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Was the 2017 Crash of the Crypto-currency Market Predictable?

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ABSTRACT

The cyber-space of crypto-currency market is a main issue in terms of security and stability. The novelty and the high volatility of crypto-currencies question their speculative nature. Recently, the crypto-currency price exponentially increased and reached an important burst in the end of 2017. The objective of this article is to detect and test the prediction of this crypto-currency market crash using the Log-Periodic Power Law model (LPPL). We consider 2 main crypto-currencies, Bitcoin and Ether. We find that the LPPL model allows to estimate the date of the crash in the crypto-currency market depending on the window sensitivity.

Keywords: Crypto-Currencies, Bitcoin, Bubble, LPPL, Speculation

1. INTRODUCTION

The crypto-currency market represents an important issue for cyber-security. It provides a cyber-space that allows to make financial exchanges using crypto-currencies in which all the exchange system is based on cryptographic principles. In this system, third-parties (i.e. financial institutions such as banks or central banks) are replaced by a technology, the "Blockchain" which ensures proper exchanges execution in a transparent distributed network. This space is vulnerable to cyber-attacks, especially on exchange platforms. An example for this is the recent hack of a South Korean exchange platform, named Coinrail (loss of \$40 million in June 2018). In addition, trust in crypto-currencies is often questioned, notably regarding their cryptographic principles as well as the high volatility of their price.

Bitcoin is the most famous crypto-currency whose value progressively increased during the period 2015-2016, reaching \$1,002.5 on January 2, 2017. It continued to grow in an exponential way reaching \$19,395.83 on December 18, 2017 (i.e. an increase of 90% in approximately one single year) before experiencing a 40% decrease in the following days (\$13,668 on 25 December 2017) and a continuous decrease in the following months until it reached the value of \$6,000 in September 2018.

This volatility raises the question of the crypto-currencies economic value and more specifically the existence of a bubble. Based on historical bubbles such as the "Tulip mania" or the "Dot-com" bubble, Chang et al. [1] find common sources for the apparition of bubbles: the "showmanship" of the promoters (convince investors about a new asset and inflate the prices) and the speculation about a new product, venture or technology. They

highlight the "positive feedbacks loop" of this phenomenon, a concept shared by [2].

Indeed, Filimonov and Sornette define financial bubbles as "transient upward accelerations of the observed price above a fundamental value. The paradox is that the determination of a bubble requires, in this definition, a precise determination of what is the fundamental value. But, the fundamental value is in general poorly constrained. In addition, a transient exponential acceleration of the observed price that would be taken as the diagnostic of a developing bubble is not distinguishable from an exponentially growing fundamental price" [2]. Different empirical methods have been used to detect and predict a bubble and more precisely a crash after an important exponential increase in prices. Moreover, the methods are generally trying to detect a bubble using the fundamental value of the assets.

The "Log-Periodic Power Laws" (hereafter LPPL) based on the work of Johansen et al. [3] suggests a model for the detection but also for the prediction of the critical time of crash without using the fundamental value. This model is widely used in the research on financial markets [4] [5] [6] [7] [8] [9] ; and more recently, in the research on the crypto-currency market where the fundamental value remains an important issue [10] [11] [12].

This research aims to estimate the date of the major crypto-currency market crash in December 2017/January 2018 based on historical data and using the LPPL model. For this purpose, we are going to consider two main crypto-currencies to test this crash, namely: Bitcoin and Ether (from the Coindesk website). The main contribution is to examine the major peak/burst of the crypto-currency market related to the December 2017/January 2018 period which has not been studied extensively in the literature. In addition, this research allows to test the ability of the LPPL model to detect a bubble and moreover predict a crash date in the crypto-currency market as well as to analyze its adjusting sensitivity (especially the window issue).

The rest of the paper is structured as follows: The literature review of crypto-currencies and bubbles is presented in Section 2. Section 3 describes the Bubble model. Section 4 discusses the results. Section 5 proposes some robustness tests. Section 6 presents the conclusion.

