Boost and Burst: Bubbles in the Bitcoin Market[†]

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Abstract. This study investigates bubbles and crashes in the cryptocurrency market. In particular, using the log-periodic power law, we estimate the critical time of bubbles in the Bitcoin market. The results indicate that Bitcoin bubbles clearly exist, and our forecast of critical times can be verified with high accuracy. We further claim that bubbles could originate from the mining process, investor sentiment, global economic trend, and even regulation. For policy makers, the findings suggest the necessity of monitoring the signatures of bubbles and their progress in the market place.

Keywords: Cryptocurrency, Bubble, Crash, Log-periodic power law.

1   Introduction

Cryptocurrency is a digital asset that relies on blockchain technology[1] and has attracted much attention from the public, investors, and policy makers. Due to its rapid growth with extreme market volatility, concerns and warnings of bubbles in the cryptocurrency market have continued. As per the dot-com bubble of the 1990s, bubbles might occur during the introduction of new technology [1,2]. Though it is uncertain whether the post-bubble effect on society is good or not [2], bubbles could create disastrous harm and danger as a consequence. Accordingly, understanding bubbles in the cryptocurrency market and implementing effective policies are vital to prevent such disruptive consequences.

As the market has grown, more than 3,000 cryptocurrencies have emerged. However, Bitcoin still holds leadership: Bitcoin consistently dominates others, the so-called altcoins,[2] in terms of market capitalization, number of transactions, network

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[1] "Cryptocurrency" is a medium of exchange designed as a digital currency (and/or asset) which uses cryptography, i.e., blockchain technology, to control the transactions and creation of new units. "Blockchain" is a growing list of blocks that are linked records of data using cryptography.
[2] "Altcoins" refers to all cryptocurrencies other than Bitcoin: the other cryptocurrencies launched after Bitcoin.

effects, and price discovery role [3-5]. Therefore, the literature largely discusses the turmoil in the cryptocurrency market through the experiences of Bitcoin [4,6]. Moreover, there have been several well-known episodes of bubbles and crashes in the Bitcoin market that seem to have similar patterns at first glance, but the origins and consequences are clearly different because of the internal structure of price formation (e.g., over-/undervaluation of price, market efficiency, and investor maturity) and/or environmental changes (e.g., governmental policy, public sentiment, and global economic status) [7]. In this context, we attempt to evaluate two well-known episodes of Bitcoin bubbles and the crashes that followed.

A bubble indicates excessive asset value compared to market equilibrium or that price is driven by stories and not by fundamentals [8,9]. A market bubble includes its own limit and can "burn" itself out or experience "explosion" associated with several endogenous processes [10]. Much of the relevant studies attempted to test a speculative bubble with unit root tests [11-13] using the present value model [14,15]. Besides, the log-periodic power law (LPPL) model has gained much attention with several successful predictions made on well-known episodes about bubbles and crashes [13,16-22], so it has recently been applied to the Bitcoin market as well [23,24]. In this study, we aim to address the following questions: Is there a clear signature for bubbles in the Bitcoin market? Can we precisely predict a critical time at which the bubble in the Bitcoin market will burst? What can be the possible inducers that contribute to the emergence of bubbles?

2 Method and Data

2.1 Log-Periodic Power Law (LPPL)

The LPPL combines both the power law and endogenous feedback mechanisms [10,25,26]. The former indicates the existence of a short head that occurs rarely but has enormous effects and a long tail that occurs frequently but with much less impact. The latter, which imply underlying self-organizing dynamics with positive feedback, describe herding behavior in the market place such as purchases in a boom and sales in a slump. Therefore, we can predict the critical time through a signature of faster-than-exponential growth and its decoration by log-periodic oscillations [17,19]:

$$Y_t = A + B(t_c - t)^{\beta}\{1 + C\cos[\omega\log(t_c - t) + \phi]\}, \qquad (1)$$

where $Y_t > 0$ is the log price at time t; $A > 0$ is the log price at critical time t_c; $B < 0$ is the increase in Y_t over time before the crash when C is close to 0; $C \in [-1, 1]$ restricts the magnitude of oscillations around exponential trend; $\beta \in [0, 1]$ is the exponent of the power law growth; $\omega > 0$ is the frequency of fluctuations during a bubble; and $\phi \in [0, 2\pi]$ is a phase parameter.

