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Collapsing bubbles in the prices of cryptocurrencies

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ABSTRACT

This paper investigates the existence of bubbles in the daily prices of the most popular cryptocurrencies, Bitcoin (BTC), Ether (ETH), and Ripple (XRP), employing the recursive methods of Phillips et al. (2015) and Phillips et al. (2011) for testing and date-stamping episodes of exuberant behaviour over a period spanning seven years (2018–2024), including the COVID-19 pandemic crisis (2020–2021). The critical values of the tests are computed through the composite wild bootstrap technique by Phillips and Shi (2020) to make them robust to time-varying unconditional heteroscedasticity and the multiplicity issue in recursive tests. Results indicate that the prices of the most popular cryptocurrencies traded on decentralized ledgers, BTC and ETH, exhibited multiple episodes of exuberant behaviour, unambiguously for BTC and depending on the tests for ETH. Bubbles detected in the prices of BTC were due to the halving of the crypto, to market exuberance and to the pandemic crisis; bubbles detected on ETH prices were due to the launch of NFTs on the Ethereum blockchain, and to the change in investors' expectations (from exuberant to pessimistic); the change in the stance of monetary policy burst the bubbles of BTC and ETH prices in 2024. No test supports the exuberance of XRP that is traded on a centralized ledger; weekly data confirm the absence of multiple bubbles. By looking at the presence of bubbles in these different digital ecosystems, we also consider how the technological differences can impact, possibly asymmetrically, bubbles' formation.

1. Introduction

According to the efficient market hypothesis (Fama, 1970), speculative bubbles do not occur because mispricing by irrational investors is offset by arbitrage. However, in real financial markets, frictions, inefficiencies, and the irrational behaviour of agents lead prices (and returns) of assets to deviate from their natural levels (Brunnermeier, 2009; Perdomo Strauch, 2020); bubbles accumulate and eventually burst. Technological revolutions and financial innovation can lead to bubbles (Pástor & Veronesi, 2009).

The paper aims to answer to the following research question: are there collapsing bubbles in the price of the most popular cryptocurrencies over the period 2018–2024? The presence of bubbles in the crypto market can have relevant effects on financial stability, not limited to the digital ecosystem, because of the interconnections in the global financial system. This paper looks at the most recent and disruptive innovation in the global financial system, that of cryptocurrencies, and contributes to the literature on financial bubbles

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by applying recursive methods for testing and date stamping episodes of exuberant behaviour during a period of seven years (2018–2024), before and after the global pandemic crisis (2020–2021). The turbulence in financial markets caused by the COVID-19 outbreak has been under intense scrutiny, but it is critical to consider the following years when the financial systems came back to a new normality.

Decentralized finance (DeFi) has grown in the last few years, and the market capitalization of cryptocurrencies reached $2 trillion in 2024 (CoinMarketCap). Investors can trade cryptos on the respective blockchains or via digital intermediaries; crypto trades have become very popular, even among unsophisticated investors. Prices of cryptocurrencies exhibit a remarkable volatility during the period under analysis, and the paper investigates whether that leads to bubbles (Fig. 1).

The trades of the most popular and most capitalized cryptos (Bitcoin, Ether, and Ripple) take place in very different technological infrastructures. Bitcoins (BTC) have been traded since 2009 on a decentralized blockchain that uses the proof-of-work consensus mechanism of mining, which is very slow; the supply of BTC is limited and pre-defined in the protocol of the blockchain at 21 million tokens, with a decreasing path over time. The limited supply scheme naturally pressures the price of BTC and limits the volume of transactions.

Ether tokens have been traded since 2013 on the Ethereum blockchain, a decentralized ledger that adopts the proof-of-stake consensus mechanism of mining, which is faster than that of BTC. The supply of Ether (ETH) is not limited by the protocol of the blockchain, smoothing pressures on prices.

Ripple is an open-source project to develop a payments' system and is also the name of the digital currency (XRP) traded on a centralized ledger managed by financial intermediaries, with no mining involved; it is a bridge between traditional and digital finance, with a predefined supply of 100 billion tokens. Ripple has been accused by the US authorities of manipulating prices (in 2018) and raising funds from investors (in 2021), claiming it operates as an unregistered security; these events led to speculation and volatility of XRP prices in 2018 and 2021 (Fig. 1). The court ruled in favour of XRP in 2023; it is definitely not considered as a security and should not comply with the Security and Exchange Commission (SEC) regulation.

By looking at the presence of bubbles in these three different digital ecosystems, the paper also considers how the technological differences can impact, eventually asymmetrically, bubbles' formation, the second contribution to the literature.

Although bubbles are not a prerequisite for boom-bust episodes to occur, understanding them is relevant for anticipating explosive price behaviour and safeguarding financial stability; this is of special relevance for innovative financial assets like cryptocurrencies that enjoy reduced public monitoring and limits (Bazán-Palomino, 2022) (p. 6).

