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Bubbles all the way down? Detecting and date-stamping bubble behaviours in NFT and DeFi markets

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ABSTRACT

Amid surging market values and widespread regulatory discussion, NFT and DeFi markets are widely perceived as being simply speculative in nature. This paper detects the existence and dates of price bubbles in the NFT and DeFi markets by applying SADF and GSADF tests. We document that NFT and DeFi markets both exhibit speculative bubbles, with NFT bubbles being more recurrent and having higher average explosive magnitudes than DeFi bubbles. The price bubbles in the NFT and DeFi markets are highly correlated with market hype and with more general cryptocurrency market uncertainty. We do find periods where bubbles are not detected, suggesting that these markets do have some intrinsic value and should not be dismissed as simply bubbles.

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NFTs; DeFi; price bubbles; SADF and GSADF; explosiveness

1. Introduction

It is a common thought that no investor intends to hold a speculative instrument at the point when a price spiral collapses. Smart money and wise investment decisions are thought to dictate rational acting in most financial markets. Nevertheless, the history of financial markets is replete with the remains of collapsed bubbles. Here we examine two relatively new markets, those for Non-Fungible Token (NFT) and Decentralised Finance (DeFi).[1] As of 31 January 2022, the market capitalisation of the NFT and DeFi markets was $47.81bn and $141.08bn, respectively, an increase from $340 m and $15.79bn on 1 January 2021,[2] which may raise suspicion for a purely speculative character of the digital instruments. In order to better assess the likelihood of a crash, it is important to examine the price dynamics of these new markets closely.

NFT and DeFi token are two instruments in the digital space that remarkably extend the spectrum of decentralised financial assets. According to the framework of Kinlaw, Kritzman, and Turkington (2017), NFTs could be characterised as instruments that display

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heterogeneous properties internally as well as externally with other asset classes. Conversely, DeFi tokens display fully fungible characteristics within their individual category that lead them to act internally homogeneous. Nevertheless, both instruments may display differing price dynamics that are not yet fully investigated, specifically under the aspect of price explosiveness. More recently and closer to this study, Maouchi, Charfeddine, and El Montasser (2021) investigate and predict the price bubbles of the NFT and DeFi markets in the COVID-19 pandemic by applying an optimised Generalised Supremum Augmented Dickey–Fuller (GSADF) test with four multivariate models. They conclude that specific bubbles in DeFi- and NFT assets occurred in summer 2020 that indicate distinct price dynamics for both markets in contrast to cryptocurrencies. Furthermore, DeFi and NFT bubbles are less recurrent but have higher magnitudes than past cryptocurrency bubbles. However, to date such studies have had to rely on individually selected digital assets. Therefore, we should take as merely indicative the findings of Maouchi, Charfeddine, and El Montasser (2021), and more recently Karim et al. (2022) and Wang (2022) which examine selected representative NFTs, DeFi and cryptocurrencies' assets. Furthermore, as pointed out by Dowling (2022a) with growing market maturity in DeFi and NFT markets, their inherent price dynamics may also evolve to a more efficient state.

This study contributes to the existing literature by systematically examining the occurrence of price bubbles in a unique strand of the entire NFT and DeFi markets. To achieve this goal, we use the time-series NFT Index (NFTI) and DeFi Pulse Index (DPI) as two composite indices to represent the wider NFT and DeFi markets. Moreover, this study also includes several major capitalised NFT and DeFi assets from their earliest issue time to 31 January 2022, including Bored Ape Yacht Club (Ape), CryptoPunks, The Sandbox (Sandbox), Art Blocks (ArtBlocks), Terra (LUNA1), Avalanche (AVAX), Wrapped Bitcoin (WBTC), and Chainlink (LINK) to reach to a holistic conclusion about explosive bubble behaviours in both markets. Our main empirical approach is similar to Corbet, Lucey, and Yarovaya (2018) as we detect and date-stamp the price bubbles based on the SADF (Supremum Augmented Dickey-Fuller) and Generalised Supremum Augmented Dickey–Fuller (GSADF) tests, with the Log-Periodic Power Law Singularity (LPPLS) test being a robustness measure. After identifying the price bubbles in the DeFi and NFT markets, we extend our analysis by linking these price explosive periods to the flash events related to DeFi and NFT assets. At the same time, we discuss the price mechanisms in the DeFi and NFT assets. In addition, we put our empirical results into a comparable context and demonstrate the differences in price bubbles between DeFi & NFT markets and cryptocurrency markets.

This study could additionally contribute to the previous studies that have developed and employed various time-series econometrics framework to measure price bubbles in financial markets (LeRoy and Porter 1981; West 1987; Diba and Grossman 1988b, 1988a; Johansen, Ledoit, and Sornette 2000; Homm and Breitung 2012; Phillips, Shi, and Yu 2015; Sharma and Escobari 2018; Corbet, Lucey, and Yarovaya 2018). To the best of our knowledge, this paper is the first to comprehensively identify price explosive behaviours in the DeFi and NFT markets by using SADF and GSADF tests.

