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A systematic review of the bubble dynamics of cryptocurrency prices

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ABSTRACT

This paper surveys the academic literature concerning the formation of pricing bubbles in digital currency markets. Studies indicate that several bubble phases have taken place in Bitcoin prices, mostly during the years 2013 and 2017. Other digital currencies of primary importance, such as Ethereum and Litecoin, also exhibit several bubble phases. The Augmented Dickey Fuller (ADF) as well as the Log-Periodic Power Law (LPPL) methodology are the most frequently employed techniques for bubble detection and measurement. Based on much academic research, Bitcoin appears to have been in a bubble-phase since June 2015, while Ethereum, NEM, Stellar, Ripple, Litecoin and Dash have been denoted as possessing bubble-like characteristics since September 2015. However, this latter group possess little academic evidence supporting the presence of bubbles since early 2018. An overall perspective is provided based on a robust bibliography based on large deviations of market quotes from fundamental values that can serve as a guide to policymakers, academics and investors.

1. Introduction

Bubbles have existed across many differing investment assets, with research developing across a number of related strands including information source, contagion effects, the speed of development, signal processing and the role of algorithm trading and news dissemination through social media. The reasons for this broad interest are far from difficult to understand as extreme price fluctuations in investment forms have always attracted considerable academic debate and the interest of investors, policymakers and regulators. Moreover, sudden upheavals or abrupt decreases in market values of assets have been of primordial interest for their societal influencing, such as the generation and escalation of both social and economic disparities.

Unsurprisingly, this has spurred substantial interest in bubble-formation within cryptocurrency markets (Frehen et al., 2013; Corsi and Sornette, 2014; Vogel and Werner, 2015), especially when the asset under scrutiny constitutes a new, developing and promising tool that can be used for both liquidity and reserve management with an intriguing level of appeal to speculative investors seeking unexploited profit opportunities. Notably, a broad spectrum of alternative perspectives as regards the definition of bubbles has been brought about. The best-known among them is the asset-pricing approach that considers assets as investment tools capable of differentiating their nominal value from their fundamental value in a large extent (West, 1987; Diba and Grossman, 1988). It should be noted that the nominal value of an asset is defined as the market value by which it can be sold or bought whereas its fundamental value is lower and generally based on its costs of production. Continuous increases in the multiplicity through which

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nominal prices exceed fundamental values lead to explosive behaviour and the formation of bubbles. Such deviations from fundamental prices are mainly generated through highly optimistic investor sentiment that thereby lead to an increased level of aggregate demand for assets. This phenomenon of sharp demand elevation is reinforced if supply is stable or decreasing, as is found to be the case when considering the majority of digital currencies.

Digital currencies have been an axis of interest with regards to the presence of a number of specific characteristics, such as their nature and functions and whether they constitute a commodity or fiat money. Baur et al. (2018) found that Bitcoin is a hybrid of commodity money and fiat money. While digital coins employ peer-to-peer (P2P) networks and open-source software in order to prevent double spending and bypass the need for intermediation by commercial banks (Dwyer, 2015). Most cryptocurrencies are highly decentralised coins. Determinants of the value of Bitcoin are the demand for this currency in combination with its limited supply. Nadler and Guo (2020) estimated the pricing kernel with which users price factors affecting their token holdings, identifying that blockchain specific risk factors are priced in to the price of cryptocurrencies. Ammous (2018) argued that only Bitcoin can serve as a store of value, as it is considered more credible than other virtual currencies, its supply can be predicted and can resist manipulation due to its incumbency in the cryptocurrency market. Nevertheless, Baur et al. (2018) found that Bitcoin cannot be considered as a strong safe haven during crises. A complete survey about cryptocurrencies as a financial asset has been conducted by Corbet et al. (2019). Symitsi and Chalvatzis (2019) and Akhtaruzzaman et al. (2019) found statistically significant diversification benefits from the inclusion of Bitcoin which are more pronounced for commodities.

This paper surveys the key relevant literature in the area of bubble price formation in digital currencies and provides in the most representative manner the colourful nomenclature in relevant academic papers. A profound understanding of large deviations of nominal prices from fundamental ones allows an in-depth overview of inflation determinants of cryptocurrency values and also casts light on price formation of other assets of primary importance. This study aims to ascribe further foresight into bubble formation matters as a better understanding of this phenomenon is useful not only for academics, market participants or individuals, but also for society as a whole.

Section 2 presents the most popular definitions of asset bubbles and the most important bubble formation events in economic history. Section 3 offers a comprehensive review on the most popular methodological approaches for testing and measuring the bubble character of cryptocurrencies. Section 4 lays out a survey on the literature about bubble price formation in virtual decentralised currencies. Finally, in Section 5 discussion of findings and their economic underpinnings takes place. Tables A.1 and A.2 in the Appendix provide a brief overview of the studies investigated and the bubbles detected in these academic papers, respectively.

2. Defining and presenting a brief history of asset bubbles

Bubble formation has been a term that has received a number of alternative though not contradictory definitions throughout the years. A simple definition of bubbles can be presented as '*systematic deviations of the market value from the fundamental value of the asset*', where the latter is defined as the net present value of the future cash flows emanating from it. Van Horne (1985) supported this definition, stating that 'a balloon might be a better metaphor for certain financial promotions. It is blown up, to be sure, but not to the extent that it pops. The eventual deflation is less abrupt.' Garber (1990) argued that the term 'bubble is a fuzzy word filled with import but lacking any solid operational definition' documenting that one should not try to define bubbles as just financial events, as we have just to date being unable to understand the exact driving forces within. The author considers that such deviations cannot be explained based on any of the fundamentals. O'Hara (2008) provided support to such a theory on bubbles, noting that they depend on combinations of the rationality or not of agents and markets. Brunnermeier and Oehmke (2013) identify that bubbles consist of: (a) a run-up phase that leads in formation of bubbles and imbalances; and (b) a crisis phase, where accumulated risk materialises and the crisis breaks out. Moreover, Shiller et al. (1984) reveals that asset markets are directed by mercurial investors acting on the basis of short-lived enthusiasms and bubbles. Brunnermeier and Oehmke (2013) described bubbles as dramatic price increases which lead to bursting, while Kindleberger and Aliber (2011) considered bubbles as fast increases in the market value of an asset and that the initial upwards spur triggers expectations of a series of price enlargements. This is what feeds elevated interest about that particular asset and results in higher demand for investment in it. This is the so-called 'irrational exuberance' in investors' behaviour (Shiller, 2015).

A standard pricing pattern arises for new investment assets, such as digital currencies. When a new form of liquidity is developed, the first coins of this currency are sold in a very high price. One should take into consideration that there is an upper limit in the quantity of supply of a large number of cryptocurrencies, for example Bitcoin will stop being produced when it reaches 21 million coins. This supply will continue to increase in decreasing steps until 2040 and then will remain at that level forever (Baur et al., 2018). Azariadis (1981) and Frehen et al. (2013) consider that the three most important historic bubbles have been; the Dutch 'tulip mania,' the South Sea bubble in England and the collapse of the Mississippi Company in France. These events are considered to have been the prominent landmarks in the financial economic events history as the vertical ascents in prices that took place had been phenomenal. Van Horne (1985), based on a large bulk of evidence regarding financial market anomalies, takes into consideration the possibility of bubbles and manias and argues that during the tulipmania a single bulb could be sold for many years' salary. Garber (1990) believes that the Dutch experience of Tulipmania during the period 1634–7 was characterised by amazingly high prices of single bulbs of rare and prized varieties of tulips. Emphasis should be paid in that towards the most intense phase of the Tulipmania in the early 1637, just before the burst of this bubble, even common tulip varieties skyrocketed with approximately 2000% increases in prices within a month.

