advantages than the others given the features of their gear. Obviously, those with stronger mining tools have a comparative advantage in price discovery. Also, each technological jump creates new sources of asymmetry among miners. In theory, this heterogeneity due to technological aspects should be attenuated with times, when the total Bitcoin monetary mass will become stable, due to the fact that mining will become more and more cost-intensive.

If technology does represent a first source of behavioral asymmetry, another source of inefficiency is the breakdown of memory and computational capacity among miners. From this point of view, miner profiles vary strongly from a solo miner to pool mining and farms. A solo miner might use some classic technology like a central processing unit, a graphical unit, or application specific Integrated Circuit (ASIC) for generating Bitcoins on a standalone basis. In theory, the average time of a solo miner using a standalone computer to solve a block is around 2,000 years. Thus, the only economically feasible solutions are either massive inflation of the mining capacity or joining mining pools. Mining farms started becoming a trend in countries where the cost of electricity and rent were cheap, energy consumption being the main variable cost in the mining process.

Certainly, a mining farm or mining pool would have a net informational advantage compared to solo miners or smaller pools. Higher capacity of solving the cryptographic game implies a higher rate of block solving, thereby giving a better view on the Bitcoin inflows. If a Bitcoin pool trades forex against a real currency, they will have more information on the volume of Bitcoin that would enter the market. Structurally, they are better and more informed than a solo miner. This is a crucial source of market inefficiency, as a pool can generate bearish or bullish momentum on the market depending on the circumstances. Power market has similar issues in countries where there are big producers or quasi-monopolies. For example, in Germany the main energy producer RWE has obviously more information on the electricity market than a small broker, due to the position of the underlying main supplier and trader.

Table 3: Tests for assessing the efficient market hypothesis (weak-form).

Test name	Statistic	Critical value (95%)
Portmanteau	0.8522142	3.8
Chow and Denning	2.115319	1.959964
Wright (R1 statistics)	5.266816	1.917136
Wright (R2 statistics)	4.338164	1.903357
Wright (S1 statistics)	4.569499	1.930746
Lo and Mackinlay test	2.115319	1.95
Wald	4.474573	3.84

Notes: The tests are performed on the time series of daily returns of the Bitcoin–USD exchange rate from July 22, 2010, to February 21, 2018, assuming a holding period of 10 trading days.

Table 3 exhibits a series of tests for market efficiency (weak-form). All test statistics computed over a holding period of 10 trading days are higher than the 95% confidence level value, thereby rejecting the efficiency of the Bitcoin–USD rate from the following perspectives.

We recall the Lo and MacKinlay (1988) test for the random walk process, where they used stock-market returns. This involves the use of specification tests based on variance estimates. In particular, the method exploits the fact that the variance of the increments in a random walk is linear in the sampling interval, a hypothesis rejected in the case of the Bitcoin–USD rate in the Chow and Denning (1993) test, a generalization of the Lo and Mackinlay test, obtained from the maximum absolute value of the individual which statistics which confirms the results. Wright’s (2000) alternative nonparametric test using signs and ranks is complementary to Lo’s test. Both signs (R1 and R2) and ranks (S1) statistics reject the hypothesis of random walk. The Richardson and Smith (1991) version of the Wald test and the portmanteau test by Escanciano and Lobato (2009) for auto-correlation also confirm these findings. Markets do not become efficient automatically from their origin.

It is the actions of investors and various traders, sensing arbitrage opportunities and putting into effect schemes to generate profits from the markets, that make markets efficient.

From another point of view, bringing efficiency in the Bitcoin system is related to the mining capacity. Not all miners possess the

same mining capacity and the mining capacity needs to increase much faster compared to the Bitcoin transactions. A double-edge effect can occur. On the one hand, there could be a massive increase in the number of new investors that purchase and trade Bitcoins, without mining. On the other hand, the mining capacity remains constant or progresses at a much lower level. This could be the reason why

Figure 5: Efficiency tests applied to Bitcoin–USD daily returns for a rolling window of 200 days: Portmanteau test, Wright test, Wald test, Lo and MacKinlay test and Chow–Denning test.

the Bitcoin–USD became massively inefficient during 2013, when a massive inflow of demand was followed in an asymmetric manner in terms of mining ability. Figure 5 exhibits the random walk test applied over a rolling window of 200 days for a holding period of 10 trading days. The nonparametric Wright test underlines the non-random walk effect that occurred in 2013.