In the end, the findings from this study are valuable for investors, alternative investment analysts, academics, market regulators and policymakers due to price bubble detection can serve as an early warning signal. Similar to cryptocurrency markets,

continuous trading on NFT and DeFi markets is highly impacted by news or flash events (Lucey et al. 2022) and (Wang et al. 2022). Therefore, investors need to be aware of the underlying dynamics, as it is known that bubbles may burst unexpectedly. The appearance of bubbles in the NFT and DeFi markets may display different formation mechanisms fostered by market hype, herding behaviour, and oscillation frequency, among others. These properties contribute to a significant level of uncertainty and volatile price behaviour in NFT and DeFi markets. Therefore, it may even be crucial that market regulators and policymakers emphasise risk management practices to avoid worse damage caused by price bubbles from NFT and DeFi markets. For several reasons, price bubble detection in the DeFi and NFT markets is more important for policymakers in developing countries. First, to achieve high and sustainable economic growth, it could be better to launch more efficient market policies on time to maintain the stabilisation of financial markets and prevent the shocks from DeFi and NFT crises. Second, NFT and DeFi offer new economic possibilities like easier financial transactions and property rights enforcement, which could be especially beneficial for developing economies.

This paper is further organised and developed as follows. The section 2 outlines previous literature on price bubble detections, NFT assets and DeFi markets, further identifies research gaps and introduces hypothesis developments. The section 3 the data for the price bubble detecting tests, while section 4 introduces the econometric models applied. section 5 and findings presents the empirical analysis results and robustness test. Finally, section 6 reviews the main findings of this study and its implications.

2. Literature review

There is a vast body of literature on the speculative price bubble formation in financial markets in the context of stocks (Pástor and Veronesi 2009) and (Phillips, Wu, and Yu 2011), real estate (Kivedal 2013) and (Jordà, Schularick, and Taylor 2015), and commodities (Sornette, Woodard, and Zhou 2009) and (Figuerola-Ferretti and McCrorie 2016). Scholarly works, examining the price behaviour of cryptocurrencies conversely raise evidence of explosive patterns in the price formation of several major capitalised digital currencies, pointing towards a speculative character of the digital instruments (Kyriazis, Papadamou, and Corbet 2020). Pioneering research by Garcia et al. (2014) first evidence two positive feedback loops that positively affect the fluctuation in Bitcoin prices and may enforce price bubbles without exogenous interference. MacDonell (2014) utilises Autoregressive Moving Average (ARMA) methodologies in combination with the LPPLS – framework and finds investor sentiment, proxied by the CBOE volatility index (VIX), to be of influential nature for changes in Bitcoin values. Cheah and Fry (2015) confirm first evidence of explosive bubble behaviour in Bitcoin prices that manifest in dramatic price rises, leading to the estimate that the fundamental value of the digital token is close to zero. Urquhart (2016) finds the Bitcoin market to be generally inefficient but acknowledges that prices do seem to approach a random distribution pattern with growing market maturity. By deploying a bubble detection methodology from the traditional financial markets, Cheung, Roca, and Su (2015) conduct the PSY (GSADF) test to examine price bubbles in Bitcoin.

These findings give a first indication about inefficient pricing mechanisms in the largest capitalised cryptocurrency and could spur further research intentions on other

cryptocurrencies. Following the econometric test framework of the GSADF- or SADF test, several papers have detected price bubbles in Bitcoin, Ripple, Ethereum, Litecoin, Nem, Dash, Stellar and Dogecoin (Su et al. 2018; Corbet, Lucey, and Yarovaya 2018; Li et al. 2019; Bouri et al., 2019; Geuder, Kinateder, and Wagner 2019; Li et al. 2021; Shahzad, Anas, and Bouri 2022.) Conversely, Wheatley et al. (2019) further explore price bubble formations in Bitcoin values by means of a combinatorial approach of applying a generalised metcalf's law in line with an LPPLS model to closer study potential bubble dynamics in Bitcoin markets. The results indicate the occurrence of four distinct bubbles, characterised by high overvaluation and LPPLS-like trajectories that entails crashes or strong corrections (ibid.). Further methods containing the LPPLS approach have also been used by other scholars to capture explosive behaviour in the digital currency area (Geuder, Kinateder, and Wagner 2019; Gerlach, Demos, and Sornette 2019; Wheatley et al. 2019; Shu and Zhu 2020, 2020).

Numerous scholars also address the potential recurrence and degree of magnitude for price bubbles in cryptocurrency markets. Gerlach, Demos, and Sornette (2019) study the price dynamics of Bitcoin and specifically characterise the time duration of price bubbles based on their temporal nature. The authors evidence several long- and short-term bubbles in the time span of 2012 to 2018 that point to a multiscale character of the bubble dynamics in Bitcoin prices. Geuder, Kinateder, and Wagner (2019) further underline these findings by raising evidence of frequent bubble periods in the price formation of Bitcoin and emphasise the recurring character of the bubbles. Bouri et al. (2019) detect several price explosivity periods for seven major-capitalised cryptocurrencies that suggest a re-emerging character of bubble dynamics in different markets with varying scales of magnitude and a certain degree of co-movement between the different digital assets. Conversely, Chen and Hafner (2019) test for speculative bubbles in the entire cryptocurrency market, mirrored by the CRIX index, via a profound sentiment-induced econometric framework. The authors simultaneously detect several short-term bubble phases for the market in the years 2017 to 2018 that indicate recursive regime shifts in the price explosivity potentially induced by investor sentiment.

Corbet, Lucey, and Yarovaya (2018) lead a consecutive study on the price discovery of Bitcoin and Ethereum and oppositely do not find clear evidence that a persistent bubble is evolving within both markets. However, it can conclude that the findings do not indicate that prices meet efficient standards and the authors attest short-term influential interlinkages between the price formation of both cryptocurrencies and fundamental drivers such as blockchain position, liquidity, or hash-rate that could support bubble forming behaviour. Hafner (2020) argues in favour of bubble occurrences in cryptocurrency markets while studying the price properties of the 11 major-capitalised cryptocurrencies. By accounting for time-varying volatility in the price dynamics of the cryptocurrencies, the author identifies explosive bubble patterns in the index, although it could constitute that the effect is much less pronounced compared to a constantly assumed volatility component. Li et al. (2019) particularly focus on the potential formation of Bitcoin price bubbles in China and the U.S., thereby examining the nature of the bubble proliferation across time. The authors find evidence of several explosive price bubbles that accompany highly volatile economic events, suggesting spillover effects of foreign financial risk to cryptocurrency markets. As NFTs and DeFi assets are embedded in similar blockchain

ecosystems, the potential for bubble formation may reveal similar tendencies compared to cryptocurrency markets.