According to Johannessen (2017), rampant speculation on the stock exchanges in the various Dutch towns based on the stock prices of tulip bulbs became a frequent phenomenon. It is noteworthy that the price of such a bulb was between 10 and 25 guilders in 1612 whereas reached approximately 6650 guilders 25 years later due to collective optimism in the Dutch market. This optimism had been the product of institutional innovation (stock exchanges) and product innovation. Johannessen (2017) argued that the motivation for founding South Sea Company was the refinancing of the massive national debts that the British and French had acquired during the Spanish War of Succession. In no more than a decade, the share value of South Sea Company had reached the enormous amount of £ 200 million. Its rally in prices was based on attracting investors from France by promising enormous profits in the French colonies in North America. It is widely accepted that the South Sea bubble (1720) was generated as many investors from the Continent had purchased South Sea Company shares in London (Brunnermeier and Oehmke, 2013). As there was not in reality any perspective of significant trade and profits, the company's value decreased and fell to lower levels than before the start of the bubble. The Mississippi bubble (1719–20) was the result of Compagnie d'Occident ('Company of the West') that John Law created in order to have the exclusive privileges to develop the vast French territories in the Mississippi River valley of North America. This company had the monopoly power over the French tobacco and African slave trades and Law used it for selling its shares to the public in exchange for state-issued public securities. The mania of the public to sell debt for shares of the company weakened when inflation rose too high because of over-issuing of public debt. Thereby, the bubble collapsed and triggered a crash in equity markets in France. Frehen et al. (2013) provide evidence that all three bubbles had innovation and irrational investor exuberance as key drivers of bubble expectations. They reject clientele-based theories that attribute emphasis to bubble-riding and short-sales restrictions.

3. Methodological approaches for defining, detecting and measuring bubbles

3.1. Main existing literature on detecting bubbles

Academic work used for the process of identifying bubbles in asset prices based on fundamental values, possesses roots in the asset pricing model of Lucas Jr. (1978). This has been the axis on which a number of important contributors have developed econometric methodologies in order to test for bubble behaviour in prices. Blanchard and Watson (1982) argue that bubbles can follow many types of processes and that certain bubbles lead to violation of variance bounds implied by a class of rational expectations models. Shiller et al. (1984) support that social movements and habits in specific time periods are responsible for increases in asset prices. Investing incentives and asset price fluctuations are due to observations of participants in the market and to human nature. Tirole (1985) reveals that there are three conditions for bubble creation: durability, scarcity and common beliefs. He argues that scarcity is based on new units having the same price as old ones and claims that limited supply may prevent bubbles. This could be very intuitive as regards Bitcoin. Furthermore, he distinguishes between the financial bubble, which depends on market price, and the real bubble that is established by fundamentals of this market. Notably, he supports that overlapping generations models should focus on speculative assets rather than money. Evans (1989) argued that in rational expectations models sunspots and other 'rational bubble' solutions present only weak or no expectational stability and that in linear models there is at most one strongly expectational stable solution.

Diba and Grossman (1988) support the view that stock prices do not contain explosive price bubbles, moreover, claiming that it is impossible for negative rational bubbles in stock prices to exist, thereby if a bubble bursts then there is no opportunity that it will ever restart. Froot and Obstfeld (1989) focused on rational intrinsic bubbles dependent only on dividends, that is bubbles that derive all their fluctuations from exogenous economic fundamentals but not from extraneous factors. They find evidence in favour of bubbles in the US stock market that are difficult to be explained by alternative models. Gurkaynak (2008) documents that asset bubble tests cannot manage to offer adequate information about the existence or not of bubbles. He finds that inclusion of model assumptions about time-varying discount rates, risk aversion or structural breaks permit the appearance of bubbles only in a very weak extent. Furthermore, there is no way to distinguish bubbles from time-varying or regime-switching fundamentals. Overall, the author argues that when bubble detection tests indicate the existence of a bubble we could be far from certain that this bubble exists.

3.2. Definition of bubbles: intrinsic versus extrinsic rational bubbles

Rational bubbles appear when asset prices keep rising due to investors' beliefs that there will be a possibility to sell the overvalued asset at a higher price in the future (Flood and Hodrick, 1990). As investors are aware of the risk of bubble bursting at some future point in time, they require compensation for bearing that risk which gets higher as time passes because risk becomes higher. The continuing requirement for higher profits leads to overgrowing of prices and finally the bubble bursts. Dale et al. (2005) argued that intrinsic rational bubbles are formed when investors systematically and continuously conduct wrong estimations of asset fundamentals. This is more common when it comes to advanced technology products where it is more difficult to determine the exact fundamental value. Crashes are usually the result of informational dynamics after long periods of price increases have taken place. Extrinsic rational bubbles, also called as 'sunspots', occur when rational investors have to confront large levels of uncertainty concerning the economic environment. This is what leads investor to ascribe a value – with regards to price prediction to endogenously determine factors that do not have both a real or significant influence on fundamental values of assets. The main source of extrinsic rational bubbles is reliance on misinformation that results in poor management skills.

3.3. Approaches for detecting and measuring bubbles

No consensus is apparent as regards the tracing and measurement of price bubbles. Rational bubbles could appear in the form of deterministic time trends, as explosive AR(1) processes or even more complex stochastic processes. Among others, there have been four principal alternative approaches in order to define bubbles. The first view about defining bubbles is more traditional and lies on the comparison between the fundamental value and the nominal value of the underlying asset. It should be noted that the fundamental value is defined as the present value of the payoffs deriving from the assets since all relevant information has been taken into consideration (Taipalus, 2012). Thereby, the asset-pricing approach considers that bubbles exist when the nominal value that coincides with market value is not equal to the fundamental value of the asset.

Another approach for modelling the fundamental value is provided by Foster and Wild (1999) by using the sigmoid (or logistic) curve approach. This methodology is beneficial when aiming to capture the different phases in the evolution of a bubble, such as the expansion phase, the inflexion phase and the saturation phase. All three are considered typical phases during price bubble formation. The expansion phase presents positive growth, the inflexion phase is characterised by stability whereas the saturation phase represents a fall in prices. Tracing the date of launch of the saturation phase is what this approach wants to succeed. It is worth noting that the period of positive growth is in practice not equal to that of negative growth in prices. The main drawback of adopting the sigmoid curve approach is its doubtful effectiveness in measurement during multiple bubbles.

A methodology suitable for testing about single or multiple bubbles is offered by the Markov-switching Augmented Dickey-Fuller (MSADF) unit root test that detects explosive autoregressive roots. This procedure has been proposed by Hall et al. (1999) in order to track alterations from non-bubble to bubble regimes. The main drawback of this method is the difficulty in tracing whether high volatility or explosive autoregressive behaviour exists in regimes. Among the popular methodologies for detecting price bubbles could be found the Phillips et al. (2014) and Phillips et al. (2015) procedures. This is about a bubble test based on the assumption that bubbles follow a mildly explosive behaviour, that is an autoregressive root $\theta = 1 + gT^{-m}$, where g is positive and m, c parameters lie in the interval between 0 and 1. This test abides by the theory that suggests differences in tendencies of prices during upwards phases in comparison to tendencies in downswing periods. Thereby, sub-martingale behaviour in bullish markets is considered to be different from martingale behaviour in bearish times.