In this study, we estimate the critical time by mainly following Dai et al. [19]: In the first step, we produce the initial value for seven parameters using a price gyration method [27-29]; and in the second step, we optimize these parameters using a genetic algorithm [30,31].

2.2 Data

The Bitcoin market operates for 365 days with a 24-hour trading system. Thus, we retrieve daily closing prices, i.e., Bitcoin Price Index, from Coindesk[3] at 23:00 GMT. The data span for two periods: from July 2010 to December 2013 and from January 2015 to December 2017. We choose two well-known episodes of bubbles and crashes[4]: Period 1 is from July 18, 2010, when the Bitcoin market was initiated, to December 4, 2013, when the biggest peak reached at 230 USD in 2013; and Period 2 is from January 14, 2015, when the lowest point was reached after the crash in Period 1, to December 16, 2017, when the historical price run reached nearly 20,000 USD. Then we convert the data into log returns:

$$x_t \equiv \ln\left(\frac{p_{t+\Delta t}}{p_t}\right),$$

where p_t represents Bitcoin price at time t.

Table 1 summarizes the descriptive statistics for each period. The data from Period 1 are more volatile, skewed, and leptokurtic[5] than those from Period 2. The high volatility is due to decentralization and speculative demands [27]. Bitcoin exhibits positive skewness, implying more frequent drastic rise in price and investor risk-loving attitude. Lastly, excess kurtosis is obvious, indicating that a high proportion of returns are at the extreme ends of distribution.

Table 1. Summary statistics of the log returns.

	Obs.	Mean	Max.	Min.	Std.	Skewness	Kurtosis
All	1,859	8.86×10^{-3}	6.48×10^{-1}	3.75×10^{-1}	6.76×10^{-2}	1.10	11.23
Period 1	849	1.48×10^{-2}	6.48×10^{-1}	3.75×10^{-1}	8.48×10^{-2}	0.97	8.11
Period 2	734	6.88×10^{-3}	2.54×10^{-1}	$- 2.19 \times 10^{-1}$	4.36×10^{-2}	0.63	6.46

3 Results and Discussion

Table 2 reports parameter estimates from the LPPL including critical time t_c, and clearly shows the proximity of critical time, model implied, to the actual crash. All estimated parameters are well within the boundaries reported in the literature. Two

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[3] www.coindesk.com

[4] In technical perspective, the identification of a peak of the bubble is based on the following two conditions: (i) prior to the peak, there is no higher price than the peak from 262 days before; and (ii) after the peak, there is more than 25% decreased ongoing prices by following 60 days [19,26]. In the economic context, the bursting of a bubble, for example, dramatic collapse of the market, could bring the economy into an even worse situation and dysfunction in the financial system.

[5] A leptokurtic distribution exhibits excess positive kurtosis: kurtosis has a value greater than 3. In the financial market, a leptokurtic return distribution means that there are more risks coming from extreme events.

conditions such as (i) $B < 0$ and (ii) $0.1 \leq \beta \leq 0.9$ ensure faster-than-exponential acceleration of log prices [28]. In particular, the exponent of power law β during Period 2 is 0.2, which corresponds to many crashes on major financial markets $\beta \approx 0.33 \pm 0.18$ [29]. Both angular log-frequencies ω are higher than the range of 6.36 ± 1.56, which is observed in major financial markets [30,31]. Moreover, the value of ω during Period 2 exhibits the presence of second harmonics at around $\omega \approx 11.5$ [29], which is associated with strong amplitude and hides the existence of fundamental ω, which is common in emerging markets [31].

Table 2. LPPL parameters of the best fit.

Time Span[6]	t_c	A	B	β	C	ω	ϕ
Jul 18, 2010 – Nov 04, 2013	1,249 Dec 16, 2013	5.44	- 0.01	0.90	- 0.25	9.70	3.46
Jan 14, 2015 – Nov 16, 2017	1,079 Dec 27, 2017	13.19	- 1.92	0.20	- 0.01	11.28	3.02

Figure 1 displays the data and prediction results of the LPPL model for the two periods. Each curve represents the best fit among estimates.[7] A strong upward trend is observed, indicating fast-exponential growth of Bitcoin price and providing clear evidence of a bubble in the market. Moreover, the prediction of critical times, namely corresponding estimate, exhibits the typical hallmark of the critical time of the bubble in 2013 and 2017 (vertical arrows with red color) with high accuracy around the actual crash. The actual crashes of each term date are Dec 4, 2013 and Dec 16, 2017 (see Appendix A).