It can be constituted that NFT and DeFi markets have gained significant scholarly attention recently and research efforts considerably focus on examining financial properties alongside the economic attributes of both markets. As novel instruments, NFTs and DeFi assets specifically provoke research on the matter of market efficiency (Maouchi, Charfeddine, and El Montasser 2021) and (Dowling 2022a), volatility dynamics (Wang 2022; Aharon and Demir 2022; Umar et al. 2022), risk-return relationships (Borri, Liu, and Tsyvinski 2022) and trade network attributes (Nadini et al. 2021).

In this context the emerging literature so far has only sparsely accounted for any form of price explosive patterns in NFT or DeFi markets. First studies by Dowling (2022a) and Maouchi, Charfeddine, and El Montasser (2021) assess the price behaviour of the new instruments by focusing on specific categories in the area of metaverse and DeFi token. The studies reach to a common consent that NFT and DeFi assets do possess inefficient and bubble-like price explosiveness at different time spans that are driven by unique price dynamics in both markets. Corbet et al. (2021) confirm pronounced bubble dynamics in DeFi markets and suggest that the bubble formations are mainly self-generated. Hence, the early scholarly evidence seems to indicate that bubble dynamics within both markets seem to be driven by unique token pricing factors. However, current research is far from systematically explaining bubble dynamics in NFT and DeFi markets. To fill this research gap, we detect and date-stamp bubble behaviours in NFT and DeFi markets. We, therefore, propose the research hypothesis:

H_1: In NFT and DeFi markets do exist price bubbles

3 Data

The two capitalisation-weighted composite indices, NFTI[3] and DPI[4] are selected to represent the NFT and DeFi markets, separately. The overall price bubble magnitude in the NFT and DeFi markets can be investigated by examining these two composite indices, which can be collected from CoinMarketCap.[5] Due to the composition of the NFTI, we are able to capture price movements in two distinctive NFT sub-markets related to the category of metaverse and game token. In turn, the constellation of the DPI allows us to mirror the price dynamics of a wide range of markets for majorly traded DeFi tokens.

Additionally, several popular NFT and DeFi assets are collected to further measure the price bubbles in the NFT and DeFi markets in detail. Sorted by the volume all time and all-time sales thresholds, Ape, CryptoPunks, Sandbox, and ArtBlocks are selected for the NFT market, and LUNA1, AVAX, WBTC, and LINK are chosen for the DeFi market. NFT and DeFi assets data are, respectively, obtained from CoinMarketCap and NonFungible.[6]

All the assets are priced in USD. Due to NFT and DeFi collections being traded infrequently, and also differing in terms of *quality*, we cannot simply look at price differences of the assets. Therefore, we use daily average price data for all the selected NFT and DeFi assets. The daily average price data is widely used as a proxy to represent the NFT and DeFi markets (Aharon and Demir 2022; Dowling 2022b, 2022a; Karim et al.

Table 1. Descriptive statistics.

	NFT Index	Bored Ape Yacht Club	CryptoPunks	The Sandbox	Art Blocks
Panel A: NFT assets					
Start point	2021–03-05	2021–04-25	2017–06-22	2019–12-02	2020–11-27
Observation	333	282	1685	792	431
Mean	1463.91	35,575.74	46,036.13	1960.46	2865.43
Min	353.56	183.62	22.94	25.35	19.78
Max	4325.82	94,230.55	571,998.19	17,012.67	15,011.11
Range	3972.26	94,046.93	571,975.25	16,987.32	14,991.33
Std. Dev.	1011.78	27,642.60	118,850.51	4032.31	3416.70
MAD	764.29	42,935.95	190.35	239.43	1490.62
Skewness	0.94	0.26	2.85	2.59	1.56
Kurtosis	− 0.44	− 1.14	7.00	5.31	1.69
SE	55.70	1651.96	2897.07	143.46	164.96
Ljung-Box test	327.17 ***	274.63 ***	1678.6 ***	787.09 ***	412.86 ***
J.-B. test	51.439 ***	18.091 ***	5739.6 ***	1825.9 ***	226.78 ***
Panel B: DeFi assets					
Start point	2020–09-15	2019–07-26	2020–09-22	2019–01-30	2017–11-09
Observation	504	921	497	1097	1545
Mean	296.06	11.98	36.67	22,940.84	8.95
Min	59.56	0.13	2.91	3395.98	0.15
Max	633.24	99.72	134.53	67,549.23	52.20
Range	573.68	99.59	131.62	64,153.25	52.05
Std. Dev.	135.55	21.07	33.99	19,138.79	11.30
MAD	133.54	0.78	32.99	7435.18	3.32
Skewness	− 0.12	2.10	0.99	0.78	1.22
Kurtosis	− 0.82	3.74	− 0.10	− 0.98	0.37
SE	6.06	0.69	1.53	578.37	0.29
Ljung-Box test	489.15 ***	911.78 ***	489.79 ***	1092.3 ***	1531.1 ***
J.-B. test	14.936 ***	1215.9 ***	82.295 ***	155.28 ***	391.62 ***

Notes: Ljung-Box test for the distribution of residuals in a variable (Box and Pierce 1970) and (Ljung and Box 1978), and it can examine the autocorrelation of squared returns series. Jarque-Bera (J.-B.) statistics can be used to check the normal distribution characteristic of the data (Jarque and Bera 1980) and (Bera and Jarque 1981). * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

2022; Wang 2022). Also, because the NFT and DeFi markets are novel financial markets, no starting point for these observations is set. Data are collected in the range between the earliest available time and 31 January 2022. Descriptive statistics are shown in Table 1 where it is clearly visible that the NFT market is more volatile than the DeFi market.

