Are cryptocurrencies real financial bubbles?
Evidence from quantitative analyses

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Abstract

The growth of peer-to-peer exchanges and the blockchain technology has led to a proliferation of cryptocurrencies and to a massive increase in the number of investors who actually negotiate digital money. Cryptocurrencies trade at prices which is mainly driven by investor sentiment, becoming a potential source of financial bubbles and instabilities.

In this work, we draw upon the close relationship between statistics, physics and mathematical finance to apply quantitative models to the study of Bitcoin and Ether, two of the most famous cryptocurrencies. Our bubble detection methodology combines the Log Periodic Power Law (LPPL) model, originally created by Johansen, Ledoit and Sornette (JLS), and the statistical model developed by Phillips, Shi, and Yu (PSY). In particular, we employ three different versions of LPPL model, i.e. Ordinary Least Square (OLS), Generalised Least Squares (GLS) and Maximum Likelihood Estimation (MLE), and two PSY statistical tests (BSADF and BSADF*). We find that, during the sample period 1st December 2016 – 13th December 2017, Bitcoin shows strong bubble signals, starting in May-September 2017 and reaching a critical time in mid December 2017. Ether, instead, presents bubble signals in mid-June 2017, corresponding to the crash actually observed on 12th June, while the sharp rise observed in November 2017, though, is too short for our models to detected valid bubble signals.

These findings are consistent with the large crash (-30%) observed in the cryptocurrency markets between 17th and 22nd December 2017. Further study on other cryptocurrencies and Initial Coin Offerings (ICOs), an innovative structure for raising funds to support new ideas and ventures, is in progress.

JEL classifications: C22, C32, C51, C53, C58, E41, E42, E47, E51, G1, G17

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1. Introduction

Since Bitcoin brought cryptocurrencies into the spotlight in 2009, the number and diversity of digital coins expanded dramatically [1], [2]. There are two key innovations behind cryptocurrencies: the technology employed and the way they are governed. The first innovation, technology, is the blockchain, a public ledger that contains all transaction records since the inception of the currency, with the name of users stored under their public addresses (which are strings of characters akin to bank account numbers). The second innovation of cryptocurrencies is its decentralized governance [3].

The extraordinary returns generated by cryptocurrencies such as bitcoin has led to a frenzy of investment activity and interest from traditional investors. However, most of the established and highly traded cryptocurrencies, such as Bitcoin and Ether, qualified as commodities rather than securities, and thus not subject to securities laws. Hedge funds that trade in these cryptocurrency commodities, or “crypto funds,” fall almost entirely outside the extensive securities regulations that would apply to traditional hedge funds [4].

Cryptocurrencies, unlike other alternative investment classes that have real assets, are digital assets and their fundamental value is hard to comprehend. Their store of value can be related to the development of the technology underneath, such as blockchain, and to the computing power engaged in mining. As a result, the cryptocurrency market is mainly driven by investor sentiment, leading to a high volatility [5]. Holders of large amounts of bitcoin are often known as whales. They can send prices plummeting by selling even a portion of their holdings. About 40 percent of bitcoin is held by perhaps 1,000 users, they can coordinate their moves or preview them to a select few. Bittrex, a digital currency exchange, recently wrote to its users warning that their accounts could be suspended if they banded together into “pump groups” aimed at manipulating prices [6].

There’s no agreed authority for the price of Bitcoin, and quotes can vary significantly across exchanges. For example, In Venezuela, where inflation is skyrocketing and basic necessities run in short supply, many took to bitcoin mining despite government efforts to crack down on miners [7]. In Zimbabwe, following a lack of confidence in the local financial system, the cryptocurrency has traded at a persistent premium over $10,000. Russia is preparing to issue a government-backed cryptocurrency, the CryptoRuble. Unlike decentralised
cryptocurrencies such as bitcoin and Ether, there is no mining involved in CryptoRuble – all transactions are recorded via blockchain and verified by a centralised government authority [8].

Prices and volumes are difficult to assess. Bloomberg publishes a price that draws on several large bitcoin trading venues [9]. The CME CF Bitcoin Reference Rate (BRR) provides a once-a-day reference rate for the US dollar price of bitcoin which aggregates the trade flow of major bitcoin spot exchanges during a calculation window into the US dollar price of one bitcoin. The BRR is designed around the Iosco principles for financial benchmarks. Bitstamp, GDAX, itBit and Kraken are among the exchanges currently contributing the pricing data for calculating the BRR [10].