4. Literature on cryptocurrency bubble price formation

There has a been an increasing number of empirical papers that investigate the bubble price dynamics in cryptocurrency markets. The majority of them have been investigating price formation in Bitcoin but also studies on the CRIX index, the remaining digital coins of major importance and comparisons with national currencies have been conducted. Further issues such as the role of cybercriminality and illicit behaviour have also been analysed in substantial detail (Corbet et al., 2019b). To date, it has been identified that cryptocurrencies contain a number of pricing inefficiencies (Urquhart, 2016; Sensoy, 2019; Mensi et al., 2019; Corbet et al., 2019c; Ma and Tanizaki, 2019), persistence (Caporale et al., 2018; Corbet and Katsiampa, 2018), to be correlated or in isolation from other traded assets (Gil-Alana et al., 2020; Sifat et al., 2019; Corbet et al., 2018a), news response (Aysan et al., 2019; Flori, 2019; Nguyen et al., 2019, 2019; Zargar and Kumar, 2019); derivative development (Akyildirim et al., 2019); contagion effects (Handika et al., 2019; Omane-Adjepong and Alagidede, 2019; Beneki et al., 2019); evidence of price clustering (Urquhart, 2017; Kallinterakis and Wang, 2019), pricing bubbles (Corbet et al., 2018b), regulatory ambiguity (Fry, 2018; Shanaev et al., 2020), and exceptional levels of both complex and uncomplex fraud (Gandal et al., 2018). Much concern has been placed on the valuation of cryptocurrencies, with particular emphasis on placed on pricing efficiency, market dynamics and the potential presence of a pricing bubble. Hayes (2019) found that the marginal cost of production plays an important role in explaining Bitcoin prices, while Van Vliet (2018) investigated the role that Metcalfe's Law played in the valuation of Bitcoin. Dwyer (2015) found that the use of cryptocurrency technologies and the limitation of the quantity produced can create an equilibrium in which a digital currency has a positive value. Bedi and Nashier (2020) provide insights into sharp disparity in Bitcoin trading volumes across national currencies from a portfolio theory perspective. Panagiotidis et al. (2018) investigated using a LASSO framework, the influence on Bitcoin prices of factors such as stock market returns, exchange rates, gold and oil returns, the Federal Reserve and ECB's rates and internet trends on Bitcoin returns for alternate time periods. Search intensity and gold returns emerge as the most important variables for Bitcoin returns. Fry (2018) showed that liquidity risks may generate heavy-tails in Bitcoin and cryptocurrency markets. There have also been investigations of interactions between cryptocurrencies themselves. Wei (2018) found that Tether issuance do not impact subsequent Bitcoin returns, however, they do impact traded volumes using a VAR methodology, which in fact ran contrary to market expectations. While investigating ICOs, Felix and von Eije (2019) found that there exists an average level of under-pricing of 123% for USA ICOs and 97% for the other countries examined. Hendrickson and Luther (2017) went as far as to investigate the process of banning Bitcoin. The authors found that a government of sufficient size can prevent an alternative currency from circulating without relying on punishments, where they can ban the cryptocurrency as long as it disseminated sufficiently severe punishments.

The continued evolution of cryptocurrencies and the underlying exchanges on which they trade has generated tremendous urgency to develop our understanding of a product that has been identified as a potential enhancement of and replacement for traditional cash as we know it. Bitcoin has now developed in so far that it now possesses a robust and liquid derivatives market when compared to a number of other traditional financial products (Corbet et al., 2018c; Fassas et al., 2020). As our understanding of FinTech evolves (Goldstein et al., 2019) and the growing value of blockchain (Chen et al., 2019), one key area of research focuses on the interactions between cryptocurrencies and other more traditional financial markets. Regulatory bodies and policy-makers alike have observed the growth of cryptocurrencies with a certain amount of scepticism, based on this growing potential for illegality and malpractice. Foley et al. (2019) estimate that around $76 billion of illegal activity per year involve Bitcoin (46% of Bitcoin transactions). This is estimated to be in the same region of the U.S. and European markets for illegal drugs, and is identified as 'black e-commerce'. While thorough investigation of the issues surrounding cryptocurrencies continues to develop, we continue to set out to analyse the potential mechanisms through which these new products can influence unsuspecting populations. Their potential use by companies attempting to take advantage of 'crypto-exuberance' must be considered (Akyildirim et al., 2020). This research has raised much concern about the central rationale surrounding investment in this new investment asset class, but one fundamental issue has remained, namely, what exactly is the price of one unit of cryptocurrency? We set out to establish a review of the broad estimates while considering the broad use of bubble-identifying techniques.

While considering research specifically analysing the potential for bubbles in the markets for cryptocurrencies, Cheung et al. (2015) use daily Bitcoin data over the period from July 17, 2010 to February 18, 2014 and adopt the Phillips et al. (2012) methodology in order to examine whether price bubbles exist in Bitcoin's biggest exchange up to then, the Mt. Gox. Estimations by the generalised Supremum Augmented Dickey Fuller (GSADF) statistic reveal that most of the bubbles do not last for long as their duration does not exceed a few days period. Three very large Bitcoin bubbles have been detected. The first bubble starts on April 24, 2011 and ends on July 3, 2011. The second one begins on January 27, 2013 and ends on April 15, 2013. Finally, the third Bitcoin bubble in Mt. Gox is the largest one as it begins on November 5, 2013 and ends on February 18, 2014. It can be seen that bubble behaviour lasts for larger time periods as time passes. The burst of the last bubble is perhaps responsible for the collapse of the Mt. Gox. MacDonell (2014) uses weekly data covering the period from July 18, 2010 until August 25, 2013 and employs Autoregressive Moving Average (ARMA) methodologies and the Log Periodic Power Law (LPPL) models by Johansen-Ledoit-Sornette (JLS) in order to predict crashes. Findings by ARMA methodologies indicate that investment sentiment as expressed by the CBOE Volatility Index drives Bitcoin prices. It can be noted that the LPPL model safely predicts the crash that took place in December 2013. Cheah and Fry (2015) employ daily closing prices about the Bitcoin Coindesk Index spanning the period from July 18, 2010 to July 17, 2014 in order to perform price modelling and detect the existence of bubbles. By following Johannessen (2017) they use a price model including a Wiener process and a jump process in order to control whether the intrinsic rate of return and the intrinsic level of risk are constant. They examine the bubble component as well as run a BDS test to trace bubble behaviour. Results reveal that a bubble character exists in the Bitcoin market and the random walk hypothesis is rejected. The speculative character of Bitcoin fed by high volatility and explosive behaviour of the currency is reinforced by econometric outcomes.