4 Methodology

Asset price bubble detecting models are all based on an asset pricing equation, which can be expressed as Equation 1:

$$P_t = \sum_{i=0}^{\infty} \left(\frac{1}{1+r_f}\right)^i \mathbb{E}_t(D_{t+i} + U_{t+i}) + B_t, \tag{1}$$

where P_t is the after-dividend. Or, where dividends do not exist. The price of the financial asset, r_f is the risk-free interest rate, $\mathbb{E}_t$ is the expected return, D_t is the investment return received from the financial asset, U_t denotes the unobservable fundamentals. In the end, B_t represents the bubble component, and it satisfies the sub-martingale property, which can be defined as: $\mathbb{E}_t(B_{t+1}) = (1 + r_f)B_t$. Market fundamental can be measured as: $P_t^f = P_t - B_t$.

According to the price bubble sub-martingale property, when U_t in Equation 1 are at most unit-roots (random walks) and D_t is stationary without a trend after differencing, price bubbles can be captured from the explosive behaviour in asset prices or the price-dividend ratios. For the asset pricing equation in Equation 1, several econometrics models can identify the price bubble components in the asset pricing models (see as examples Hall, Psaradakis, and Sola 1999; Zhou and Sornette 2003; Cochrane 2005; Pástor and Veronesi 2006; Ferguson 2008; Kindleberger and Aliber 2011; Fry and Cheah 2016; Cagli 2019; Cretarola and Figà-Talamanca 2021; Waters and Bui 2022). No matter the framework of the price bubble detecting econometrics models, explosive or mildly explosive behaviour in asset prices is a key indicator of the existence of price bubbles (Phillips and Magdalinos 2007). More particularly, recursive right-sided unit root tests can be used as significantly effective models to detect price bubbles in financial assets (Phillips, Wu, and Yu 2011), with potential for near real-bubble detection (Phillips, Shi, and Yu 2015).

Following Phillips, Wu, and Yu (2011) (PWY) and Phillips, Shi, and Yu (2015) (PSY), this study assumes prices follow a pure random walk process in a martingale null with an asymptotically negligible drift to capture the mild drift in price processes, which can be expressed as Equation 2:

$$y_t = dT^{-\eta} + \theta y_{t-1} + \varepsilon_t, \varepsilon_t \sim^{iid} (0, \sigma^2), \theta = 1, \tag{2}$$

where d is a constant, T is the sample size, η is a localising coefficient that controls the magnitude of the intercept and drift as T approaches infinity in the PWY test, but drift as T approaches unity in the PSY test. In our model, $\eta > \frac{1}{2}$ because this study assumes a pure random walk process, where the drift is small relative to the order of magnitude of y_t. ε_t is the error term.

Next, a recursive approach with a rolling window standard ADF regression could be applied in order to capture the price bubbles in financial assets, which can be denoted as Equation 3:

$$\Delta y_t = \alpha + \beta_T + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \ldots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t, \tag{3}$$

where α is a constant, β and γ are the coefficients on a time trend. β_T stands for the sum of a deterministic trend. δ is the theoretical autocorrelation. p is the lag order of the autoregressive process. ε_t is a stationary error process. The null hypothesis is a unit root, and the alternative hypothesis is a mildly explosive process, which can be denoted as: H_0: $\gamma = 1$; H_A: $\gamma > 1$.

In order to further explain the PWY and PSY price bubble detection strategies, some notations should be set. T is the sample size, and the sample interval is as (0,1). The estimated coefficient in Equation 3 can be denoted as: γ_{c_1,c_2}. ADF $_{c_1,c_2}$ represents the corresponding ADF value over the normalised sample $[c_1, c_2]$. Moreover, c_w is the fractional window size of the ADF regression and c_0 is the fixed initial window. The fraction c_1^{th} is the start point of the rolling window standard ADF regression, and the c_2^{th} is the end point, thus resulting in $c_2 = c_1 + c_w$.

Based on Equation 3, a simple right-tailed version of the standard ADF unit root test, a rolling ADF (RADF) test, a PWY SADF test, and a PSY GSADF test can be further developed. Phillips, Wu, and Yu (2011) and Phillips, Shi, and Yu (2015) prove that the SADF and GSADF tests perform better in price bubble detecting than the standard ADF

test, which uses the whole sample. Furthermore, by applying Monte Carlo simulations, Homm and Breitung (2012) prove that the SADF test results in higher power in the single periodically collapsing price bubble detecting, and Homm and Breitung (2012) confirm that the GSADF outperforms the other methods in the multiple periodically collapsing price bubble detecting. Nevertheless, many scholars still prefer to apply the SADF and GSADF simultaneously and compare the results to capture price bubbles. For example, see for cryptocurrency Li et al. (2021), stocks Wang, Chang, and Min (2021), commodities Sharma and Escobari (2018). As DeFi- and NFT markets are young financial markets without multiple bull or bear periods, multi-periodical collapses cannot be guaranteed. Therefore, this study will seek and date price bubbles based on both SADF and GSADF tests.