The recursive methods employed in this paper for testing and date stamping episodes of exuberant behaviour in prices (Phillips et al., 2011, 2015) are currently used by policymakers to detect bubbles in their very early stages; "these procedures are useful as warning alerts in surveillance strategies conducted by central banks and fiscal regulators with real-time data" (Phillips et al., 2015). Building on recursive right-tailed unit root tests, such real-time monitoring approach is capable of detecting periods that display patterns typical of bubbles. To mitigate the size distortion induced by time-varying heteroscedastic volatility and multiplicity issues in recursive testing procedures, the tests critical values (CVs) have been computed through the composite wild bootstrap method suggested by Phillips and Shi (2020). Others have used this econometric method to detect bubbles in daily prices of Bitcoin and Ether over different and shorter periods; we consider also weekly data that smooths the econometric problems related to (the excessive) volatility of daily financial data.

The paper is organized as follows. The second section reviews the literature on bubbles and cryptocurrencies; the third describes the empirical strategy employed to investigate the presence of bubbles. The fourth section contains the description of daily data and a

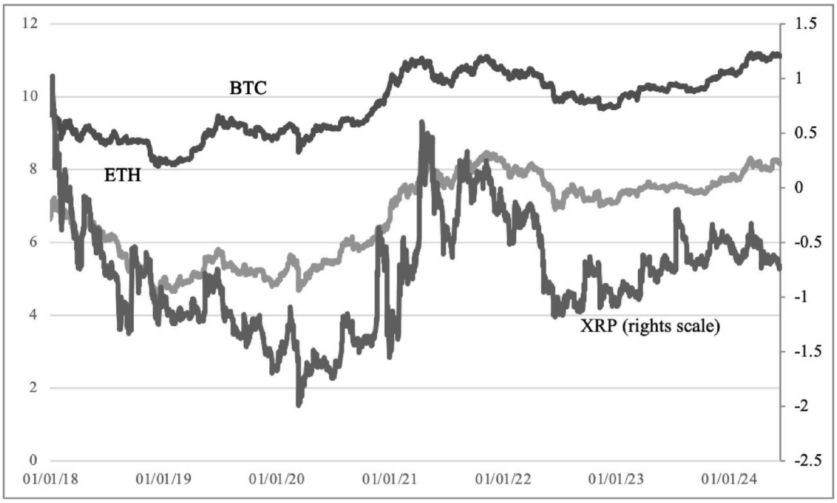

Fig. 1. Ln of price of Bitcoin (BTC), Ether (ETH) and Ripple (XRP), daily data 01/01/2018–14/06/2024
Source: https://www.investing.com/crypto/.

synthesis of relative results; it also presents a summary of the robustness check based on weekly data; more detailed results are reported in the Appendix. The fifth section concludes.

2. Literature review

2.1. Speculative bubbles

Speculative bubbles (Blanchard, 1979; Flood & Hodrick, 1990) have been deeply studied by scholars, most often as a result of market crashes. Hyman Minsky developed a detailed distinction for bubble formation and addressed the following five stages. The first stage is the *displacement stage*, wherein financial innovations such as digital cryptocurrency increase expectations of future profits. Positive expectations accelerate the investment boom, leading to the *boom stage* (the second stage), wherein asset prices increase exponentially, causing assets to become overpriced, exceeding their fundamental value. The third stage is the *euphoria stage*, where trading becomes an investment frenzy. In this stage, even though investors are conscious of explosive behaviour or become suspicious about a bubble, they believe they can sell the asset to unsophisticated investors. Therefore, asset trading is maintained at this stage. This stage is then followed by the fourth stage, *profit-taking*, wherein experienced investors reduce their investments by taking profit. Profit-taking continues if sufficient demand from inexperienced investors remains. 'However, prices eventually fall sharply when demand from inexperienced investors ends, causing *panic* (the fifth stage) in the market' (Haykir & Yagli, 2022) (p.5). The vast popularity of cryptos and the presence of unsophisticated investors let us consider the present as a *euphoria stage*.

Brunnermeier (2009) described four different models to explain bubble formation. The first is the *rational bubble model*, which assumes that investors are rational and share identical information. Rational bubbles stem from expectations regarding increased asset prices. Essentially, traders hold an overvalued asset only if they expect the explosive behaviour to continue. Hence, rational bubbles occur when trading opportunities are available. The second is the *asymmetric information bubble model*, where investors are rational but possess divergent information. Unlike the rational bubble model, there is no common belief regarding bubble behaviour. In this model, the main factor is a lack of common knowledge. Therefore, the asymmetric information bubble suggests that traders tend to hold an overvalued asset with the expectation that they can resell it for higher prices to unsophisticated investors or those with divergent expectations. The third model, *heterogeneous belief bubbles*, is attributable to investors' divergent prior experiences. In this model, market participants share common knowledge but make different investment decisions based on their backgrounds, suggesting psychological bias. Bubble formation is more likely when heterogeneous beliefs are combined with short-selling restrictions as asset prices increase sharply. Moreover, demand from optimistic investors is not offset by pessimists' short sales. In the fourth model, bubbles can emerge owing to *limited arbitrage*. According to the efficient market hypothesis, bubble behaviour does not occur because mispricing by irrational investors is offset by arbitrage. However, noise traders and synchronization risks inhibit rational investors from opposing irrational investors' transactions. Essentially, limited arbitrage fails to eliminate the transactions of irrational traders, causing bubble behaviour to prevail (Haykir & Yagli, 2022) (p.5). Cryptocurrencies do not have any fundamental value (Cheah & Fry, 2015), and rational investors cannot offset the trading of irrational ones; the cryptocurrency market can thus be described as characterized by *limited arbitrage*.