Lately, the sharp rise in Bitcoin has sparked analogies to past irrational financial exuberance, from the tulip mania to the dotcom boom and bust. In fact, in the middle of December, Bitcoin surpassed $20,000 in a matter of hours, taking 2017’s price surge to almost 12-fold as buyers shrugged off increased warnings that the largest digital currency is an asset bubble. A possible explanation for the appeal of Bitcoin is also given by the limited nature of supply, as new coins can only be created through complex calculations, and the total number of coins is limited to 21 million. Even as analysts disagree on whether the largest cryptocurrency by market capitalization is truly an asset, its $170 billion value already exceeds that of about 95 percent of the S&P 500 Index members [11].

A recent study investigated the behaviour of cryptocurrencies time series, finding that their dynamics is quite complex, displaying extreme observations, asymmetries and several nonlinear characteristics which are difficult to model. Differently from foreign exchange currencies, leverage effect has a substantial contribution in the volatility dynamics. On average, volatility increases more after negative shocks than after positive shocks as in the equity market, hence, crypto–currencies time–series incorporate the so–called leverage effect with some degree of heterogeneity across the series [12].

Until December 2017 no derivatives were available on bitcoin, when CBOE and CME Group launched bitcoin futures [13]. Bitcoin exchange-traded funds seem to agree on the fact that once a derivative is launched, a bitcoin ETF will follow [14].

While most global banks support the use of distributed ledgers and blockchain with innovative projects, some bankers have explicitly opposed the idea of investing in bitcoin. Most notably, JP Morgan chief executive Jamie Dimon called bitcoin a fraud, and Nobel Prize–winning economist Joseph Stiglitz, along with a host of economists and financiers, denounced the crypto rally as a craze [15], [16]. However, according to other analysts, the introduction of financial instruments indexed to bitcoin has the potential to elevate cryptocurrencies to an emerging asset class, such as gold. Bitcoin has not yet overtaken gold in terms of investment levels, total value in circulation or transaction volumes, but it has grown rapidly and could make more progress to match or even surpass the use of gold.

In Figure 1 we show some market data related to the two cryptocurrencies, i.e. prices, market capitalizations, exchange traded volumes, historical volatilities and correlations.

Regarding trading volumes, prior to the fall in February 2014, Mt. Gox, a popular Bitcoin exchange, dominated an estimated 80-90% of the Bitcoin-Dollar trades. The bankruptcy of Mt. Gox resulted in an alleged loss of 850,000 Bitcoin leaving the troubled exchange insolvent and many customers out of pocket [17]. The exchanges today claim to have learned from Mt. Gox and present themselves as advanced models with better security mechanisms in place. The trading volumes rise again which implies that the market is fairly liquid. The trading volume during the day is closely linked to the trading times the US and European stock markets [18] The biggest change, however, could continue to be the sharp decrease in Bitcoin’s dominance should Ether and other tokens capture a larger percentage of overall trading.
The historical volatility in Figure 1 is calculated as standard deviation of logarithm returns, based on thirty daily closing prices (that is thirty business days for Bitcoin, gold spot price, EUR/USD exchange rate and thirty calendar days for Ether). We observe that Bitcoin results more volatile than any fiat currency or gold spot price and Ether shows even bigger swings. A factor that could help limit cryptocurrency volatility is an emergence of derivatives such that investors can hedge or short sell their positions by using Futures contracts [19].

The correlations between Bitcoin daily returns and the daily returns of Ether, fiat currency and safe haven asset oscillate within the range -40% and +50%. Thus, adding digital currencies to a portfolio can act as a powerful source of diversification.

![Figure 1: Prices, market capitalizations, exchange traded volumes. Source: Coinmarketcap. Historical volatilities (bottom panels) are calculated using the time series of gold spot price (Bloomberg: XAU BGN Currency), EUR/USD exchange rate (Bloomberg: EURUSD BGN Currency), Bitcoin (Bloomberg: XBTUSD Currency) and Ether (Etherscan), with rolling windows including 30 market data, and normalized to 1 year. Correlation between daily returns is measured on the time series described above. Bitcoin and Ether refer to the left-hand side axis, EUR/USD exchange rate and Gold refer to the right-hand side axis.](image)

This paper is structured as follows: Section 2 describes the our methodology for financial bubble detection. Section 3 shows the procedures and analyses the results of our test for bubbles in the Bitcoin and Ether markets. Finally, Section 4 presents our conclusions.
2. Methodology

2.1. Quantitative Analysis of Financial Bubbles

Financial markets exhibit a complex organization and dynamics with individual market agents characterized also by herding behaviour, such as imitation, self-organized cooperativity and positive feedback. Such phenomena influence the dynamics of asset prices and may lead to the development of endogenous instabilities.