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[6] We also opt for the data period as follows: (i) the time window starts from the end of the previous collapse (the lowest point since the last crash); (ii) the day with the peak value is the point of the actual bubble burst; and (iii) the endpoint is from one month before the critical point [25,26].

[7] To reduce the possibility of false alarms, we conduct two diagnostics to demonstrate the robustness of our prediction. (i) Firstly, using unit root tests (augmented Dickey-Fuller and Phillips-Perron tests) with 0 to 4 lags for each term, we conclude that the residuals do not have a unit root but are stationary at the 1% significance level. (ii) In addition, the crash lock-in plot (CLIP) further confirms that our results, in particular for the value of the predicted t_c, are robust and stable.

(a) Period 1   (b) Period 2
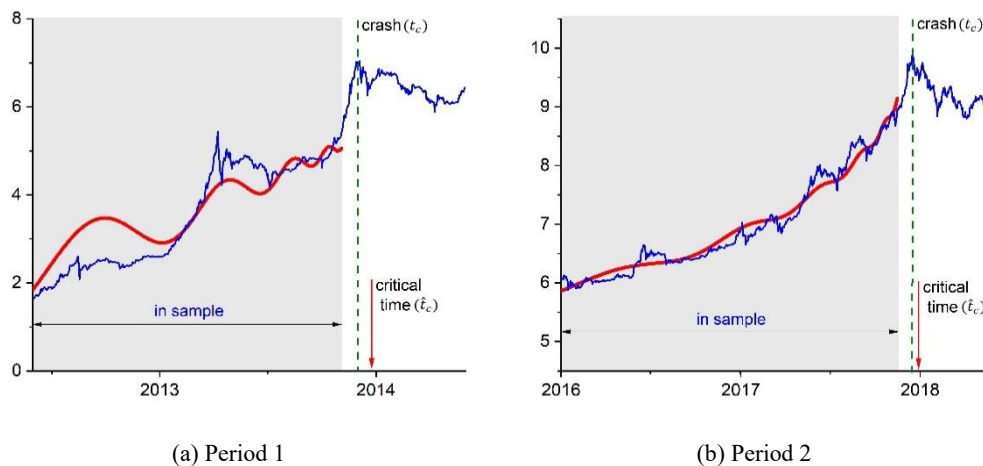
Fig. 1. Logarithm of Bitcoin prices and corresponding alarm.

We hypothesize the plausible origins of the Bitcoin bubbles. First, the decline of a newly mined volume, along with an increase in mining[8] difficulty, generated a supply-driven impact on the market (Appendix B: Figure 3). Moreover, changes in investor sentiment affected the internal structure of price formation on the market and made the price turbulent, namely boosting and bursting the bubbles (Appendix B: Figure 4). A negative surprise in global markets, such as consecutive devaluations of the Chinese Yuan (CNY) in 2015–2016, also functioned as a catalyst to rebalance the portfolios of Chinese investors (Appendix B: Figure 5). Furthermore, the Chinese government's banning of cryptocurrency trading on major exchanges in early 2017 provoked the bubble. The sudden prohibition policy merely accomplished a quick transition of the trading currency from CNY to other key currencies, specifically USD (Appendix B: Figure 6).

4   Conclusion

In most countries, the regulatory environment appears largely opposed to Bitcoin in the early stages, and one of the key concerns has been the risk of bubbles and the consequent crashes. There is distinct evidence of multiple bubbles in the Bitcoin market, and we have successfully estimated crashes, showing the typical hallmark of the critical times in 2013 and 2017. We attribute the emergence of bubbles to the mining process, investor sentiment, global economic trend, and the regulatory action. The

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[8] Mining is a metaphor for the extraction of valuable things or materials from various deposits. In cryptocurrency, when computers solve complex math problems on the Bitcoin network, they produce new Bitcoins or make the Bitcoin payment network trustworthy and secure by verifying its transaction information.

findings strongly suggest the necessity of ex-ante monitoring, and policy makers should be aware that technology, society, and even regulation could induce bubbles.