Corbet et al. (2018) employ daily data from January 9, 2009 and from August 7, 2015 until November 9, 2017 concerning Bitcoin and Ethereum, respectively. The authors attempt to capture intrinsic bubbles, herd behaviour and time-varying fundamentals in discount factor models using a rolling-window approach with the Supremum-, the Generalised Supremum and the backward Supremum Augmented Dickey-Fuller specifications. Econometric findings provide evidence of Bitcoin bubble behaviour around the turn of the year from 2013 to 2014. Moreover, Ethereum exhibits bubble behaviour in the beginning of 2016 and in the mid-2017. Overall, bubbles in the currencies investigated do not last for long. Bouri et al. (2019) use daily data about Bitcoin, Ripple, Ethereum, Litecoin, Nem, Dash and Stellar that span the period from August 7, 2015 until December 31, 2017 in order to study co-explosivity in their markets. Bitcoin's explosivity is found to lower Ripple's explosivity. Moreover, high prices in Ethereum, Litecoin, Nem and Stellar render more probable the appearance of hikes in Ripple's market values. Ethereum's explosivity is reinforced by Bitcoin, Ripple, Nem and Dash while receives a negative impact by Stellar. When it comes to Litecoin, there is evidence that Bitcoin, Ripple, Nem, Dash and Stellar feed its bubbling. Five digital currencies are also found to positively influence the bubble behaviour of Nem and of Stellar. It can be noted that also lower capitalisation currencies prove to be influential towards larger ones. Holub and Johnson (2019) investigate the influence that the Bitcoin bubble exerted on Bitcoin's peer-to-peer (P2P) market during the bullish 2017 period. They employ daily data that span the period from January 2017 to June 2018. Thereby, the increasing, the skyrocketing and the bearish periods in Bitcoin's market quotes are examined. Furthermore, data of national currencies from 13 advanced and developing economies are used. Emphasis is paid on analysis of publicly available bid-ask spreads. Results indicate that spreads decline for the US dollar, the Hong Kong dollar, the dollar of New Zealand, the Swedish Krone and the Singapore dollar. Nevertheless, the Euro, the United Kingdom pound, the Australian dollar, the Brazilian real, the Norwegian Krone, the Polish Zloty, the Russian Rouble and the South African Rand do not present significant falls in spreads while they abide by the thinking that higher Bitcoin prices lead to wider spreads. This presents credence to currency and country dependency of the bubble's effect on Bitcoin prices in the P2P market.

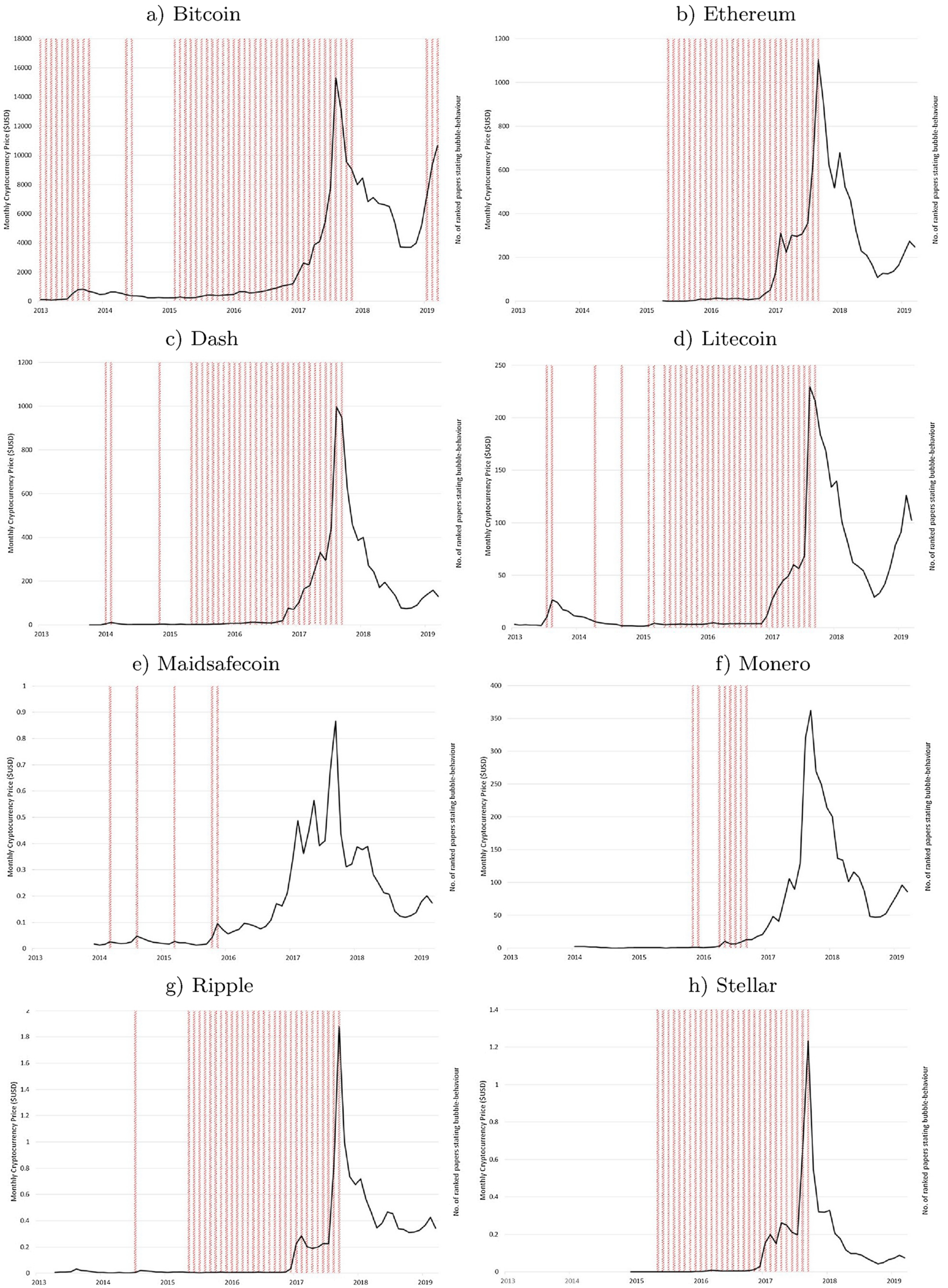
The SADF methodology is used for detecting bubbles by including a sequence of forward recursive ADF unit root tests in right tails. In case that there are numerous episodes of booms and busts due to rapid alterations in market conditions, then the generalised SADF (GSADF) specification is preferable. This allows changing in starting points and end points of recursive schemes over flexible windows, thereby it allows right-sided double recursive test for detecting unit roots. Moreover, the backward SADF (BSADF) enables conducting a supremum ADF test by backward expanding on a sample sequence with a fixed end point but not a fixed starting point.