3. Testing for Bubbles

Since the South Sea Company frenzy in the early 18th century, financial markets faced many bubbles and as many crashes, the Black Tuesday from 1929 being one of the most dramatic ones.

The features of financial bubbles are explored in the academic literature. Zhao (2014) studied the unusual and puzzling stock price performance of USEC Inc., a company specialized in producing enriched uranium for nuclear plants. In July 2013, the stock price surged as much as 10 times over a mere 16 day trading period without apparent value-changing information being released and the hypotheses of market manipulation and speculative bubbles were analyzed.

Geng and Lu (2017) studied bubble-creating stock attacks, an interesting form of market fraud which is a mixture of manipulation and speculative bubbles in which speculators implicitly coordinate to pump up the stock price without any significant fundamental news and exploit behavioral-biased investors. The research provided empirical evidence in the Chinese stock market, underlining that stocks with low mutual fund ownership and stocks with high average purchase costs of existing shareholders are more likely to be attacked.

Johansen *et al.* (1999) presented a synthesis of all the available empirical evidence in the light of recent theoretical developments for the existence of characteristic log-periodic signatures of growing bubbles in a variety of markets.

Few straightforward methods for testing a market for bubbles are proposed by the recent works of Peter Phillips (Phillips *et al.*,

2011, 2013). These approaches come with enhanced versions of the augmented Dickey–Fuller (ADF) test (Dickey and Fuller, 1979 and Said and Dickey, 1984): sup ADF test and generalized sup ADF (GSADF) test.

The testing procedure for the ADF test for a unit root in time-series is based on the model as follows:

$$y_t = \alpha + \beta y_{t-1} + \gamma_1 \Delta y_{t-1} + \cdots + \gamma_p \Delta y_{t-p} + \varepsilon_t, \quad (1)$$

where p is the lag order and $\varepsilon_t \propto N(0, \sigma_t)$.

Phillips *et al.* (2013) improved the basic version of the ADF test with a recursive approach that involves a rolling window with the implementation of the ADF style regression. If the rolling window regression sample starts from the r_1^{th} fraction of the total sample and ends at the r_2^{th} fraction of the sample, where $r_2 = r_1 + r_w$ and r_w is the fractional window size of the regression, the empirical regression model can then be written as follows:

$$y_t = \alpha_{r_1, r_2} + \beta_{r_1, r_2} y_{t-1} + \gamma_{r_1, r_2}^1 \Delta y_{t-1} + \cdots + \gamma_{r_1, r_2}^p \Delta y_{t-p} + \varepsilon_t, \quad (2)$$

where α_{r_1, r_2} is the intercept, β_{r_1, r_2} the coefficient on a time trend, and p the lag order of the auto-regressive process computed on the window $r_1 T$, $r_2 T$. Under these circumstances, the unit root null hypothesis is $\mathbf{H}_0 : \beta = 1$ and the explosive root right-tailed alternative hypothesis is $\mathbf{H}_a : \beta > 1$. The ADF statistic (based on this regression is denoted by $\text{ADF}_{r_1}^{r_2}$ Phillips *et al.* (2011) where ADF_0^1 is the ADF statistics for the full sample. Right-sided unit root tests provide information about explosive or submartingale behavior³ in the time series and can be used in speculative bubble detection.

The sup ADF test introduced (Phillips *et al.*, 2011) for single bubble detection searches for the maximum value of the test, for all forward looking windows for a given sample. The window size r_w

³It should be recalled that a discrete-time submartingale is a price time series $y_1, y_2, y_3, \dots$ satisfying $\mathbf{E}[y_{n+1} | \Phi_n] \geq y_n$, Φ_n being the filtration with all information at the moment when the price is y_n .

varies from the smallest sample window noted r_0 to the maximum value of 1. In terms of the formalism in equation (2), the starting point r_1 is 0; and the end point of r_2 is chosen in such a way that the statistic $\text{ADF}_0^{r_2}$ is maximized, and the fact can be written as

$$\text{SADF}(r_0) = \sup_{r_2 \in [r_0, 1]} \text{ADF}_0^{r_2}. \quad (3)$$

A further improvement of the sup ADF test is the GSADF leveraging the idea of repeatedly running the ADF test regression on subsamples of the data in a recursive fashion. Thus, in addition to varying the end point of the regression r_2 from r_0 to 1, the GSADF test allows the starting point r_1 to change from 0 to $r_2 - r_0$. The GSADF statistic searches for the biggest ADF statistic over all possible starting points and possible window lengths,

$$\text{GSADF}(r_0) = \sup_{r_2 \in [r_0, 1], r_1 \in [0, r_2 - r_0]} \text{ADF}_{r_1}^{r_2}. \quad (4)$$

The bottom line of this test is to search for a period where the prices exhibit consistently increasing exponential trajectories.