Appendix

A. Diagnostic tests

We further demonstrate the accuracy of our predictions using unit root test for the LPPL residuals of the best fit. As shown in Table 3, for both the ADF and PP tests with 0 to 4 lags, we reject the null hypothesis, meaning that the residuals do not have a unit root but are stationary.

Table 3. Unit root test for the residuals of the best fit.

Time Span	ADF	PP
Jul 18, 2010 – Nov 04, 2013	0.02**	0.02**
Jan 14, 2015 – Nov 16, 2017	0.00***	0.00***

Note: ** and *** indicate that we can reject the null hypothesis that a unit root is present in a time series at the 5% and 1% significance levels, respectively.

Moreover, we implement the CLIPs with the rolling window, tracking the progress of a bubble, and examining whether a probable crash is imminent [32]. The two CLIPs for both periods shown in Figure 2. indicate that the results of recursive estimations converge upon the actual crash dates. These further demonstrate that the closer the crash is, the more robust and precise result the LPPL model proposes.


(a) Period 1   (b) Period 2
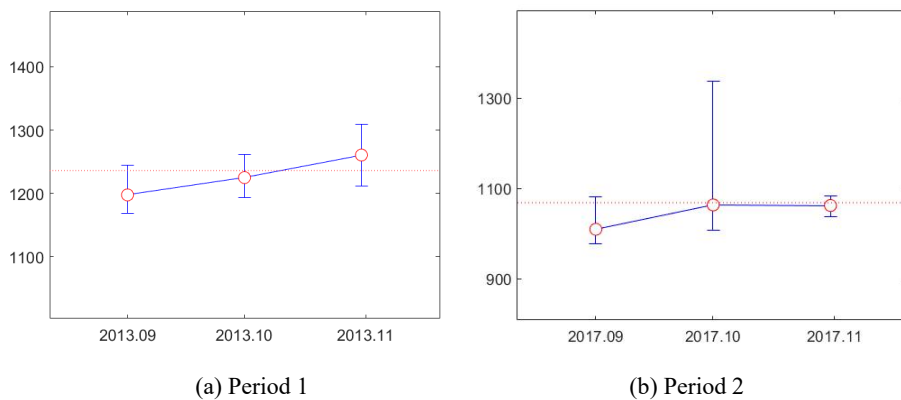
Fig. 2. Crash lock-in plots with rolling estimation window.

Note: We implement a CLIP by changing the last observation of our sample from one to three months before the actual crash. We can see that our results are stable and robust. Error bars represent the 95% confidence interval for the forecast of critical time.

B. Plausible origins of the Bitcoin bubbles

The amount of newly mined volume is one of the distinctive causes of the bubbles. As mining difficulty increased, the supply of new Bitcoins became less predictable, and it further increased the price. As presented in Figure 3(b), the net spillover from the newly mined volume to Bitcoin price increased sharply around the two standard deviations for the two bubble periods.
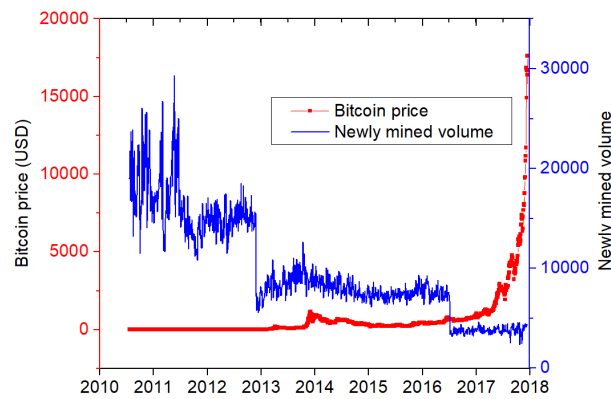