Another strand of research on cryptocurrencies focuses on investigations based on the Log-Periodic Power Low (LPPL) framework. MacDonell (2014) uses weekly data covering the period from July 18, 2010 until August 25, 2013 and employs Autoregressive Moving Average (ARMA) methodologies and the Log Periodic Power Law (LPPL) models by Johansen-Ledoit-Sornette (JLS) in order to predict crashes. Findings by ARMA methodologies indicate that investment sentiment as expressed by the CBOE Volatility Index drives Bitcoin prices. It can be noted that the LPPL model safely predicts the crash that took place in December 2013. Bianchetti et al. (2018) employ daily data of Bitcoin and Ethereum covering the period from December 1, 2016 until January 16, 2018 in order to detect bubbles in their prices. The methodologies adopted are the Log Periodic Power Law (LPPL) model by Johansen, Ledoit and Sornette (JLS) and the model of Phillips, Shi and Yu (PSY) and genetic algorithms. To be more precise, the Ordinary Least Squares (OLS), the generalised Least Squares (GLS) and the Maximum Likelihood Estimation (MLE) specifications of the JLS model are adopted. Moreover, the two versions of the PSY methodology are employed. Estimations reveal that a Bitcoin bubble appears in mid-December 2017 and in the first half of January 2018. When it comes to Ethereum, bubble behaviour is traced in mid-June 2017 and a weaker bubble sign is detected around January 12, 2018. Wheatley et al. (2018) employ a generalised Metcalfe's law in combination with the Log Periodic Power Law Singularity (LPPLS) model in order to predict bubbles and crashes in the markets of digital currencies. They define bubbles as deviations of the Market-to-Metcalfe value that they define and document that four bubbles have aroused in the Bitcoin market with varying height and length among them. These bubbles have taken place by starting on: August 28, 2012, April 10, 2013, December 5, 2013 and December 28, 2017. Therefore, these results give credence to the belief that no random walk exists in cryptocurrency markets.

The Log-Periodic Power Law (LPPL) model is based on econophysics and seeks to determine whether a critical point is reached. It is supposed that bubbles or crashes obey a particular power law with log-periodic fluctuations. This model predicts the date of occurrence of a bubble or crash as it contains a component that captures the market's excessive volatility before a crash.

A range of alternative estimation frameworks have been adopted in order to detect price bubbles. Bouoiyour et al. (2014) employ data of the Bitcoin Price Index (BPI) and the exchange-trade ratio (ETR) and users' attractiveness to Bitcoin in order to examine the Granger causality between Bitcoin's price and transactions as well as between Bitcoin's price and investors' attractiveness. The data adopted are of daily frequency and span the period from December 2010 to June 2014. Moreover, it is revealed that bubble behaviour in Bitcoin markets exists as the attractiveness to Bitcoin influences the Bitcoin Price Index at short- and long-run frequencies and there is a reverse (feedback) effect at lower frequencies. This cyclical nexus is found not to have duration of a stable length. Furthermore, Bouoiyour et al. (2016) employ the innovative technique of Empirical Mode Decomposition (EMD) to analyse and explain the price dynamics of Bitcoin. They use daily data of the Bitcoin Price Index (BPI) over the period from December 2010 to June 2015 and extract data into independent Intrinsic Mode Functions (IMFs) and by filtering high frequency (fluctuating process) from low frequency (slowing varying components) modes. Moreover, Pearson correlations and variance of components analysis are employed. Findings provide evidence that apart from the speculative character of Bitcoin also the long-term fundamentals as expressed by the low-frequency components are major determinants of fluctuations in Bitcoin quotes. Cheah and Fry (2015) employ daily closing prices about the Bitcoin Coindesk Index spanning the period from July 18, 2010 to July 17, 2014 in order to perform price modelling and detect the existence of bubbles. By following Johannessen (2017) they use a price model including a Wiener process and a jump process in order to control whether the intrinsic rate of return and the intrinsic level of risk are constant. They examine the bubble component as well as run a BDS test to trace bubble behaviour. Results reveal that a bubble character exists in the Bitcoin market and the random walk hypothesis is rejected. The speculative character of Bitcoin fed by high volatility and explosive behaviour of the currency is reinforced by econometric outcomes. Fry and Cheah (2016) develop an econophysics model in order to investigate the formation of bubbles in Bitcoin and Ripple. They employ data on market capitalisation and market share as well as daily closing values of Bitcoin Coindesk Index and weekly data on Ripple covering the period from February 26, 2013 to February 24, 2015. Events of exogenous and endogenous shocks in these currencies are taken into consideration. Univariate and bivariate model representations are used to test for spillover and contagion effects. Evidence documents that Ripple is over-priced in relation to Bitcoin and that the former exerted a spillover influence to the latter that exacerbated recent price falls in Bitcoin.

Holub and Johnson (2019) investigate the influence that the Bitcoin bubble exerted on Bitcoin's peer-to-peer (P2P) market during the bullish 2017 period. They employ daily data that span the period from January 2017 to June 2018. Thereby, the increasing, the skyrocketing and the bearish periods in Bitcoin's market quotes are examined. Furthermore, data of national currencies from 13 advanced and developing economies are used. Emphasis is paid on analysis of publicly available bid-ask spreads. Results indicate that spreads decline for the US dollar, the Hong Kong dollar, the dollar of New Zealand, the Swedish Krone and the Singapore dollar. Nevertheless, the Euro, the United Kingdom pound, the Australian dollar, the Brazilian real, the Norwegian Krone, the Polish Zloty, the Russian Rouble and the South African Rand do not present significant falls in spreads while they abide by the thinking that higher Bitcoin prices lead to wider spreads. This gives credence to currency and country dependency of the bubble's effect on Bitcoin prices in the P2P market. Chen and Hafner (2019) investigate whether sentiment-induced bubbles exist in markets of digital currencies by using daily data covering the period from August 8, 2014 to May 15, 2018. They test for bubbles using a transition variable and the CRIX index in a smooth transition autoregressive model (STAR) with regime switching. Moreover, volatility is expressed by a Beta-t-Exponential Generalised Autoregressive Conditional Heteroskedasticity (Beta-t-EGARCH) model. Estimations indicate that volatility has a negative nexus with the sentiment index. Multiple periods are detected in the period from May 2017 to April 2018. It is revealed



(caption on next page)

Fig. 1. Bubbles in cryptocurrency markets as identified by academic studies. *Note*: The above figures represent selected one hundred day dynamic correlations between a selected sub-set of companies in the above analysis and our selected cryptocurrency fund.

that volatility is higher during bubble periods.

In a more recent strand of research, Corbet et al. (2020) employ Generalised Autoregressive Conditional Heteroskedasticity (GARCH) and Dynamic Conditional Correlations Generalised Autoregressive Conditional Heteroskedasticity (DCC-GARCH) methodologies with 5-min data to the nexus between Kodak returns and Dow Jones Industrial Average (DJIA) as well as Bitcoin returns. The period examined spans November 22, 2017 to February 21, 2018 divided into sub periods. They provide evidence that before the KodakCoin announcement, there was a strong linkage between Kodak and the DJIA index, whereas a weal one with Bitcoin, Nevertheless, after the KodakCoin announcement, the connection between Kodak and the DJIA rendered weaker but the relation of Kodak with Bitcoin was significantly fortified. Kodak's return volatility also reveals the closer linkage with risky digital currencies after the announcement. Chaim and Laurini (2019) investigate whether Bitcoin is a bubble by adopting the strict local martingale theory of financial bubbles and employing the non-parametric estimator of Florens-Zmirou and the Hamiltonian Monte Carlo simulation scheme for estimations. Examination is also conducted with the SP500 index, the euro-dollar exchange rate, the gold-dollar prices and the market value of Brent oil for comparison purposes. It is found that Bitcoin exhibits bubble behaviour only during the period from January 2013 to April 2014. Cagli (2019) investigate explosive behaviour in the market values of Bitcoin, Ethereum, Ripple, Litecoin, Stellar, Nem, Dash and Monero by employing daily data spanning from September 2015 to January 2018. The methodology adopted is based on Chen et al. (2017). Evidence indicates that all digital currencies except for Nem present explosive behaviour and exhibit significant pairwise comovement linkages. More specifically, statistically significant bilateral co-explosive relations are detected between the pairs of: Bitcoin-Dash, Ethereum-Litecoin, Ethereum-Dash, Ethereum-Monero and Ripple-Stellar.