2. LITERATURE REVIEW

Since the creation of the so-called "crypto-currencies" such as Bitcoin in 2008 [13], scholars are trying to define their nature without converging. The existing literature shows evidence that crypto-currencies may be considered either as a currency [14] [15] [16], as a commodity such as gold [17] [18] [19] [20] or as an asset such as common stocks [21] [22] [23]. Godsiff [24], Umeh [25] and Gangwal and Longin [26] highlight that crypto-currencies generate speculative bubbles due to their asset nature rather than a currency, in addition to the rapid increase of their price beside their high volatility.

Following this idea, recent researches attempt to examine empirically the economic value of crypto-currencies such as Bitcoin and show some bubbles evidence using a common theoretical framework (namely the LPPL model). Especially, if we take a look at the graph of Bitcoin price in the Figure 1, we can notice a first peak/burst in the end of 2013 where Bitcoin's price reached, for the first time, a value of \$1,000. This first peak/burst was studied in the existing literature. As early as 2015, Cheah and Fry [11] provide two main results: first, they detect that the crash of December 2013 was preceded by a bubble, and second, they state that the fundamental value of Bitcoin is 0. One year later, the same authors go further about the same peak of December 2013 using this time a second crypto-currency, Ripple, in addition to Bitcoin. The authors find that: first, the existence of negative bubbles (defined as the result of dramatic price falls compared to a speculative bubble that is the result of dramatic price increases) for both of the aforementioned crypto-currencies and second, the existence of a spillover from Ripple to Bitcoin [12]. Analyzing the factors that drive the value of Bitcoin, MacDonnell [10] confirms the same conclusion regarding the Bitcoin prices crash in December 2013. The results also confirm that the LPPL model is relevant for the crypto-currency market. In 2017, the price of Bitcoin was again growing exponentially. Using the same method mentioned before, Corbet et al. [27] find that Bitcoin and Ether were in a phase of bubble on November 9, 2017.

At the time of writing this article (February 2019), the supposed phase of a growing bubble reached its peak (\$19,395.83) on December 18, 2017. In this article, we are going to focus on this supposed bubble for the Bitcoin and Ether crypto-currencies.

3. Bubble Models

As the Chairman of the US Federal Reserve, Alan Greenspan, stated in 2002, "We at the Federal Reserve considered a number of issues related to asset bubbles—that is, surges in prices of assets to unsustainable levels. As events evolved, we recognized that, despite our suspicions, it was very difficult to definitively identify a bubble until after the fact—that is, when its bursting confirmed its existence."¹. Scholars distinguish between "irrational" and "rational" bubbles. The former is explained by psychological effects (market sentiment, "irrationally optimistic expectations, fashions and fads") whereas the latter exists when traders expect to "sell an overvalued asset at an even higher price" [11]. The same authors present different sources of rational bubble creation: self-filling expectations (rational bubble), mispricing of fundamentals (intrinsic rational bubble)

and endowment of irrelevant exogenous variables with asset pricing value (extrinsic rational bubble).

Thus, detection of bubbles appears as a difficult and challenging task. Since the 1980s, scholars are attempting to study this phenomenon suggesting several models on the burst probability [28] [29] [30]. The main idea is that crashes are unpredictable events with a low probability of occurrence and with huge consequences when they occur (the Black Swan Theory [31]). The picture is different since the work of [6] [32] [33] [34] [35] [36]. Indeed, these articles focus on extreme events (outliers), called "dragon kings", considering the latter as rare and predictable [37]. They suggest to use a statistical model adapted from physics: the Log-periodic Power Laws model (LPPL) in order to predict the crash of an endogenous bubble [34].

LPPL model

The LPPL model defines "a bubble as a transient faster than exponential growth resulting from positive feedbacks" [2] which can be explained by two main parts:

1. **Power Law**: concerns the super exponential growth of price until a critical time where prices burst.
2. **Log periodicity**: concerns the price oscillations that go faster until the critical time.

The first appearance of the LPPL model in finance was applied by Sornette to test the market crash of October 1987, then for real-estate markets in the US during the mid-2006 bubble [4], in the UK during the mid-2004 bubble [5], and in the commodity market with the oil bubble in July 2008 [7]. The same model was applied for stock markets' crashes, the 1990s Nasdaq bubble [9] and the Chinese stock market (2005-2007 and 2008- 2009) [8] and more recently in the crypto-currency market (see the previous literature part). Whilst the prior literature focuses on performing an ex-post estimation (i.e. when the crash already happened using historical data) of the crash occurrence, recent studies of these authors attempt to predict crashes using current data. Their research is therefore kept secret until the estimated date of the crash has passed (The Financial Bubble Experiment²). The model hypotheses appear to fit the crypto-currency market: the assets pay no dividend and there is no need for incorporating the interest rate. Moreover, the fundamental value is not considered in the LPPL model. Since the fundamental value of the crypto-currencies represents an ongoing debate, we consider the LPPL model match up with the crypto-currencies. In addition, the model does not consider risk aversion, information asymmetries and market clearing conditions.