The origin of a positive bubble lies in the unsustainable pace of the asset market price growth fed by self-reinforcing over-optimistic anticipation. In a financial bubble, it is the expectation of future earnings rather than present economic reality that motivates the average investor and causes the divergence between the asset market price with respect to its fundamental value. The same dynamics appears in case of negative bubbles, where self-reinforcing pessimistic anticipation of future losses forces the asset market price below its fundamental value. During a positive (negative) bubble regime, the asset market price becomes unstable and very sensitive to exogenous factors, such as upcoming news with a negative (positive) consequence on the asset, that may lead to a collapse (rebound) of the asset market price.

The mainstream publications about modelling financial bubbles review econometric approaches, such as the model developed by Phillips, Shi, and Yu (PSY, see sec. 2.3). This model tests the possible explosive behaviour of the time series with respect to its fundamental value using statistical tests. Another stream of publications adopts a different approach relying on agent-based models, such as the model originally developed by Johansen, Ledoit and Sornette (JLS, see sec. 2.3). In this context, bubble regimes and large stock market crashes (rebounds) can be seen as the so-called critical phenomena studied in statistical physics in relation to magnetism, melting and other phase transitions. According to the JLS model a bubble regime is characterized by a super-exponential path generated by imitation and herding behaviour of investors and traders creating positive feedback in the market asset price that this critical point is decorated by oscillations describing instabilities generated by tension and competition between fundamentalists and noise traders. Such dynamics leads to a finite-time singularity at some future critical time, interpreted as the forecast of a possible crash or rebound for the asset price. As a proof, the implementation of this modelling technique is reported in several academic studies and is regularly applied by the Financial Crisis Observatory at ETH Zurich [29].

2.2. Previous Applications to Cryptocurrencies

Even if the industry of cryptocurrencies has grown exponentially over the past several months, to the best of our knowledge there are few applications of financial models to the study of this new markets.

MacDonell [20] used the JLS model to forecast successfully the bitcoin price crash that took place on December 4, 2013, showing how the model can be a valuable tool for detecting bubble behaviour in digital currencies. Malhotra et al. [21] investigated the reasons behind the steep rise and fall of bitcoin exchange rates in 2013-2014 applying the sequential ADF tests of PSY. The results from sequential root tests provided strong evidence of explosiveness in bitcoin exchange rates even if the unreliability of data obtained from internet limits the accuracy of empirical evidence. Corbet et al. [22] found evidence of price bubbles in Bitcoin and Ether using the PSY model. Fantazzini et al. [23] reviews the econometric and mathematical tools which have been proposed to model the bitcoin price and several related issues, highlighting advantages and limits.

2.3. Our Approach

In our study, we analyse two popular cryptocurrencies, Bitcoin and Ether, looking for clues of speculative bubbles in the time window that spans one year (from December 2016 to December 2017). The methodology used in this work is based on the two main approaches described in sec. 2.1 above: the statistical model originally created by PSY [24], [25], [26], and the Log Periodic Power Law (LPPL) model, originally created by Johansen, Ledoit and Sornette (JLS or LPPL model) [27], [28].

In order to test and qualitatively assess the confidence level of our findings, we employ different versions of JLS model, i.e. Ordinary Least Square (OLS), Generalised Least Squares (GLS) and Maximum Likelihood
Estimation (MLE [29]). The JLS-GLS approach has been used in this work, to our knowledge, for the first time [32]. Also, the PSY model statistical tests come in two flavours, i.e. Backward Supremum Augmented Dickey Fuller (BSADF and BSADF*).

The calibration of the models to the market data is a critical numerical problem. For JLS we adopt a multiple time windows calibration strategy where, for each date in the time series between December 2016 and December 2017, we run many calibrations with a variable window length. The procedure works as follows: for each historical series, we selected a maximum window length (72 points for Bitcoin, 69 points for Ether), which we moved forward with a step of one point of the series. For each step, we shifted forward the left extremum of the time window 20 times, performing each time a calibration with a decreasing number of points and then counting the number of possible bubble signals. Furthermore, since the LPPL function is non-linear and the corresponding fit function presents multiple local minima, we adopt a robust global multi-dimensional optimization approach based on genetic algorithms.

The PSY model requires, instead, an ADF test to calculate the statistics and a Monte Carlo simulation to calculate the relative confidence levels. The multiple time windows strategy is the same presented in [24], [32].

For both JLS and PSY implementations, we could reproduce previous results available in the literature [31], [32]. Since such calculations must be repeated for each combination of time series, calibration date and window, the resulting numerical effort is relevant and requires huge computational resources.

3. Results
In this section, we present the results of our analysis with JLS and PSY models applied to Bitcoin and Ether, aiming at determining whether they can represent a source of financial instabilities.