It should also be noted that recent academic work has focused interest on investigating which model would better fit the examination of cryptocurrency booms and busts. Cretarola and Figà-Talamanca (2019a) employ a continuous time stochastic model for Bitcoin dynamics. They provide evidence that bubbles are connected with the correlation between the market attention factor on Bitcoin and Bitcoin returns being above a non-negative threshold. Thereby, market exuberance is found to be influential for Bitcoin bubbles. Such bubbles are evident during 2012–2013 and 2017. Moreover, Cretarola and Figà-Talamanca (2019b) extend the model employed in Cretarola and Figà-Talamanca (2019a) and allow for a state-dependent correlation parameter between asset returns and market attention. It is revealed that based on the modified model the correlation between cryptocurrencies and their market attention can indicate the speed by which a bubble boosts. Both Pyo and Lee (2019) and Corbet et al. (2020) investigate the impact of FOMC announcements on Bitcoin returns by conducting regressions. They take into consideration 65 FOMC meetings related to monetary policy. Findings reveal that the Producer Price Index exerts significant effects on Bitcoin prices only one day before the FOMC announcement while no significant impacts from macroeconomic announcements are found in general. Eom (2020) by using Bitcoin data from Korea and the US and employing Generalised Method of Moments (GMM) estimations support that the high trading volume and price instability can explain the Kimchi premium. Higher Bitcoin bubbles lead to a clearer nexus between trading volume and premium. Bubbles are found to grow due to fundamental uncertainty and higher trading. Moreover, Shu and Zhu (2020) provide evidence that an adaptive multilevel time series detection methodology based on the LPPLS model and high-frequency data can effectively detect bubbles. Moreover, it can forecast bubble crashes, even for short-term bubbles. In another vein, Xiong et al. (2019) verify that bubble estimation based on the production cost by applying VAR and LPPL models display good predictive capacities. Moreover, the price-electricity cost ratio (PECR) and the bubble coefficient (BC) are found to be effective measures. Furthermore, it is argued that the next large Bitcoin bubble is expected to take place in the second half of 2020, just after Bitcoin's halving.

Emphasis should be paid in that academic evidence reveals a clearer bubble character in major cryptocurrencies, especially Bitcoin but also Ethereum, whereas the remaining highly-capitalised digital currencies present price increases in a more modest level. It should be emphasised when the CRIX index, the Bitcoin Price Index or the Mt.Gox values represent Bitcoin, bubbles are found to be more intensive. Moreover, one should underline that methodologies based on the SADF provide evidence of higher or multiple bubbles in cryptocurrency markets.

While considering all of the above research, it is very important to try to define a central estimate over time as to how estimates of the size of a bubble in cryptocurrency markets vary. While this research provides a central piece that provides a broad overview of the techniques used to measure pricing bubbles, we further attempt to provide estimates both over time frequency and by type of cryptocurrency. In Fig. 1, we observe eight examples of monthly cryptocurrency price behaviour when compared to that of the periods of time in which academic research had pre-defined the existence of bubble-like properties in each respective market using the techniques earlier outlined in our research. The collected data used to generate these figures are available in the attached Appendices. We can clearly observe that each example with the exception of Maidsafecoin and Monero exhibit sustained warnings with regards to the existence of bubbles far in advance of the sharp price increases that existed throughout 2016 and 2017. Interestingly, such warnings then disappeared when the price of each cryptocurrency subsequently collapsed throughout 2017 and during early 2018. Although there have existed many warnings throughout a variety of reputable academic sources, it would largely appear that such advice has been broadly ignored. Much of the research provided in this systematic review considers cryptocurrencies to be an exceptionally volatile product, exhibiting many behavioural traits that do not appear to be shared within traditional financial markets.

5. Concluding comments

The substantial body of evidence that seeks to test for the existence and measurement of the size of bubble price formation in financial assets has accumulated substantially during the past decades. There already exists considerable evidence that economic sentiment and speculative motives combined with overconfidence, trigger significant divergences of asset market values from the corresponding fundamental values. Bubble-formation has received a wide array of alternative definitions. The majority of these definitions agree with the view that such behaviour is generated within elevated interest of economic units due to especially favourable conditions that lead to multiple size of nominal values in relation to the fair value. The asset pricing approach considers assets as investment tools capable of proving extremely profitable for traders. The highly speculative characteristics of cryptocurrencies and the consequentially increasing popularity of Bitcoin and other digital coins fuelled the bubble price literature with some very interesting academic debate during recent years. Research interest in cryptocurrency bubbles is increasing substantially due to the ensuing challenges that high and enduring price alterations bring to the surface. There are a variety of investigative methodologies preferred across cases where a bubble is singular or when there are multiple bubbles. Moreover, different detection approaches are preferred in the case that is mildly-explosive or explosive in nature.

While investing in cryptocurrencies renders an increasingly popular option as prices elevate, substantial uncertainty remains due to the enormous levels of volatility in both returns and unpredictability, therefore risk. Bubble formation in prices of virtual coins leads to substantial difficulty in such currencies performing efficiently as a account of unit and store of value, some of the key functions in which much literature has observed substantial weakness within these developing products. Literature associated with digital currency bubbles indicates that Bitcoin has presented several bubble phases, mostly during the years 2013 and 2017. Other major coins also exhibit several bubble phases. Most studies employ daily data from free sources but papers employing high-frequency data from not publicly accessible data sources have also been authored. The most popular methodologies for detecting bubbles have been the Augmented Dickey Fuller (ADF). Moreover, the Log-Periodic Power Law (LPPL) methodology is often used in relevant research. Overall, the highly speculative, volatile and unpredictable character of cryptocurrencies is verified by empirical studies. The present study contributes to relevant literature by providing an overall perspective of empirical academic studies of bubble price formation of digital currencies and a road-map for future research. This could prove a highly valuable tool for investors, speculators, regulators and supervising authorities.

Finally, it is worth asking as to whether the bubble characteristics of digital currencies will perpetuate in the future without risk of key cryptocurrency assets such as Bitcoin bursting. To the extent that elevated investor optimism continues and irrational behaviour dominates investing strategies, prices will most likely remain in an upward trajectory. Virtual currencies created by monetary authorities (such as the Central Bank Digital Currency, CBDC) or coins attached to bank deposits or government securities (such as stablecoins) are identified to play a primordial role in the survival of cryptocurrencies. Should regulation or innovation in digital money strengthen the 'trust' of investors regarding digital forms of liquidity, such currencies could enjoy legal tender status, which could present owners of these products with the ability protect themselves from instability and frequent upheavals. A tendency towards centralisation of digital currencies could contribute towards cooling digital bubbles before bursting and leading to further crisis episodes.

Appendix A

Table A.1
Studies about bubble price formation in cryptocurrencies.