The asset price bubble carries significant additional predictive content for monetary policy forecasts. Policymakers are equipped with econometric techniques that detect bubbles in their very early stages, better guiding their policy choices; 'asset price bubbles should also provide reliable signals for central banks' ultimate primary and secondary targets of price stability, output and/or employment near potential levels' (Beckers, 2015) (p.1). The methodology set by Phillips et al. (2015) is a promising battery of monitoring tests to detect asset price bubbles based on recursive unit root tests of prices and their underlying fundamentals.

2.2. Bubbles and cryptocurrencies

The stock price of innovative firms exhibited bubbles during technological revolutions in 1830–1861 and in 1992–2005 that were 'most pronounced for technologies characterized by high uncertainty and fast adoption' (Pástor & Veronesi, 2009), as in the case of cryptocurrencies in the digital financial system.

The financial properties of prices (and returns) of cryptocurrencies have been studied in the financial literature (Neto, 2022; Ouandlous et al., 2022; Poyser, 2019), showing that the pricing efficiency of cryptos has improved (Tran & Leirvik, 2020). However, no consensus has yet been reached in the literature over their financial nature (i.e., being a currency or a financial asset) (Corbet et al., 2019).

The empirical finance literature investigated the presence of speculative and negative bubbles in the prices and returns of the most capitalized cryptocurrencies (BTC, ETH, XRP and others) (Kyriazis et al., 2020). Speculative bubbles have been detected in the daily prices and returns of the most traded cryptos from 2013 to 2014 (Chaim & Laurini, 2019), from 2015 to 2017 (Fry, 2018), and from 2015 to 2022, with two episodes of bubbles in 2017 and in 2021 (Bazán-Palomino, 2022; Fry & Cheah, 2016) found a negative bubble in 2014 and a dangerous spillover effect from Ripple (XRP) to Bitcoin that exacerbated the price fall in Bitcoin. Speculative bubbles have been associated with herding behaviour during the COVID-19 pandemic period (2020–21) (Haykir & Yagli, 2022).

Our paper contributes to this literature by testing for the presence of exuberance in the natural logarithms of the prices of BTC, ETH and XRP, with data spanning the period 2018–2024. The choice of the period is important because it begins from the onset of digital finance; it considers the entire pandemic crisis period and the following 2 years, when a few digital intermediaries bankrupted, and the prices of crypto have been very volatile. As explained in more detail in Section 3, we use the recursive unit-root tests by Phillips et al. (2011 and 2015) and that has been applied to real estate prices (Otero et al., 2022). This paper relies on crypto data and not on indices to detect and date-stamp bubbles behaviour (Wang et al., 2022).

Bubbles of BTC prices have detected with the PSY method in 2013, in 2016 and in 2019 due to market manipulation (e.g., the M. Gox incident) and to halving (Diniz et al., 2023); halving takes place every 4 years and reduces by 50 % the rate at which new BTC are created. In 2017 and 2018 market manipulation and trade restrictions in China lead to bubbles in the prices of BTCs (Zhang et al., 2021). The so called DeFi Summer of 2020 and the market exuberance in 2021 lead to bubbles in the prices of BTC, ETH and other digital assets (Maouchi et al., 2022). In the cryptocurrency literature, there is another paper that computes the CVs of these tests through the wild-bootstrap procedure (Phillips & Shi, 2020); that paper, focused on BTC daily prices and found a negative relationship with the 10 largest stock markets indices of developed and emerging countries (Gemici et al., 2023).

3. Methodology

This paper investigates the explosive behaviour in the prices of cryptocurrencies by using the recursive unit-root tests by Phillips et al. (2011 and 2015). These procedures compute various versions of the right-tailed augmented Dickey Fuller (ADF) test of unit-root to detect and date-stamp episodes of periodically collapsing bubbles in time series.

The tests and the date-stamping strategies are based on a rolling-window ADF equation, with the rolling window sample starting from the r_1^{th} fraction of the total number of observations T; the equation can be written as follows:

$$\Delta y_t = \alpha_{r_1 r_2} + \beta_{r_1 r_2} y_t + \sum_{i=1}^{k} \delta_{i,r_1 r_2} \Delta y_{t-i} + \varepsilon_t \tag{1}$$

Where Δ is the first difference operator, y_t is the variable under consideration at time t, k is the number of lags of Δy_t used to allow for serial correlation, r_1 and r_2 are the starting and ending observations used for estimation, respectively, and $r_2 = r_1 + r_w$ with $r_w > 0$ is the fractional window size of the regression (the actual window size is the integer part of $r_w T$, denoted as $\lfloor r_w T \rfloor$); ε_t is the error term; α, β, and δ are parameters.