3.1. Bitcoin
The daily Bitcoin data is collected from Bloomberg (XBTUSD Currency) where the price of one BTC in USD is given by an average from the world’s leading Bitcoin exchanges. The time window analysed spans from 1st December 2016 to 13th December 2017.
BITCOIN (JLS-OLS)

BITCOIN (JLS-GLS)

BITCOIN (JLS-MLE)
Figure 2. Bitcoin results: the first three panels starting from the top show JLS model results for each calibration technique (OLS, GLS and MLE). The left axis refers to the asset value depicted in blue, while the right axis counts the number of LPPL signals represented by the black bars in correspondence of the critical time $t_c$. In red we show one LPPL fit. The last two panels show the PSY model results. The left axis refers to the asset value depicted in blue, while the right axis refers to the value of the BSADF and BSADF* statistics. The green line represents the BSADF statistic (fourth panel) or the BSADF* statistics (fifth panel); the red line represents the 95% critical value of the corresponding statistics. See Table 1 for chart interpretation. Source: Bloomberg XBTUSD Currency.

In Figure 2 we observe that both JLS and PSY models coherently show strong bubble signals, starting between May and September 2017. JLS also predicts a critical time around 15th December 2017. Since JLS does not reveal valid bubble signals around the slump observed in early September 2017 (-28% in two weeks), we may look at it as a local swing related to exogenous information flow (the Chinese restrictions on ICOs).

3.2. Ether
The Ether time series (ETH) is downloaded from Etherscan, an exchange supplying daily prices, in the time window from 1st December 2016 to 8th December 2017. Ether is a token provided by Ethereum platform, an open source blockchain-based distributed computing platform which was formed in 2016 after the fork into "Ethereum Classic" (ETC) and "Ethereum" (ETH) [33].
Figure 3. Ether results: the first three panels starting from the top show JLS model results for each calibration technique (OLS, GLS and MLE). The left axis refers to the asset value depicted in blue, while the right axis counts the number of LPPL signals represented by the black bars in correspondence of the critical time $t_c$. In red we show one LPPL fit. The last two panels show the PSY model results. The left axis refers to the asset value depicted in blue, while the right axis refers to the value of the BSADF and BSADF* statistic. The green line represents the BSADF statistic (fourth panel) or the BSADF* statistic (fifth panel); the red line represents the 95% critical value of the corresponding statistic. See Table 1 for chart interpretation. Source: Etherscan.

As shown in Figure 3 both JLS and PSY coherently present a bubble signal, started between April and May 2017. JLS also predicts a critical time around mid-June 2017, corresponding to the crash observed on 12th June. Both models do not detect valid bubble signals after June 2017. The sharp rise observed in November 2017 is too short to produce valid bubble signals, but it’s a promising candidate in the near future.

In Table 1 a summary of cryptocurrency bubble signals for each model applied is presented.
Table 1: Summary of cryptocurrency bubble signals for each model applied. JLS bubbles are expressed as average signal date ± 1 standard deviation in days (number of signals); PSY bubbles are expressed as time window and confidence level: (*) = 50% - 70% (low), (**) = 70% - 90% (medium), (***) = 90% - 100% (high).

<table>
<thead>
<tr>
<th>#</th>
<th>Asset class</th>
<th>Time series</th>
<th>JLS OLS</th>
<th>JLS GLS</th>
<th>JLS MLE</th>
<th>PSY BSADF</th>
<th>PSY BSADF*</th>
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4. Conclusions
The growth of peer-to-peer exchanges and the blockchain technology has led to a proliferation of cryptocurrencies and to a massive increase in the number of investors who actually negotiate digital money. Cryptocurrencies trade at prices which is mainly driven by investor sentiment, becoming a potential source of financial instability.

We used quantitative models to detect financial bubbles and forecast their critical end time applied to two of the largest cryptocurrencies, Bitcoin and Ether. In particular we developed in synergism two methods: the Johansen-Ledoit-Sornette (JLS) model, with three different calibrations (OLS, GLS, MLE) and robust global optimization methods, i.e. Genetic Algorithms, and the Philips-Shi-Yu (PSY) model, with two different statistical detection strategies (BSADF, BSADF*).

We found distinct periods when bubbles patterns clearly appear. In fact, Bitcoin shows typical hallmarks of a bubble phase in December 2017, while for Ether the price dynamics reveals bubble evidence between April and May 2017, but not at the time of writing. The sharp rise observed in November 2017 is too short to produce valid bubble signals, but it’s a promising candidate in the near future. Thus, not all cryptocurrencies live in a status of irrational exuberance, at least according to the quantitative methodologies used here.

This paper provides insight into the relationship between two cryptocurrencies and the financial risk of a speculative bubble. Further study on other cryptocurrencies and Initial Coin Offerings (ICOs), an innovative structure for raising funds to support new ideas and ventures, is in progress.

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6. Disclaimer and acknowledgments

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