The SADF test is built on recursive estimation of the standard ADF regression with a fixed starting point c_0 and expanding window c_w. The window size c_w ranges from c_0 to 1. The starting point c_1 is fixed at 0, so the end point of each c_2 equals c_w. In the end, the ADF regression is repeatedly calculated while increasing the window size, which is c_2 and variates from c_0 to 1. Each recursive estimation process from 0 to c_2 can generate an ADF statistic, which can be expressed as ADF $_0^{c_2}$. The SADF test can further be defined as a supremum statistic of the ADF $_0^{c_2}$ sequence for $c_2 \in [c_0, 1]$ relied on the forward recursive regression Equation 4:

$$SADF(c_0) = \sup_{c_2 \in [c_0,1]} ADF_0^{c_2} \tag{4}$$

According to Phillips, Shi, and Yu (2015), the most significant advantage of the GSADF test is that it allows more flexible estimation windows. In other words, the starting point c_1 can vary within the range between 0 and $c_2 - c_0$. The GSADF test can be expressed as Equation 5:

$$GSADF(c_0) = \sup_{c_1 \in [0, c_2 - c_0], c_2 \in [c_0,1]} ADF_{c_1}^{c_2} \tag{5}$$

Based on Equation 2, the limit distribution of the GSADF test can be denoted as GSADF test limit distribution:

$$\sup_{c_1 \in [0, c_2 - c_0], c_2 \in [c_0,1]} = \left\{ \frac{\left(\frac{1}{2}\right) c_w \left[W(c_2)^2 - W(c_1)^2 - c_w \right] - \int_{c_1}^{c_2} W(c) dc [W(c_2) - W(c_1)]}{c_w^{\frac{1}{2}} \left\{ c_w \int_{c_1}^{c_2} W(c)^2 dc - \left[\int_{c_1}^{c_2} W(c) dc \right]^2 \right\}^{\frac{1}{2}}} \right\} \tag{6}$$

As proved by Phillips, Wu, and Yu (2011) and Phillips, Shi, and Yu (2015), the date-stamping method can also be applied to the SADF and GSADF tests to consistently estimate the origin and termination of bubbles.

In the date-stamping SADF test, all the financial price data are sorted in chronological order to be viewed as time-series data. A price bubble initiating at time T_{c_2} can be measured by comparing each element of the estimated $ADF_0^{c_2}$ sequence to the corresponding right-tailed critical values of the standard ADF statistic. T_{c_s} denotes the estimated start point of a price bubble, and it is equal to the $ADF_0^{c_2}$ that crosses the corresponding critical value from below. T_{c_e} represents the estimated endpoint of

a price bubble and is equal to the $ADF_0^{c_2}$ that crosses the critical value from above. Based on these notations, the estimated price bubble period based on the date-stamping SADF test can be given as Equation 7 and Equation 8:

$$\hat{c}_s = \inf_{c_2 \in [c_0, 1]} \left\{ c_2 : ADF_0^{c_2} > cv_{c_2}^{\beta_T} \right\}, \tag{7}$$

$$\hat{c}_e = \inf_{c_2 \in [\hat{c}_s, 1]} \left\{ c_2 : ADF_0^{c_2} < cv_{c_2}^{\beta_T} \right\}, \tag{8}$$

where T and β_T approaches to 0, and $cv_{c_2}^{\beta_T}$ denotes the $100(1-\beta_T)\%$ critical value of the standard ADF statistic based on $[T_{c_2}]$ observations.

Similarly, the estimated price bubble period based on the date-stamping GSADF test can be given as Equation 9 and Equation 10:

$$\hat{c}_s = \inf_{c_2 \in [c_0, 1]} \left\{ c_2 : BSADF_0^{c_2}(c_0) > cv_{c_2}^{\beta_{T_{c_2}}} \right\}, \tag{9}$$

$$\hat{c}_e = \inf_{c_2 \in [\hat{c}_s, 1]} \left\{ c_2 : BSADF_0^{c_2}(c_0) < cv_{c_2}^{\beta_{T_{c_2}}} \right\}, \tag{10}$$

where T and β_T approaches to 0, and $cv_{c_2}^{\beta_T}$ denotes the $100(1-\beta_T)\%$ critical value of the sup ADF statistic based on $[T_{c_2}]$ observations. BSADF (c_0) for $c_2 \in [c_0, 1]$ is the backward sup ADF statistic. Moreover, $GSADF(r_0) = \sup_{c_2 \in [c_0, 1]} BSADF_0^{c_2}(c_0)$ can link BSADF (c_0) to GSADF statistic.

5. Empirical analysis and findings

We concentrate on the results of the SADF and GSADF tests to present the price bubbles in the NFT and DeFi markets. Table 2 displays the two test statistics. We follow the methodology of Phillips, Shi, and Yu (2015), and set the finite sample critical values threshold as 90%, 95% and 99%, separately. Moreover, the finite sample critical values are generated from a Monte Carlo simulation with 2000 replications. The minimum window size is chosen based on the rule $c_0 = 0.01 + 1.8/\sqrt{T}$. From Table 2, the SADF and GSADF statistics for each index are the same, 3.640655 which exceeds their respective 1% right-tail critical values giving strong evidence that the hypothesis$_1$ of the NFT and DeFi markets have explosive sub-periods and price bubbles is reasonable.