In this model, there are two kind of traders, the rational ones who act in the same way and the noisy ones that are herding and are at the origin of the bubble growing. All traders have to decide between buying or selling depending on the decision of the others and on external influences. In the LPPL model, the "order state" that is, a state in which all traders take similar decisions (namely short positions) is considered as a bubble, whereas the "disorder state" concerns the normal market conditions when sell and buy orders coexist. In addition, a bubble can be self-sustained (meaning that the bubble can continue to grow up by itself) because of the positive feedbacks related to increasing risk and interaction between agents.

Johansen et al. [34] present two levels of modeling. At the macro modeling level, a higher probability of crash implies an acceleration in the price increase meaning that investors ask for a higher return because they take a higher risk in a bubble

¹ Remarks by Chairman Alan Greenspan; Economic volatility at a symposium sponsored by the Federal Reserve Bank of Kansas City, Jackson Hole, Wyoming August 30, 2002

² <https://www.ethz.ch/content/specialinterest/mtec/chair-of-entrepreneurial-risks/en/financial-crisis-observatory.html>

situation. At the micro level, agents trade in a network in which a local behavior can have an impact on the general behavior, called "local self-reinforcing imitation" and be modeled by the hierarchical diamond lattice.

The novelty of this model is the estimation of the critical date, t_c , on which the crash occurs in addition to detect if a bubble occurs or not. Based on this context, Johansen et al. [34] model the equation for the evolution of asset prices before a crash with 7 parameters (3 linear: A, B and C; and 4 non-linear: β , ω , φ and t_c):

$$y_t = A + B * (t_c - t)^\beta * [1 + C * \cos(\omega * \log(t_c - t) + \varphi)] \quad (1)$$

where y_t is the log prices, $A > 0$ is the value of y_t if the bubble remains until the critical time t_c , $B < 0$ is the decrease in y_t over time before crash if C is 0, C is the magnitude of fluctuations around exponential growth, $t_c > 0$ is the critical time, $t < t_c$ is any time in the bubble before the critical time t_c , β is the exponent of power law growth (power law accelerations of price), ω is the frequency of fluctuations during the bubbles and $0 < \varphi < 2\pi$ is the shift/phase parameter.

To fix the problem of local/global minimum, the equation 1 can be rewritten as:

$$y_t = A + B * f_t + C * g_t \quad (2)$$

where y_t is the log price,

$$f_t = (t_c - t)^\beta \quad (3)$$

$$g_t = (t_c - t)^\beta * \cos(\omega * \log(t_c - t) + \varphi) \quad (4)$$

In order to identify a bubble, β and ω have to follow the following constraints obtained empirically [38]. Indeed, Johansen [3] find the following thresholds using different markets and time periods.

$$\begin{cases} B < 0 \\ 0.33 - 0.18 \leq \beta \leq 0.33 + 0.18 \\ 6.36 - 1.56 \leq \omega \leq 6.36 + 1.56 \end{cases} \quad (5)$$

Eq. (2) allows to estimate an OLS model to obtain A, B and C. However, we have to find [β , ω , φ and t_c] in a first place.

Fitting LPPL model and implementation

Geraskin and Fantazzini [39] present different ways of fitting the LPPL model (most of which use meta-heuristic algorithms):

Original two step non-linear optimization: the first step consists in finding initial candidates (using taboo search, alternative grid search or peaks detection search). Then, the second step consists in a Levenberg-Marquardt squares non-linear algorithm based on the initial candidates of the first step [6] [40] [41] [42].