Authors	Currencies examined	Frequency of data	Time period examined	Data Source	Methodology	Conclusions
Puljiz et al. (2018)	Bitcoin prices by Bitfinex, BitStamp, BTC-e, Kraken, Mt.Gox	Trade-level in frequencies from 1-minute up to-1 day	March 2013–December 2016 in Bitfinex; July 2010–February 2014 in Mt.Gox; January 2014–February 2018 in Kraken; August 2011–July 2017 in BTC-e; September 2011–February 2018 in BitStamp	Bitfinex, BitStamp, BTC-e, Kraken, Mt.Gox	Scaling exponent in tails using the Hill estimator	Volatility and heavy tails
Bianchetti et al. (2018)	Bitcoin; Ethereum	Daily	December 1, 2016–January 16, 2018	Bloomberg	Log-Periodic Power Law (LPPL) by Johansen and Sornette (1999); OLS, GLS and MLE with Johansen-Ledoit-Sornette (JLS) model; Phillips-Shi-Yu (PSY) model with Backward Supremum Augmented Dickey Fuller (BSADF and BSADF*)	Yes
Bouri et al. (2019)	Bitcoin, Ripple, Ethereum, Litecoin, Nem, Dash, Stellar	Daily	August 7, 2015–November 7, 2015	Coinmarketcap.com	generalised Supremum Augmented Dickey Fuller (GSADF) by Phillips et al. (2013), logistic regression	Yes
Bouoiyour et al. (2014)	Bitcoin Price Index	daily	December 2010–June 2014	www.blockchain.info; www.quandl.com; Google	Frequency Domain Analysis – Granger Causality by Breitung and Candelon (2006)	Yes
Bouoiyour et al. (2016)	Bitcoin Price Index	Daily	December 2010–June 2015	www.blockchain.info	Empirical Mode Recognition (EMD); Kendall correlation; Pearson correlation	Yes, but also determined by long-term fundamentals
Cagli (2019)	Bitcoin, Ethereum, Ripple, Litecoin, Stellar, Nem, Dash and Monero	Daily	September 1, 2015–January 31, 2018	Coinmarketcap.com	Methodology of Chen et al. (2017)	All except for Nem and bilateral co-explosive nexus between Bitcoin-Dash, Ethereum-Litecoin, Ethereum-Dash, Ethereum-Monero and Ripple-Stellar
Chaim and Laurini (2019)	Bitcoin	Daily; 5-min frequency	January 2013–September 2018 (in sub periods)	Blockchain.com	Non-parametric estimator of Florens-Zmirou (1993); Hamiltonian Monte Carlo Simulation scheme	Yes, from January 2013 to April 2014
Cheah and Fry (2015)	Bitcoin Coindesk Index	Daily	July 18, 2010–July 17, 2014; January 1, 2013–November 30, 2013	Coinmarketcap.com	Model with Wiener process and jump process; BDS test based on Brock (2001)	Yes, intense bubble character
Cheung et al. (2015)	Bitcoins traded on Mt.Gox	Daily	July 17, 2010–February 18, 2014	Bitcoincharts.com	generalised Supremum Augmented Dickey Fuller (GSADF) by Phillips et al. (2013)	Yes, intense
Chen and Hafner (2019)	CRIX index	Daily	August 8, 2014–May 15, 2018	StockTwits Application Programming Interface (API); thecrix.de	Smooth Transition Autoregressive Model (STAR); Beta-t-GARCH model by Creal et al. (2011); Sentiment measures by Nasekin and Chen (2018)	Yes, multiple
Corbet et al. (2020)	KodakCoin; Bitcoin	5-min frequency	November 22, 2017–February 21, 2018	Bloomberg; CryptoCompare.com	generalised Autoregressive Conditional Heteroskedasticity (GARCH) by Bollerslev (1986); Dynamic Conditional Correlations generalised Autoregressive Conditional Heteroskedasticity (DCC-GARCH) by Engle (2002)	Yes
Corbet et al. (2018)	Bitcoin, Ethereum	Daily	January 9, 2009–November 9, 2017			Yes, clearly

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Table A.1 (*continued*)

Authors	Currencies examined	Frequency of data	Time period examined	Data Source	Methodology	Conclusions
				Historical API's (Application Programming Interfaces)	Backward Supremum Augmented Dickey Fuller (GSADF) based on Phillips et al. (2011), rolling-window Augmented Dickey Fuller style regression	
de Sousa and Pinto (2019)	Bitcoin, Ethereum, Ripple, Litecoin, Monero, Dash, MadeSafeCoin, Nem	Daily	Since the launch of each currency until January 27, 2017	Coinmarketcap.com	Right-tailed Augmented Dickey-Fuller (RtADF), Rowlling-Augmented Dickey Fuller (RADF), Supremum Augmented Dickey Fuller (SADF), generalised Supremum Augmented Dickey Fuller (GSADF)	Yes
Geuder et al. (2019)	Bitcoin	Daily	March 19, 2016–September 19, 2018	Coinmarketcap.com	Log-Periodic Power Law (LPPL) model by Filimonov et al., and Sornette (2013); Supremum Augmented Dickey Fuller (SADF) and generalised Supremum Augmented Dickey Fuller (GSADF) and Backward Supremum Augmented Dickey Fuller (BSADF) by Phillips et al. (2015)	Yes
Fry and Cheah (2016)	Bitcoin, Ripple	Daily; Weekly	February 26, 2015–February 24, 2015	Coinmarketcap.com; Ripplecharts.com; Coindesk.com	Univariate and multivariate models for bubbles using Wiener process and jump process	Yes
Hafner (2018)	Bitcoin, Ripple, Ethereum, Bitcoin Cash, cardano, Litecoin, IOTA, Nem, Dash, Stellar, Monero	Daily	Since the launch of each currency until December 31, 2017	Coinmarketcap.com; http://thecrix.de; CoinGecko	Spline-GARCH model of Engle and Rangel (2008); Supremum Augmented Dickey Fuller (SADF) by Phillips et al. (2012); Exponential generalised Autoregressive heteroskedasticity (E-GARCH) by Nelson (1991); Threshold generalised Autoregressive Conditional Heteroskedasticity (T-GARCH) by Glosten et al. (1993)	Yes, in Bitcoin and the CRIX
Hayes (2019)	Bitcoin	Daily	June 29, 2013–April 27, 2018	Blockchain.info	Ordinary Least Squares (OLS), Vector Autoregressions (VAR), marginal cost of production model	Yes
Holub and Johnson (2019)	Bitcoin exchanges rates in relation to 11 national currencies	Daily	January 2017 to June 2018	Bitcoincharts; Datastream	Measurement of the bid-ask spread	Yes
MacDonell (2014)	Bitcoin	Weekly	July 18, 2010–August 25, 2013	Mt.Gox	Maximum Likelihood Estimation (MLE); Log-Periodic Power Law (LPPL); Autoregressive Moving Average (ARMA)	Yes
Phillips and Gorse (2018)	Bitcoin; Ethereum; Litecoin; Monero	Daily	April 2015–September 2016; but Ethereum: August 8, 2015–September 2016	Reddit	Hidden Markov Model (HMM)	Yes
Su et al. (2018)	Bitcoin	Weekly	June 16, 2011–September 30, 2017	Wind database	Supremum Augmented Dickey Fuller (SADF); generalised Supremum Augmented Dickey Fuller (GSADF) by Phillips et al. (2013),	Yes, multiple
	Bitcoin	Daily		Bitinfocharts.com		Yes