Several conclusions and inferences can be drawn from Table 3 when investigating the single assets. Firstly, WBTC is the asset that has the most price bubbles. The most likely reason for this phenomenon is that WBTC is a tokenised version of Bitcoin and is pegged 1:1 to the value of Bitcoin. However, WBTC operates on the Ethereum blockchain network. Therefore, WBTC can share the characteristics of both Bitcoin and Ethereum. Price bubbles in both is well attested – see (Su et al. 2018) and (Corbet, Lucey, and Yarovaya 2018). Secondly, comparing the extent of bubble periods, NFTI, BoredApe, CryptoPunks, AVAX, WBTC, and LINK show more *single* periodically collapsing price bubbles (SADF > GSADF). Similarly, Sandbox, ArtBlocks, DPI, LUNA1, and WBTC show more *multiple* price bubbles (GSADF > SADF). Thirdly, considering the two capitalisation-weighted composite indices,

Table 2. The SADF and the GSADF tests of NFT and DeFi assets.

		Finite sample critical values		
	Test statistic	90%	95%	99%
Panel A: NFT assets SADF				
NFT Index	3.640655 ***	1.152928	1.387360	2.009919
Bored Ape Yacht Club	6.537691 ***	1.127017	1.377403	1.915046
CryptoPunks	14.23839 ***	1.283002	1.570895	2.048547
The Sandbox	12.5281 ***	1.242486	1.514377	2.011933
Art Blocks	9.005972 ***	1.174641	1.450992	2.015503
Panel B: DeFi assets SADF				
DeFi Plus Index	4.778333 ***	1.197979	1.465463	2.016094
Terra	11.94859 ***	1.253832	1.535946	2.030350
Avalanche	6.464056 ***	1.191630	1.465573	2.015874
Wrapped Bitcoin	6.091073 ***	1.255360	1.534416	2.026030
Chainlink	8.741543 ***	1.285516	1.576343	2.061296
Panel C: NFT assets GSADF				
NFT Index	3.640655 ***	1.888133	2.112672	2.780311
Bored Ape Yacht Club	6.537691 ***	1.844738	2.070705	2.719613
CryptoPunks	14.23839 ***	2.196822	2.435595	2.903005
The Sandbox	12.5281 ***	2.053218	2.304501	2.853601
Art Blocks	9.005972 ***	1.931227	2.188845	2.746543
Panel D: DeFi assets GSADF				
DeFi Plus Index	4.778333 ***	1.976247	2.206369	2.751208
Terra	11.94859 ***	2.091367	2.349830	2.867790
Avalanche	6.464056 ***	1.971334	2.202209	2.751060
Wrapped Bitcoin	6.091073 ***	2.139524	2.365723	2.878984
Chainlink	8.741543 ***	2.207758	2.417662	2.901934

Notes: The smallest window contains 36, 33, 91, 58, 42, 45, 64, 45, 71 and 86 observations of the NFTI, Ape, CryptoPunks, Sandbox, ArtBlocks, DPI, LUNA1, AVAX, WBTC and LINK, respectively.

the NFT market demonstrates more price bubbles than the DeFi market (SADF: 85.59% > 51.39%; GSADF: 72.67% > 56.15%). We speculate that the inflow of yield seeking money plays a key element in shaping the NFT price bubbles, especially after the cryptocurrency price bubbles popped in April 2021. These findings mentioned above are in line with the studies done by Maouchi, Charfeddine, and El Montasser (2021).

Next, we apply the real-time price bubble date-stamping strategy for both tests with results shown in Table 3. Moreover, Figure 1 and Figure 2 display the SADF and GSADF tests against the corresponding 95% critical value sequence, separately. In summary, although both DeFi and NFT classes are blockchain-based and thus closely related, they have a different design basis and thus target different audiences. This could also reflect in the fact that there are a number of differences beyond the common, overarching bubbles. Apart from WBTC, the average price bubble percentage rate of the DeFi market is around 50%, across the DPI and the other three DeFi assets. The price bubble cycles of the DeFi market correspond to major events in the cryptocurrency market, for example, the launch of Libra (18 June 2019), cryptocurrency bull market (October 2020 to May 2021), and the cryptocurrency market rebound (July 2021 to November 2021), but also exhibit own patterns like the 'DeFi summer 2020'. These echo the findings in the existing literature about cryptocurrency price bubbles (Corbet, Lucey, and Yarovaya 2018; Yao and Li 2021; Li et al. 2021). Summarising NFT assets, we could see a split with NFTI and Bored Ape Yacht Club having an average price bubble percentage rate of more than 80%, while the other NFT assets are somewhere around 20 to 30%. The reasons why the average price bubble percentage rates are significantly different between NFTI & Bored Ape Yacht Club

Table 3. Bubbles statistics of NFT and DeFi assets.