3.1. Bubble tests

The simplest test for detecting exuberant behaviour in prices is the full-range right-tailed ADF, say ADF0. Based on Eq. (1) with $r_1 = 0$ and $r_2 = 1$, ADF0 tests $H_0 : \beta_{0,1} = 0$ against $H_1 : \beta_{0,1} > 0$. It has power against exuberant behaviour, but only if the process is not characterized by episodes of periodically collapsing bubbles, as in this case the process could be mistaken for a unit-root process or even a stationary process (Evans, 1991; Phillips et al., 2011).

Phillips et al. (2011) (PWY) suggest a refinement of ADF0, based on forward recursive ADF equations. This test, referred to as the supremum right-tailed ADF (SADF), is computed as the supremum of the t-statistics $ADF_{r_1}^{r_2}$ from the sequence of equations in (1), with $r_1 = 0$ and r_w expands from the smallest sample window width r_0, set by the researcher, which initializes the procedure by providing the first t-statistic of the recursion, to the last observation.

$$SADF(r_0) = \sup_{r_2 \in [r_0, 1]} ADF_0^{r_2} \tag{2}$$

SADF is effective in detecting exuberant behaviour especially when there is only one collapsing bubble, but it may lack power in the presence of multiple episodes of periodically collapsing bubbles (Phillips et al., 2015).

Given the above limitations of ADF0 and SADF, our preferred test is the extension of SADF derived by Phillips et al. (2015) (PSY), the generalized SADF (GSADF). This procedure considers more rolling-window ADF regressions than SADF, letting r_1 vary over $[0, r_2 - r_0]$, so that

$$GSADF(r_0) = \sup_{\substack{r_2 \in [r_0, 1] \\ r_1 \in [0, r_2 - r_0]}} ADF_{r_1}^{r_2} \tag{3}$$

PSY find that GSADF has more power than SADF in detecting multiple episodes of collapsing bubbles. Both SADF and GSADF require specifying the initializing window size, r_0; we adopt the automatic rule recommended by PSY and set $r_0 = 0.1 + 1.8/\sqrt{T}$, with the actual initializing window size being $T_0 = \lfloor r_0 T \rfloor$.

3.2. Date-stamping strategies

PWY suggest a simple strategy for date-stamping episodes of periodically collapsing bubbles, which is based on the $ADF_0^{r_2}$ computed by the SADF tests.

Let r_e be the bubble origination date and r_f the bubble collapsing date, these dates can be consistently estimated by

$$\widehat{r}_e = \inf_{r_2 \geq r_0} \left\{ r_2 : ADF_0^{r_2} > cv_a^{ADF} \right\} \tag{4}$$

and

$$\widehat{r}_f = \inf_{r_2 \geq \hat{r}_e} \left\{ r_2 : ADF_0^{r_2} < cv_a^{ADF} \right\}, \tag{5}$$

where cv_a^{ADF} denotes the right-tailed α% - critical value of the asymptotic distribution of the standard Dickey–Fuller t –statistic. This strategy is successful in identifying the first episode of exuberance, but it may perform poorly in date-stamping subsequent episodes. Indeed, each forward sample will contain the first collapsing bubble, making them resemble unit-root processes, or even stationary processes, with t-statistics below the right-tailed CVs.

PSY propose an alternative strategy that is designed to solve the foregoing problem. It is based on the $ADF_{r_1}^{r_2}$ of the GSADF test. Define the backward SADF statistic (BSADF) corresponding to any $r_2 \in [r_0, 1]$ as:

$$BSADF_{r_2}(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} ADF_{r_1}^{r_2} \tag{6}$$

Then, the origination and termination dates are consistently estimated as:

$$\widehat{r}_e = \inf_{r_2 \in [r_0, 1]} \left\{ r_2 : BSADF_{r_2}(r_0) > cv_{r_2, a}^{SADF} \right\} \tag{7}$$

and

$$\widehat{r}_f = \inf_{r_2 \geq \hat{r}_e} \left\{ r_2 : BSADF_{r_2}(r_0) < cv_{r_2, a}^{SADF} \right\}, \tag{8}$$

where $cv_{r_2,a}^{SADF}$ denotes the α%-critical value of the SADF test based on $r_2 T$ observations.

4. Data and results

The period under investigation goes from January 01, 2018 to June 14, 2024 (T = 2357). Statistical data on the prices of Bitcoin (BTC), Ether (ETH), and Ripple (XRP) come from Investing.com. Daily data typically allow a large number of observations, here T = 2,357, and are promising of producing bubble tests of greater power than the ones based on lower frequencies (Otero et al., 2022). As aware as we are of the resulting loss in power, we also perform tests based on weekly data as a robustness check. We do this for mainly two reasons. First, the use of weekly data could smooth the econometric problems related to (the excessive) volatility of daily financial data. Second, weekly data reduce substantially the computational burden for the wild-bootstrap procedures, compared to daily data covering the same time span.