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Table A.1 (*continued*)

Authors	Currencies examined	Frequency of data	Time period examined	Data Source	Methodology	Conclusions
Wheatley et al. (2018)					Metcalfe's Law; Ordinary Least Squares (OLS); generalised Least Squares (GLS); Log-periodic Power Law Singularity (LPPLS) model	
Cretarola and Figà-Talamanca (2019a)	Bitcoin, Ethereum	Daily	January 1, 2012–September 30, 2019 (Bitcoin), August 2015–September 2019 (Ethereum)	Coinmarketcap.com	Extension of the model in Cretarola and Figà-Talamanca (2019b)	Correlation between cryptocurrencies and their market attention can indicate the speed by which a bubble boosts
Cretarola and Figà-Talamanca (2019b)	Bitcoin	Daily	January 1, 2012–January 20, 2018	www.blockchain.info	Continuous time stochastic model depending on a market attention factor	Bubble effects in 2012–2013 and 2017
Eom (2020)	Bitcoin	Daily	January 2015–September 2018,	Bitcoincharts.com, Coinmarketcap.com, Bank of Korea	Kimchi premium estimation, Generalized Method of Moments (GMM)	Cryptocurrency bubbles are loud, Fundamental uncertainty leads to high trading and speculative bubbles
Pyo and Lee (2019)	Bitcoin	Daily	MonthlyJuly 18, 2010–September 10, 2018	CryptoCompare.com, www.federalreserve.gov, www.bls.gov	Event-driven regression model	No significant impacts from macroeconomic announcements are found in general
Shu and Zhu (2020)	Bitcoin	Daily	January 11, 2017–April 11, 2019	Bitcoincharts.com	Adaptive multilevel time series detection methodology based on the LPPLS model	The LPPLS confidence indicator employed is an excellent tool for tracing detect bubbles and forecasting bubble crashes
Xiong et al. (2019)	Bitcoin	Daily	January 1, 2011–December 30, 2018	–	Vector Autoregressive Model (VAR), LPPL	Models display good predictive capacities The next large Bitcoin bubble is expected to take place in the second half of 2020

Table A.2
Bubbles in cryptocurrency markets according to studies.

Authors	Crypto w/ bubble character	Period of bubble behaviour
Bouri et al. (2019)	Bitcoin	October 27, 2015–November 7, 2015
	Ethereum	February–March 2016
	Bitcoin	Early January 2017
	Dash, Ethereum	February 25, 2017–March 25, 2017
	Ripple, Ethereum, Litecoin, Nem	April–May 2017
	Bitcoin	Late May–June 2017
	Bitcoin	August–September 2017
	Bitcoin, Ripple, Litecoin, Nem, Dash, Stellar	Late October 2017
Cagli (2019)	Bitcoin, Ethereum, Ripple, Litecoin, Stellar, Dash	Inside the period September 2015–January 2018
Chaim and Laurini (2019)	Bitcoin	January 2013–April 2014
Corbet et al. (2020)	KodakCoin	(Launch of KodakCoin) January 9, 2018–February 21, 2018
Corbet et al. (2018)	Bitcoin	2013–2014 turn of the year
	Ethereum	Early-2016 and mid-2017
Bianchetti et al. (2018)	Bitcoin	Mid-December 2017
	Bitcoin	First half of January 2018
	Ethereum	Mid-June 2017
	Bitcoin	Mid-January 2018
de Sousa and Pinto (2019)	Bitcoin	October 20, 2013–December 15, 2013
	Bitcoin	September 19, 2014–September 23, 2014
	Bitcoin	October 4, 2014–October 9, 2014
	Bitcoin	October 30, 2015–November 5, 2015
	Bitcoin	May 29, 2016–June 23, 2016
	Bitcoin	October 27, 2016–November 4, 2016
	Bitcoin	December 22, 2016–January 4, 2017
	Ethereum	January 15, 2016–February 1, 2016
	Ethereum	February 4, 2016–February 17, 2016
	Ethereum	February 23, 2016–March 25, 2016
	Ethereum	March 28, 2016–April 2, 2016
	Ethereum	June 13, 2016–June 18, 2016
	Ripple	November 22, 2014–January 4, 2015
	Ripple	November 22, 2014–January 4, 2015
	Litecoin	November 18, 2013–December 1, 2013
	Litecoin	August 12, 2014–August 21, 2014
	Litecoin	January 3, 2015–January 24, 2015
	Litecoin	June 16, 2015–July 10, 2015
	Litecoin	May 27, 2016–June 7, 2016
	Litecoin	June 11, 2016–June 21, 2016
	Monero	March 4, 2016–March 11, 2016
	Monero	March 20, 2016–April 8, 2016
	Monero	August 20, 2016–September 29, 2016
	Monero	December 27, 2016–January 10, 2017
	Dash	May 10, 2014–June 5, 2014; March 22, 2015–March 27, 2015; January 17, 2016–January 23, 2016; March 23, 2016–April 9, 2016; May 20, 2016–June 6, 2016; August 7, 2016–September 1, 2016; January 4, 2017–January 8, 2017
	MaidSafe	July 12, 2014–July 22, 2014; December 4, 2014–December 9, 2014; July 22, 2015–July 30, 2015; February 11, 2016–March 29, 2016
	NEM	January 18, 2016–January 24, 2016; February 1, 2016–February 17, 2016; March 6, 2016–March 16, 2016; March 25, 2016–April 3, 2016; June 13, 2016–July 7, 2016
Cheung et al. (2015)	Bitcoin	April 24, 2011–July 3, 2011
	Bitcoin	January 27, 2013–April 15, 2013
	Bitcoin	November 5, 2013–February 18, 2014
Geuder et al. (2019)	Bitcoin	May–June 2016
	Bitcoin	End of October–start of November 2016
	Bitcoin	December 2016–January 2017
	Bitcoin	Mid-May 2017 to early July 2017
	Bitcoin	Early August 2017–mid-September 2017
	Bitcoin	Mid-October 2017–January 2018
Hafner (2018)	Bitcoin	November 7, 2013–December 18, 2013
	Bitcoin	November 27, 2017–up to the time of writing
	CRIX index	May 5, 2017–up to the time of writing
Su et al. (2018)	Bitcoin (in the US)	Short period in August 2012
	Bitcoin (in the US)	November 7, 2013–December 12, 2013
	Bitcoin (in the US)	Early 2017
	Bitcoin (in the US)	May 18, 2017–September 14, 2017

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Table A.2 (*continued*)

Authors	Crypto w/ bubble character	Period of bubble behaviour
	Bitcoin (in China)	February 7, 2013–April 18, 2013
	Bitcoin (in China)	November 7, 2013–December 12, 2013
	Bitcoin (in China)	Early 2017
	Bitcoin (in China)	May 18, 2017–September 14, 2017
Phillips and Gorse (2018)	Monero	Sep-16
	Ethereum	January 2016–April 2016
Wheatley et al. (2018)	Bitcoin	May 25, 2012–August 18, 2012
	Bitcoin	January 3, 2013–April 11, 2013
	Bitcoin	October 7, 2013–November 23, 2013
	Bitcoin	June 8, 2015–December 18, 2016
	Bitcoin	March 31, 2017–December 18, 2017

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