	Main bubble period	SADF					GSADF				
		BD	Pct	HM	AM	APC	BD	Pct	HM	AM	APC
Panel A: NFT assets											
NFT Index	2021/04/09 – 2021/05/20; **2021/07/23 – 2022/01/05**	285/333	85.59%	446.71%	147.91%	6.85%	242/333	72.67%	446.71%	183.26%	6.77%
Bored Ape Yacht Club	**2021/05/31 – 2021/08/29**; 2021/11/11 – 2021/12/21 2022/01/01 – 2022/01/31	229/282	81.21%	616.11%	100.28%	4.76%	199/282	70.57%	702.11%	126.97%	5.65%
CryptoPunks	**2021/02/04 – 2021/03/19**; 2021/04/30 – 2021/05/20 2021/07/30 – 2021/12/15	371/1685	22.02%	512.39%	131.04%	8.45%	341/1685	20.24%	456.00%	104.28%	11.61%
The Sandbox	2020/02/19 – 2020/03/05; **2021/11/01 – 2022/01/26**	260/792	32.83%	690.97%	106.00%	11.36%	270/792	34.09%	734.40%	117.80%	11.68%
Art Blocks	**2021/02/07 – 2021/03/16**; 2021/08/09 – 2021/09/09	134/431	31.09%	700.54%	237.93%	12.19%	144/431	33.41%	1015.39%	363.44%	13.78%
Panel B: DeFi assets											
DeFi Plus Index	**2021/01/03 – 2021/05/20**; 2021/08/05 – 2021/09/09	259/504	51.39%	578.10%	125.23%	4.49%	283/504	56.15%	593.96%	130.45%	4.60%
Terra	2020/05/17 – 2020/08/30; **2021/02/01 – 2021/05/18** 2021/08/03 – 2022/01/20	457/921	49.62%	1126.47%	501.44%	4.51%	529/921	57.44%	1191.08%	633.79%	4.45%
Avalanche	**2021/01/08 – 2021/02/22**; 2021/08/20 – 2021/10/03 2021/11/03 – 2021/12/04; 2021/12/15 – 2022/01/04	305/497	61.37%	853.90%	238.69%	5.70%	273/497	54.93%	1205.01%	352.73%	5.80%
Wrapped Bitcoin	2019/04/10 – 2019/09/25; 2019/10/26 – 2019/11/08 2020/01/28 – 2020/03/07; **2020/05/21 – 2021/05/27** 2021/08/06 – 2021/09/19; 2021/09/30 – 2021/12/03	1068/1097	97.36%	918.71%	354.93%	2.74%	898/1097	81.86%	619.76%	145.33%	2.13%
Chainlink	2019/06/10 – 2019/07/26; 2020/01/17 – 2020/03/11 **2020/06/01 – 2020/09/15**; 2020/11/08 – 2020/12/07 2021/01/03 – 2021/05/18	724/1545	46.86%	1409.36%	307.50%	4.10%	680/1545	44.01%	808.06%	332.43%	4.23%

Notes: Main price bubble periods are selected according to the SADF and the GSADF tests. A price bubble period can be selected only when the same price bubble lasts more than 14 days in both the SADF and GSADF tests. BD is bubble days. The bubble magnitude quantifies the percentage change between the highest and lowest prices in each price bubble period. The highest magnitude (HM %) calculates the highest record bubble magnitude. The average bubble magnitude (AM %) measures the average bubble magnitude across all bubble periods. APC% means the absolute value of average price bubble percentage change across all bubble days experienced by each digital asset.

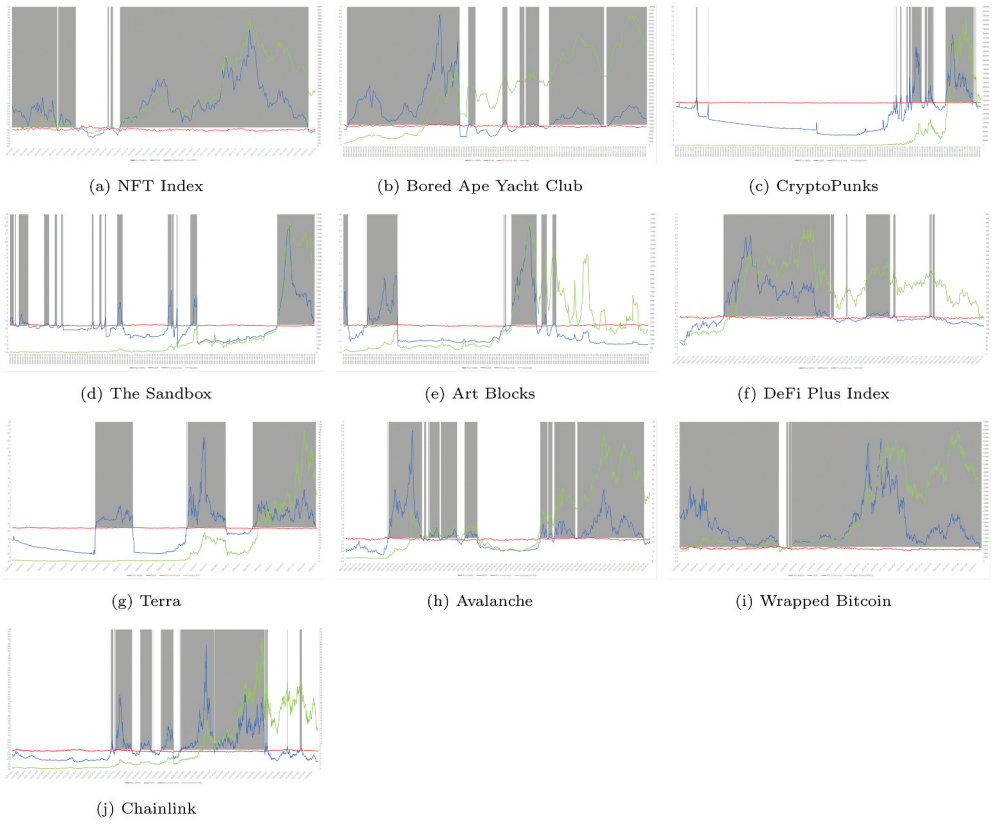

Figure 1. Date-stamping bubble periods in the NFT and DeFi assets: the SADF test. Notes: These plots show the SADF test against the corresponding 95% critical value sequence. The selected indices, SADF statistics, and 95% critical value sequence are tagged by green, blue, and red separately. The price bubble periods are highlighted in grey.