4.1. Daily data

Table 1 shows the descriptive statistics of the daily-data natural logarithms of the three crypto-prices. It reports also two popular standard unit-root tests. The first is the ADF test using an upper bound for the lag order as determined by the (Schwert, 1989) formula $p_{max} = int[(12(T/100)^{1/4}]$, then we refine the test reducing the lag order by applying the sequential-t rule by (Ng & Perron, 1995).[1] The second is the Phillips-Perron test, which accommodates serial correlation (up to a lag order p of choice) and heteroskedasticity nonparametrically using Newey-West standard errors. The lag order in this case is given by the Newey-West short formula, $p_{short} = int[(4(T/100)^{2/9}]$. Although these tests are not informative on explosive behavior of the series for the reasons already discussed, they show a first interesting discrepancy between BTC and ETH prices on the one hand, and XRP prices on the other. For the formers the presence of a unit root can never be rejected, while it can always for the latter and such evidence is robust to all of the unit-root tests that we tried, also based on different lags (results are available on request by the Authors).

We conduct the analysis of exuberant behavior in the programming environment of R, based on the package **psymonitor** (Caspi et al., 2018). The baseline implementation of the bubble tests follows the practical recommendation by PSY to set a lag order of zero and the minimum window size as $r_0 = 0.1 + 1.8/\sqrt{T}$. We also try a lag order selected by the BIC with a maximum order of 7 days. As a last check, we also report test results for a fixed lag order of 7 days.

The Monte Carlo CVs for SADF and GSADF tabulated in the original PSY paper and available in the R core team (2020) package **exuber** (Vasilopoulos et al., 2020) are not robust to two potential inference issues: 1) time-varying unconditional heteroscedasticity in the ADF errors and 2) the multiplicity issue (the probability of a false positive increases with the number of hypotheses tested), which is common to all the recursive testing procedures (Cretarola & Figà Talamanca, 2020). To mitigate the impact of these two issues simultaneously, Phillips and Shi (2020) (PS) suggest a composite wild bootstrap procedure for computing robust CVs, which combines the heteroscedasticity-robust procedure by Harvey et al. (2020) and the multiplicity-robust procedure by Shi et al. (2020). The PS procedure involves the following steps.

1. Based on the whole sample, estimate the ADF equation

[1] We trim the longest lags from the ADF regression, one by one, until the longest remaining has a t-statistic no smaller than 1.6 (p-value < 0.1).

Table 1
Descriptive statistics of ln(price) of BTC, ETH and XRP (daily data 01/01/2018–14/06/2024).

	Bitcoin BTC	Ether ETH	Ripple XRP
Obs.	2357	2357	2357
Mean	9.78	6.701	−0.789
Std. Dev.	0.839	1.154	0.511
ADF test (p-value)	−2.270 (0.450)	−2.461 (0.348)	−3.858 (0.014)
Phillips-Perron test (p-value)	−2.177 (0.503)	−2.100 (0.546)	−3.756 (0.019)

The lag order for ADF is determined by the Ng-Perron criterion from an upper bound given by the Schwert formula, int[(12(T/100)$^{1/4}$]. The lag order for Phillips-Perron is the short Newey-West formula, int[(4(T/100)$^{2/9}$].

$$\Delta y_t = \alpha + \beta y_t + \sum_{i=1}^{k} \delta_i \Delta y_{t-i} + \varepsilon_t \tag{9}$$

under the null hypothesis $\beta = 0$ and save the OLS estimates, $\widehat{\alpha}$ and $\widehat{\delta}_i$, and the OLS residuals, e_t.

2. Let T_b denote the length of the time window over which the probability of a false positive conclusion is to be controlled. For a bootstrap sample size $T_0 + T_b - 1$, generate a bootstrap sample from $\Delta y_t^b = \widehat{\alpha} + \sum_{i=1}^{k} \widehat{\delta}_i \Delta y_{t-i}^b + e_t^b$, using the actual values $y_t, t = 1, \ldots k+1$ as initial values and $e_t^b = w_t e_l$, where w_t is a random draw from the standard normal distribution and e_l is bootstrapped from the residual sequence obtained in Step 1.
3. Based on the bootstrap sample of Step 2, calculate the PSY statistic as in Eq. (3), say $GSADF^b$.
4. Repeat Steps 2–3 B times to get the sequence of bootstrap statistics $GSADF^1 \ldots . GSADF^B$
5. Take the 95 % percentile of the sequence at Step 4 as the critical value of the GSDAF test.

Step 2 implements a wild bootstrap to address heteroscedasticity. Steps 3–5 generate critical values (CVs) that accommodate the multiplicity issue in the test recursion. The choice of the bootstrap window T_b is subjective, taking into account that a larger window T_b leads to a more conservative test, as noted by Shi and Phillips (2023).