Genetic Algorithm: based on "Darwin evolution", this algorithm reflects the process of natural selection. The first step of this algorithm is to generate the initial population of 50 members with a vector of parameters (in our case, the 4 non-linear parameters). The second step, called the breeding mechanism, is to choose the highest 25 members to realize an offspring (mean of 2 parents). As much as 25 members are drawn according to the mutation mechanism in the third step. Finally, we add all the new members together with the initial population (50+25+25) and then we choose the 50 best members [43].

Two step/Three step ML approach - anti-bubbles:

the main idea is to reverse the time series and then estimate the LPPL model using Broyden, Fletcher, Goldfarb, Shanno algorithms with cubic/quadratic step length methods (STEPBT).

Other suggestions: in the LPPL literature, we find other fitting methods such as the Simulated Annealing Algorithm or the Evolution Algorithm.

Among these possibilities, Filimonov and Sornette [2] suggest a modification of the Eq. (2) in order to use the Evolution Algorithm instead of Meta-heuristic algorithms which are quite difficult to apply. Indeed, these authors [2] modify the model in order to obtain 3 non-linear parameters instead of 4. The main idea is to decompose the variable C into 2 variables (C_1 and C_2) containing the phase φ in order to obtain 3 non-linear parameters (β , ω and t_c) and 4 non-linear parameters (A, B, C_1 and C_2). Eq. (2) can be rewritten as:

Let define:

$$X = (t_c - t) \quad (6)$$

$$C_1 = C * \cos \varphi \quad (7)$$

$$C_2 = C * \sin \varphi \quad (8)$$

And finally, we obtain this equation:

$$y_t = A + B * (t_c - t)^\beta * C_1 * X^\beta * \cos(\omega * \log(X)) + C_2 * X^\beta * \sin(\omega * \log(X)) \quad (11)$$

Thus, there are henceforth 3 non-linear parameters instead of 4 that allows to prevent the using of meta-heuristic algorithm presented above. Filimonov and Sornette [2] modify the aforementioned conditions (see Eq. (5)) called the "stylized features of LPPL":

$$\begin{cases} B < 0 \\ 0.1 \leq \beta \leq 0.9 \\ 6 \leq \omega \leq 13 \\ C_1^2 + C_2^2 < 1 \end{cases} \quad (12)$$

The conditions on parameters B and β allow to respect the "faster-than-exponential" growth of prices. Parameter ω is within a range [6;13] so that it is not too slow, or too fast. Finally the condition on the parameters C_1 and C_2 makes sure that the hazard rate remains positive [10] [38].

Thus, we implement the LPPL model in R³ using the function CMA_ES (Covariance Matrix Adaptation Evolution Strategy)⁴. CAM_ES is an Evolutionary algorithm based on a stochastic search method. The Evolutionary algorithm runs on a continuous search space compared to the Genetic Algorithm that operates on trees. The former algorithm is used for non-linear non-convex with unconstrained or bounded constraint optimization problems. The efficiency of the CMA_ES algorithm has been tested and validated by various studies [44] [45] [46] [47].

Data

In order to be able to predict the bubble crash using the LPPL model, our study makes use of the Coindesk website by extracting the daily closing prices of Bitcoin and Ether in USD. Bitcoin prices cover the period of October 2013 until November

³ based on <https://github.com/gchevalley/lpl/>

⁴ <https://cran.r-project.org/web/packages/cmaes/cmaes.pdf>

2018, whereas Ether prices are from August 2015 until November 2018 (see Figure 1).

First, we run the LPPL model for the Bitcoin crash at the end of 2017. As we can see on Figure 1, the actual date of the Bitcoin crash is on December 18, 2017 (\$19,395.83). The size of the window as well as the choice of the starting and ending date is a sensitive task. Brée and Joseph [38] suggest that the starting day be the "day on which the index reaches its lowest value". Based on the literature and graphical analysis, we consider 3 starting days for Bitcoin: October 1, 2017 which represent the 60-days before the actual crash ("window 1") [10]; January 1, 2017 ("window 2"); April 1, 2017 ("window 3"). Regarding the ending date, we decide to make this date flexible following the "expanding window" [8].

Second, the actual crash date for Ether is shifted some days after, precisely on January 14, 2018 with a price of \$1,397.27. Similarly, we consider two different starting dates: November 1, 2017 for the 60-days window ("window 1") and May 1, 2017 for the second window ("window 2").