4. The Bitcoin Rush

Gold miners have been attracted throughout history to regions rich in gold and silver. From Dacia in antiquity, to California and Alaska in the early years of the industrial revolution, to Sierra Leone and Kirghistan in the present days, the perspective of generating quick profits from mining ignited the spirit of many generations. Similarly,

Table 4: Testing for bubbles.

Test name	Statistic	Critical value (95%)
sup ADF test	27.56	0.99
GSADF test	27.56	1.92

Note: Sup ADF and GSADF have both statistics above the 95% critical value, thereby rejecting the null hypothesis of a no-bubble-episode in the considered Bitcoin–USD time series.

Figure 6: Bubble detection tests on Bitcoin prices. The sup ADF test indicates two bubbles during 2013. The GSADF test indicates also another mini bubble during 2012.

the foreseeable gains that the cryptocurrency world seems to generate through a new Bitcoin rush translated not only in a high number of new comers in the crypto-world but also a bubble of Bitcoin’s value. As of 2017, the number of Bitcoin wallet users is around 10 million, compared to only 80,000 in early 2013.

The assessment of the formation and propagation of bubbles in markets can be utilized in many ways. The results obtained from applying this bubble detection approach to the Bitcoin–USD rate daily returns is shown in Table 4. The critical values from a 95% confidence level are the asymptotic values communicated in Phillips *et al.* (2013).

Figure 6 shows the evolution over time for the statistics of two tests and indicates the corresponding timing of the bubbles. The sup AGF test indicates two bubbles during 2013 and one in 2017. The GSADF test indicates also another mini bubble formed during 2011.

Bubbles are periods when markets change their features dramatically and also give a positive and biased signal to behavioral investors. During bubble periods, market prices are far removed from the fundamentals and investors may take irrational decisions. Bitcoin is no exception.

The episodes of the Bitcoin bubble resulting from the Phillips test are shown in Table 5. The main bubble episodes are from November 2013 to January 2014, when Bitcoin peaked at USD 1,151, and from May 2017 to January 2018 when Bitcoin peaked at USD 19,498.68. The 2013 bubble ended after the MtGox event (Frunza, 2015) that

Table 5: Timeline of Bitcoin bubbles.

Bubble timeline	Initial price (USD)	Peak price (USD)
2011-02-01/2011-02-18	0.95	1.1
2011-04-23/2011-06-13	1.7	35
2013-03-05/2013-03-05	40.04	237
2013-11-06/2014-01-11	258.23	1,151
2017-05-07/2018-01-21	1,560.41	19,498.68

Note: The main bubble episodes are from November 2013 to January 2014 and from May 2017 to January 2018.

Figure 7: Efficiency tests applied to Ethereum/USD daily returns for a rolling window of 200 days: Portmanteau test, Wright test, Wald test, Lo and MacKinlay test and Chow–Denning test.

led to the theft of 10% of all available Bitcoins at the time. The 2017 bubble ended when Bitcoin futures were listed on the Chicago Mercantile Exchange.

The same tests applied to Ethereum prices (Figure 7) showed no bubble effect as presented in Table 6. Thus, the price inflation of

Table 6: Testing for bubbles.

Test name	Statistic	Critical value (95%)
sup ADF test	-0.78	0.99
GSADF test	-0.15	1.92

Note: sup ADF and GSADF have both statistics above the 95% critical value, thereby rejecting the null hypothesis of a no-bubble episode in the considered Ethereum USD time series.

Bitcoins was not reflected with the same amplitude on Ethereum markets. An extended study on the presence of bubbles on altcoins will be addressed in a future research.

5. Conclusions

This chapter explores the occurrence and the timing of bubbles in the Bitcoin–USD rates. Being a very new and innovative currency, Bitcoin exhibits unique features that makes it different from other currencies. The problem is studied in two steps: first, the econometric features and the efficiency hypothesis are assessed and second, a bubble test procedure is developed and tested on Bitcoin prices.

The results from the first part indicate that Bitcoin’s econometric features include volatility clustering and heavy tails. The weak efficiency hypothesis was breached on few occasions, during the 2013 price inflation.

The second part shows that bubble episodes occurred in 2013 and in 2017. The bubble effect on other altercoins will be addressed in a future study.

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