This explains why in most of the empirical applications implementing the PS bootstrap procedure T_b is fixed as a small fraction of the total sample size. For example, Phillips and Shi (2020), analysing the S&P 500 market, used a dataset with 547 monthly observations and set $T_b = 24$ months. The dataset used by Shi and Phillips (2023) contains 76 quarterly observations for eight Australian housing markets, and the bootstrap window was set at $T_b = 1$ quarter for each market. Zhang et al. (2021) analysing exuberance in BTC and ETH ln prices from March 1, 2014 to May 31, 2019 fix a relatively larger bootstrap window of $T_b = 730$ days. We conform to the practice of setting a relatively small bootstrap window and fix $T_b = 183$ days (half a year), conscious of the reduced test power that may result from setting a relatively larger T_b and for the sake of computational tractability. We nonetheless did some experiments with $T_b = 730$ days (reported in the Appendix) and found fewer episodes of exuberance for the three crypto-currencies, compared to $T_b = 183$, which makes us suspect that indeed some loss in power may have occurred.

The GSADF tests in this paper are based on the robust PS CVs, computed by B = 499 wild bootstrap replications. Table 2 shows tests results with bootstrap CVs and fixed lag order = 0 for the daily series of Bitcoin, Ether and Ripple ln prices. Starting with the Bitcoin, GSADF rejects the hypothesis of unit-root at the 1 % significance level, decidedly supporting explosive behaviour in BTC prices. We then proceed to the date-stamping analysis. Fig. 2, plotting the series of the BTC ln prices, shows four bubble episodes, shaded in green, where the BASDF statistic exceeds its 95 % bootstrapped critical values (Table A1 in appendix reports the detailed date-stamping analysis for the daily data). The first bubble episode starts on 2018-11-24 and terminates on 2018-12-08 with a break in between. The second starts on 2019-05-11 and terminates on 2019-06-28 with several breaks in between. Previous papers confirmed that the bubbles in 2018 and 2019 were due to the halving of BTC (Diniz et al., 2023). The third is the longest interval, spanning four months, from 2020-12-19 to 2021-03-13 with several breaks in between. This bubble episode relates to market exuberance following the pandemic crisis (Maouchi et al., 2022). The last starts on 2024-02-28 and terminates on 2024-03-15 with two breaks in between. This recent bubble episode can be due to the halving of BTC, as observed in the past and to the change in the stance of monetary policy at the global level, from expansionary to restrictive. GSADF with the BIC lag order produces virtually the same results (Table 3, Fig. A1). With

Table 2
GSADF Tests with bootstrap CVs and fixed lag order = 0 (daily data 01/01/2018–14/06/2024).

GSADF	RTBS90	RTBS95	RTBS99
BITCOIN (BTC)			
3.709***	1.246	1.500	2.086
ETHER (ETH)			
2.289***	1.210	1.513	2.124
RIPPLE (XRP)			
3.966***	1.340	1.769	2.104

Number of obs. T = 2357; initializing window size $\lfloor r_0 T \rfloor = 110$; RTBS: right-tail Bootstrap CVs for 90, 95, 99 percentiles based on wild bootstrap with 499 replications and bootstrap window $T_b = 183$.

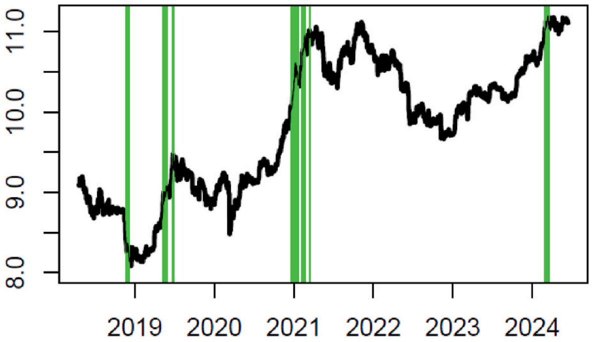

Fig. 2. Bitcoin BSADF test lag order = 0, Bootstrap window = 183 (daily data 01/01/2018–14/06/2024)
The solid line is the ln of BTC price and the shaded areas are the periods when the BSADF statistics exceeds its 95 % bootstrapped critical value.

Table 3
GSADF Tests with bootstrap CVs, BIC-selected lag order with max lag = 7 (daily data 01/01/2018–14/06/2024).

GSADF	RTBS90	RTBS95	RTBS99
BITCOIN (BTC)			
3.588***	1.194	1.399	1.958
ETHER (ETH)			
2.144***	1.150	1.414	2.020
RIPPLE (XRP)			
3.698***	1.252	1.654	1.973

Number of obs. T = 2357; initializing window size $\lfloor r_0 T \rfloor$ = 110; RTBS: right-tail Bootstrap CVs for 90, 95, 99 percentiles based on wild bootstrap with 499 replications and bootstrap window T_b = 183.

a fixed lag order of 7 the GSADF test still supports exuberant behavior at 1 % (Table 4), although the date-stamping procedure fails to detect the 2018 and 2024 episodes (Fig. 3). When broadening the T_b window to 730 days, expectedly the bootstrapped critical values increase and, while GSADF still supports exuberant behavior at the 1 % level, the date-stamping procedure fails to detect the 2024 bubble episode. The other three episodes are still identified, but are shorter (Table A2 and Fig. A2 in the appendix).