4. Results

Bitcoin

In this part, we report the main results regarding Bitcoin. As we said, the detection of bubble is linked to the constraints applied to the parameters (see Eq. (5) and Eq. (12)). Indeed, if the above conditions of the parameters, β and ω , are met, then the detection of a bubble is positive, and therefore we obtain an estimated critical time, t_c . The first window is the one that gives us the most acceptable results: 9 results respecting the constraint from the Eq. (12) and 17 results respecting the conditions from the Eq. (5). The best window is from October 1, 2017 to November 11, 2017 which estimates the crash date on December 19, 2017 (one day after the effective crash). The second window that starts in January 2017 provides only results that respect constraints presented in the Eq. (5) (83 results) and finds an estimated, t_c around December 17, 2017 (one day before the effective crash). The third window does not give us any acceptable results to analyze with respect to the constraints from the Eq. (5) and Eq. (12). More precisely, we observe that the more t_2 (the ending date of the window) is close to the effective crash date, the more the LPPL model fits a t_c close to the effective date. Moreover, we can notice, as well, that the identification of a bubble depends on the respect of this criteria: most of the estimated results that indicate a bubble are the ones which follow the constraints of the Eq. (5).

Ether

The Ether "bubble" ends a few days after the Bitcoin's one (January 14, 2018). In the same vein, we fit the LPPL model according to different windows, first, the 60-days window started on mid-November 2017 which corresponds to the first high increase in the Ether price (see Figure 1), then the price slightly decreased before it grew up again in May. This is why window 2 starts in May 2017. In the same sense, only the window which starts in November 2017 ("window 1") provides significant results (13 for constraint from Eq. (12) and 24 for constraint from the Eq. (5)). The best result is given by the window of November 1st, 2017 to November 26, 2017 with a critical time of January 14, 2018 (the actual date). Similarly, the starting and ending dates of the windows play a significant role in fitting the critical time (the nearest t_1 and t_2 provide a closer t_c related to the reality).

5. Robustness

We provide in this section different types of robustness tests in order to test the influence of the number of iterations. We select the "best" window by crypto-currency, the one that appears to respect the conditions in all the optimization and we test the stationarity of their residuals.

The first robustness test consists in increasing the number of iterations in order to obtain more robust results: we iterated 1,000, 10,000 and 100,000 times the model. Based on these different simulations, we always find that the best window for Bitcoin (i.e. the one which provides a critical crash close to the reality) is the window of October 1, 2017 to November 30, 2017. Table 1 and Figure 2 show the fitting LPPL for this specific window. We implement the same methodology for testing Ether and we find results slightly different compared to the initial optimization when we increase the number of iterations. The best window seems to be November 1, 2017 to January 6, 2018. Table 1 and Figure 3 show the fitting LPPL for that window.

Based on the fixed windows, we run tests of stationarity (unit root tests) because if the logarithm price in bubble phase is attributed to a deterministic LPPL component, the residuals of the LPPL fitting can be modeled by a mean-reversal Ornstein-Uhlenbeck [6] [36]. For the best windows, we use Augmented Dickey-Fuller, Phillips-Peron and KPSS tests. The null-hypothesis of ADF and PP is unit root (non-stationary) whereas the null-hypothesis for KPSS is stationarity. We find that residuals from the fitting LPPL model of Bitcoin regarding the window of October 1, 2017 to November 30, 2017 are stationary. This result confirms those obtained by the different optimizations procedures that always display this window as the best one to predict the actual crash. Ether also obtains stationary results even though the ADF test exhibits non-stationary residuals which may explain the fact that the studied window is only significant when the iteration of the optimization is high. In addition, we notice that sometimes the estimated crash, t_c , is not the actual crash but a "small" decrease in prices that actually happened but does not have the same impact as the main actual crashes. For example, the LPPL results of Bitcoin suggest an expected crash on November 12, 2017 (t_c is 2017,864) based on the window of October 1, 2017 to November 3 2017. Indeed, during this period the Bitcoin price is reaching \$7,400 on November 9, 2017 before decreasing at \$5,675 a few days after (November 13, 2017).