(a) Mining volume and the Bitcoin price
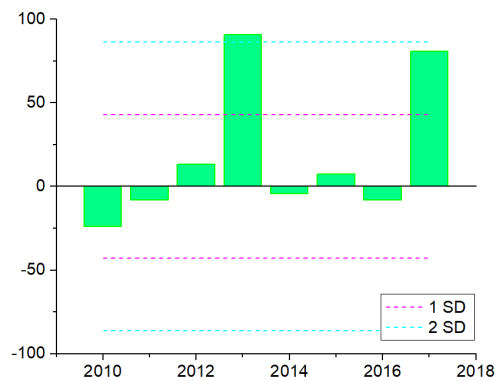
(b) Net spillover effects from newly mined volume to the Bitcoin price

Fig. 3. Newly mined volume and spillover effects.

We use Google Trend as a proxy for investor sentiment [33]. As shown in Figure 4, the result exhibits a positive linear relationship between the investor sentiment and Bitcoin price during the two periods. Specifically, the Bitcoin price is more sensitive to sentiment proxy during Period 2 than during Period 1. We conjecture that this sentiment could be a substituting factor, further explaining the change in the price, especially in the volatile early-stage market.
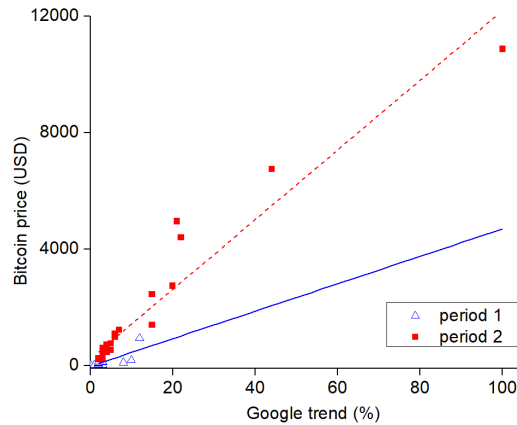


Fig. 4. Investor sentiment and the Bitcoin price.

There were two distinguishable phases in the development of the Bitcoin market in Period 2. The first phase originated from the devaluation of the CNY during 2015 and 2016. We can recognize the opposite direction in the price of Bitcoin and CNY: appreciating Bitcoin and depreciating CNY from early 2015.
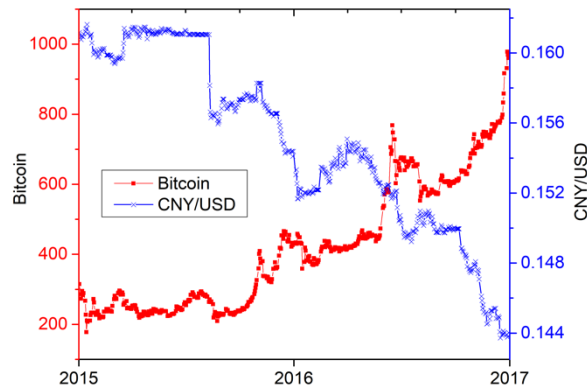
Fig. 5. Global economic trend and the Bitcoin price.

The second phase, in the development of the Bitcoin market in Period 2, was triggered by the Chinese regulatory policy introduced in early 2017. The People's Bank of China implemented policies against three major cryptocurrency exchanges (BTC China, OKCoin, and Huobi) in January 2017, and announced that the Bitcoin trading platform was running outside its business scope and provided shadow financing to investors. Accordingly, this policy resulted in a quick transition of the trading currency from CNY to other key currencies, mainly the US Dollar. Since then, the upward trend of the Bitcoin price has continued.
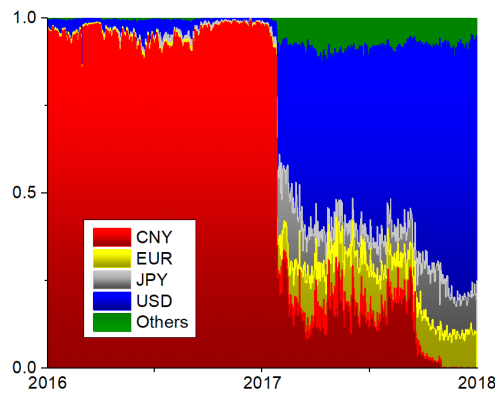
Fig. 6. Regulatory action and trading currencies.

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