Likewise BTC, the GSADF test with lag order = 0 applied to ETH ln prices rejects the presence of unit-root at the 1 % level, supporting exuberant behavior (Table 2). The PSY date-stamping procedure evidences four short-lived bubble episodes: from 2021-01-04 to 2021-01-10; from 2021-05-05 to 2021-05-14 with two breaks in between; from 2022-06-13 to 2022-06-18 with a break in between; and, finally, from 2024-03-04 to 2024-03-13 with a break in between (Fig. 4). The bubble of ETH price in 2021 was driven by the launch of Non-Fungible Tokens (NFTs) on the Ethereum blockchain, where ETH acts as the gas fee. NFTs have been very popular among digital investors and their market capitalization peaked in May 2021, when a significant reduction took place. In June 2022, the prices of cryptocurrencies have been negatively influenced by pessimistic forecasts on digital finance growth and stability, and by the rise of inflation rates. The 2024 bubble can be due to the change in the stance of monetary policy at the global level. Results are virtually the same with the BIC-selected lag order (Table 3, Fig. A3). With a fixed lag order of 7, the GSADF test still supports exuberant behavior at 1 % (Table 4), although the date-stamping procedure fails to detect the bubble episode of May 2021 and that in 2022 (Fig. 5). When broadening the T_b window to 730 days, expectedly the bootstrapped critical values increases so that the GSADF test supports exuberant behavior only at the 5 % level and the date-stamping procedure only detects the January 2021 bubble episode (see Table A2 and Fig. A4 in appendix).

Finally, for XRP ln prices the GSADF test with zero lag order rejects unit root at the 1 % level (Table 2), but only a short-lived single

Table 4
GSADF Tests with bootstrap CVs and fixed lag order = 7 (daily data 01/01/2018–14/06/2024).

GSADF	RTBS90	RTBS95	RTBS99
BITCOIN (BTC)			
3.791***	1.601	1.980	2.818
ETHER (ETH)			
2.693***	1.685	2.089	2.582
RIPPLE (XRP)			
1.208	1.766	2.157	2.867

Number of obs. T = 2357; initializing window size $\lfloor r_0 T \rfloor$ = 110; RTBS: right-tail Bootstrap CVs for 90, 95, 99 percentiles based on wild bootstrap with 499 replications and bootstrap window T_b = 183.

Fig. 3. Bitcoin BSADF test lag order = 7 (daily data 01/01/2018–14/06/2024)
The solid line is the ln of BTC price and the shaded areas are the periods when the BSADF statistics exceeds its 95 % bootstrapped critical value.

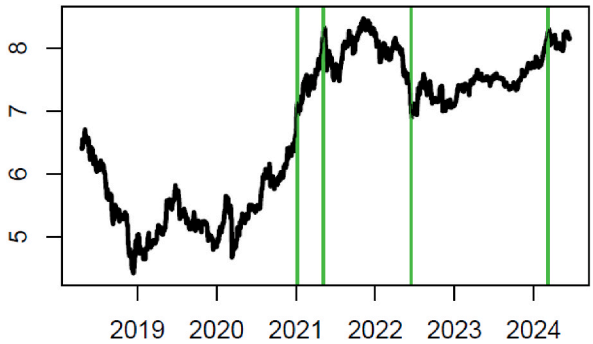

Fig. 4. Ether BSADF test lag order = 0, Bootstrap window = 183 (daily data 01/01/2018–14/06/2024)
The solid line is the ln of ETH price and the shaded areas are the periods when the BSADF statistics exceeds its 95 % bootstrapped critical value.

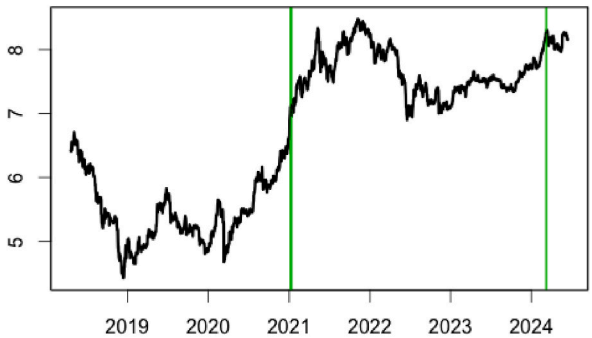

Fig. 5. Ether BSADF test lag order = 7 (daily data 01/01/2018–14/06/2024)
The solid line is the ln of ETH price and the shaded areas are the periods when the BSADF statistics exceeds its 95 % bootstrapped critical value.

bubble is found, from 2020-11-23 to 2020-11-25 (see Fig. 6). During this period, the digital asset was under scrutiny by the US financial market authorities, but had no consequences. The same results emerge with the lag order determined by the BIC from a maximum lag order of 7 (Table 3, Fig. A5). With a fixed lag order of 7, GSADF does not support exuberant behavior at all (Table 4). When considering T_b as 730 days the GSADF still rejects the unit root at the 1 % level, but the single episode of exuberance shortens from 2020-11-23 to 2020-11-24 (see Table A2 and Fig. A6 in the appendix).