6. Conclusion

This paper makes use of the Log-Period Power Law model of Johansen et al. [34] to predict the crashes on the crypto-currency market using the 2 most popular crypto-currencies, Ether and Bitcoin. We find that the LPPL model allows to detect a critical time close to the reality and seems to be an interesting method to predict bubbles in the crypto-currency market. However, the results depend on the selected window, on the number of iterations of the optimization process as well as on the criteria provided previously by empirical analysis. The contributions of this paper are twofold: first, it provides an application field (the crypto-currencies) to the LPPL and bubble literature; second, this paper contributes to the crypto-currency literature, especially the one relating to bubbles by testing ex-post the main peak/burst in 2017.

Regarding the methodology and robustness, it could be interesting to fit the LPPL model using a "shrinking window" in

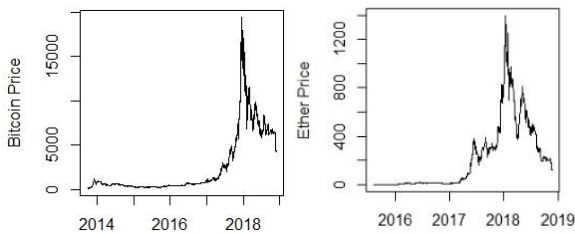
addition to an "expended window" as well as checking other diagnostic tests [36], and sensitivity tests, such as the Lomb spectral analysis used in [8] to confirm the robustness of our results.

Regarding the data, further research could test crash prediction on some other crypto-currencies and the dependence to each other in the same vein as [12] and [48] (that focus on "Efficient Crashes").

In addition, recently in November 2018, the data showed a general decrease in prices in the crypto-currency market after a stability during the previous months without any exponential increase before. The LPPL model is a model in which the bubble is self-sustained and in which the hypotheses are constrained. Because markets are not perfect, some frictions are present, such as information asymmetries. Risk aversion and interest rate could also be included in a bubble model. Some existing research shows how Bitcoin is related to monetary policy decisions, such as a "store of refuge" during the Cyprus crisis in 2014, or related to the FED monetary policy. Additional research may also focus on the issue whether Bitcoin has economic value.

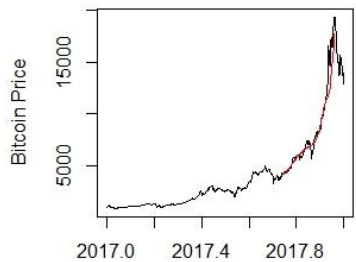
7. Tables and Figures

Figure 2 - Bitcoin and Ether US Prices



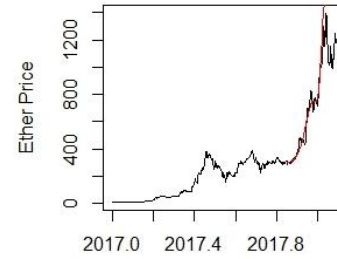
Key: This figure shows the Bitcoin and Ether Price expressed in US dollar (USD) over the period October 2013 to November 2018 for Bitcoin (left) and August 2015 to November 2018 for Ether (right).

Figure 3 - LPPL fitting Bitcoin Market Price



Key: This figure shows the fitting LPPL model for Bitcoin Market Price expressed in US dollars (USD) over the period October 1, 2017 to November 30, 2017. The red line is the LPPL Eq. (11).

Figure 1 - Figure 2 - LPPL fitting Ether Market Price



Key: This figure shows the fitting LPPL model for Ether Market Price expressed in US dollars (USD) over the period November 1, 2017 to January 6, 2018. The red line is the LPPL Eq. (11).

Table 1 - The best fitting LPPL windows for Ether and Bitcoin

	Bitcoin	Ether
t_1	2017-10-01	2017-11-01
t_2	2017-11-30	2018-01-06
t_c	2017.963	2018.051
Expected Date	2017-12-19	2018-01-17
β	0.51	0.29
ω	5.00	5.10
A	9.96	8.83
B	-3.51	-4.79
C_1	-0.22	0.27
C_2	0.01	0.05

Key: This Table present the "best" windows for Ether and Bitcoin that respect the criteria and provide a critical date, t_c , close to the actual date based on several optimizations increasing the number of iterations. t_1 is the starting date of the window, t_2 is the ending date of the window, t_c is the critical time and Excepted date is its corresponding date. β , ω , t_c , A , B , C_1 and C_2 are presented in the Eq. (11).

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