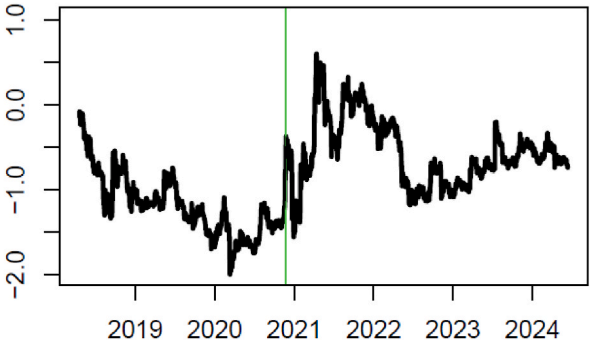

Fig. 6. Ripple BSADF test lag order = 0, Bootstrap window = 183 (daily data 01/01/2018–14/06/2024)
The solid line is the ln of XRP price and the shaded areas are the periods when the BSADF statistics exceeds its 95 % bootstrapped critical value.

4.2. Weekly data

The period under investigation is the same as for the daily analysis, covering from week 1 of 2018 to week 24 of 2024 (T = 336). Also the minimum window size is determined as in the daily analysis, $r_0 = 0.1 + 1.8/\sqrt{T}$. Table A3 shows GSADF results with bootstrap CVs, fixed lag order = 0 and a bootstrap window of half a year, 26 weeks, as in the daily analysis. Table A4 in the appendix reports the detailed date-stamping analysis for the weekly data. GSADF rejects the hypothesis of unit-root in BTC ln prices at the 1 % significance level, decidedly supporting explosive behaviour. The expected loss of power due to the lower frequency of data becomes evident in the date stamping analysis (Fig. A7), where the 2018 and 2019 episodes detected by the daily analysis are absent. For ETH, the GSADF test supports exuberance at 1 % (Table A3) and, interestingly, the date stamping analysis leads to the same episodes as in the daily analysis (see Fig. A8). Regarding XRP, the GSDAF test only supports exuberant behaviour at 10 % level (Table A3), so that we did not conduct the date-stamping analysis.

We also considered the GSADF test with lag order selected by the BIC from a maximum lag order of 5 weeks, as computed by the Schwert formula $k_S = int\left[4(T/100)^{1/4}\right]$. Test results (Table A5) and the date-stamping analysis (Figs. A9 and A10) are very close to those for the zero-lag-order test for all crypto-currencies.

5. Conclusion

Bubbles in the prices of Bitcoin emerged and collapsed in 2018, 2019, 2020, 2021 and 2024; the halving of the cryptocurrency and market events were at the roots of the episodes in 2018 and 2019. The enthusiasm over digital finance during the pandemic period fuelled the rise of the price of digital assets in 2020 and in 2021. Bubbles in the price of ETH emerged and collapsed in 2021, 2022, and 2024. The bubble of ETH price in 2021 was driven by the launch of NFT's on the Ethereum blockchain, while the bubble in 2022 was due to changing expectations of investors. During the pandemic period, monetary and financial authorities implemented extraordinary expansionary policies to avoid a global crisis of the financial system. In 2023–2024, the restrictive monetary policy reduced excess liquidity and investors modified their portfolio allocation by selling cryptos. According to our results, this proactive monetary policy approach has been successful and bubbles busted without much damage.

The debate over the ability of policy authorities to 'lean against the wind' should consider digital assets as well as traditional ones. The presence of bubbles in the prices of the most popular cryptos (BTC, and ETH) should be considered by policy authorities that look after financial stability, inclusion and growth.

A growing number of unsophisticated and euphoric investors, together with limited arbitrage lead to bubbles' formation in the digital financial system. Bubbles in the crypto market can be due to the asymmetric structures in which they are traded. The results of this paper show that trading cryptos on centralized ledgers, as in the case of Ripple, does not favour the bubble formation, while decentralized ledgers allow for the bubbles' formation. Further research is needed on cryptos traded on centralized ledgers, but this asymmetry should be considered by policymakers when addressing the supervision and monitoring of the digital financial system. The econometric method applied in this paper can be of help for policymakers, since it can detect bubbles' formation and not merely testify to their presence or evaluate their size and impact after their burst.

The question of whether monetary authorities should react to bubbles in crypto prices as soon as they emerge, given the lack of supervisory power and capital requirements of digital intermediaries, remains unanswered. Further research in this challenging area of financial economics should investigate the presence of bubbles in the prices of other digital assets that exhibit lower volatility, like stablecoins.

CRediT authorship contribution statement

Chiara Oldani: Writing – original draft, Data curation, Conceptualization. **Giovanni S.F. Bruno:** Writing – original draft, Methodology, Formal analysis. **Marcello Signorelli:** Writing – review & editing, Validation, Supervision.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Legenda of abbreviations

ADF	Augmented Dickey Fuller
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
BTC	Bitcoin
CV	Critical value
ETH	Ether
DeFi	Decentralized Finance
GSADF	Generalized Supremum Augmented Dickey Fuller
PS	Phillips and Shin
PSY	PhillipsShin and Yu
PWY	Phillips, Wu and Yu
SADF	Supremum Augmented Dickey Fuller
XRP	Ripple

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jeca.2025.e00420.

Data availability

Data used in this paper is publicly available; crypto prices data come from https://www.investing.com/crypto/.

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