and the other NFT assets may be caused by the different nature of the instruments. The NFTI is a capitalisation-weighted composite index for the NFT markets, and Bored Ape Yacht Club represents the single NFT asset that outperforms the wider NFT markets (Wang 2022). In addition to the correspondence to general cryptocurrency markets (similar to DeFi), the NFT markets are especially driven by herding behaviour and media induced mania in 2021. Moreover, when we compare the percentage of bubble days in the DeFi and NFT markets with that in the cryptocurrency markets (Corbet, Lucey, and Yarovaya 2018) and (Maouchi, Charfeddine, and El Montasser 2021), we could find DeFi and NFT markets contain more price explosive bubbles than cryptocurrency markets (NFT(%) > DeFi(%) > Cryptocurrency(%))), indicating the extreme price inefficiency in DeFi and NFT markets.

When analysing the timing of the bubble periods, some general peculiarities can be identified. We can identify a general bubble in DeFi assets in the summer of 2020. LUNA1, WBTC and LINK are together in a bubble at least from June to August. This correlates with the first strong market appearance of DeFi tokens and is in line with the 'DeFi-summer' mentioned in the literature (Maouchi, Charfeddine, and El Montasser (2021)). Between

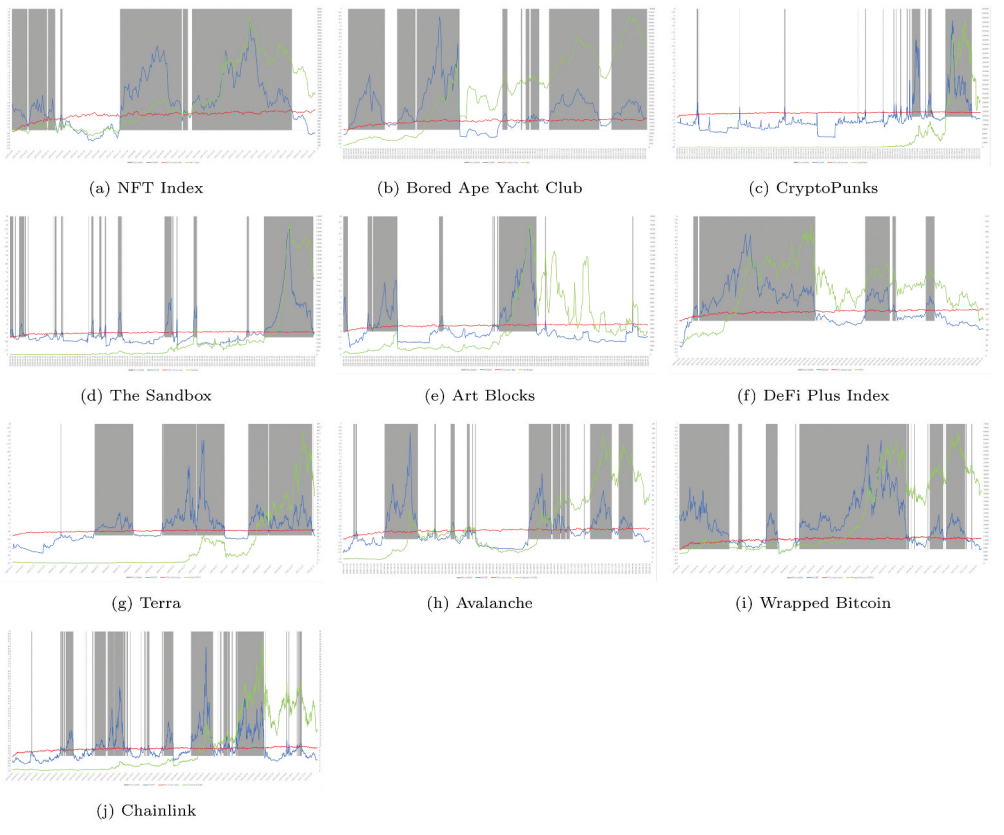

Figure 2. Date-stamping bubble periods in the NFT and DeFi assets: the GSADF test. Notes: These plots present the GSADF test against the corresponding 95% critical value sequence. The selected indices, GSADF statistics, and 95% critical value sequence are tagged in green, blue, and red. The price bubble periods are highlighted in grey.

February and June 2021, another major episode of bubble behaviour can be identified in which, except for Sandbox, all assets show bubble behaviours at some point. In this period, several factors have come together in form of a strong increase in the prices of cryptocurrencies in general as well as the first hype around NFTs, as can be seen, for example, in sharply increasing market volumes and NFTs attention Horky, Rachel, and Fidrmuc (2022) and (Wang 2022). This mix can trigger herding behaviour, as has been extensively studied in the cryptocurrency markets (see, e.g. Bouri et al., 2019; Horky, Mutascu, and Fidrmuc 2021; Youssef 2022). Analogous to 'DeFi Summer 2020', this first phase of the NFT hype could be called 'NFT Spring 2021'. Finally, we see another big bubble at the end of 2021 to the beginning of 2022, but mainly affecting NFT assets. After a minor cool-down phase (including the bursting of the cryptocurrency bubble in April 2021 (Hossain 2021; Letho, Chelwa, and Alhassan 2022; Marobhe 2021)), another stronger NFT hype occurred, with the mania of the NFT market, especially after June 2021. Although the percentage of price bubble days of CryptoPunks is only around 20%, this asset has been available since June 2017. The percentage of price bubble days of CryptoPunks are calculated between January 2021 to January 2022 as 66.16% and

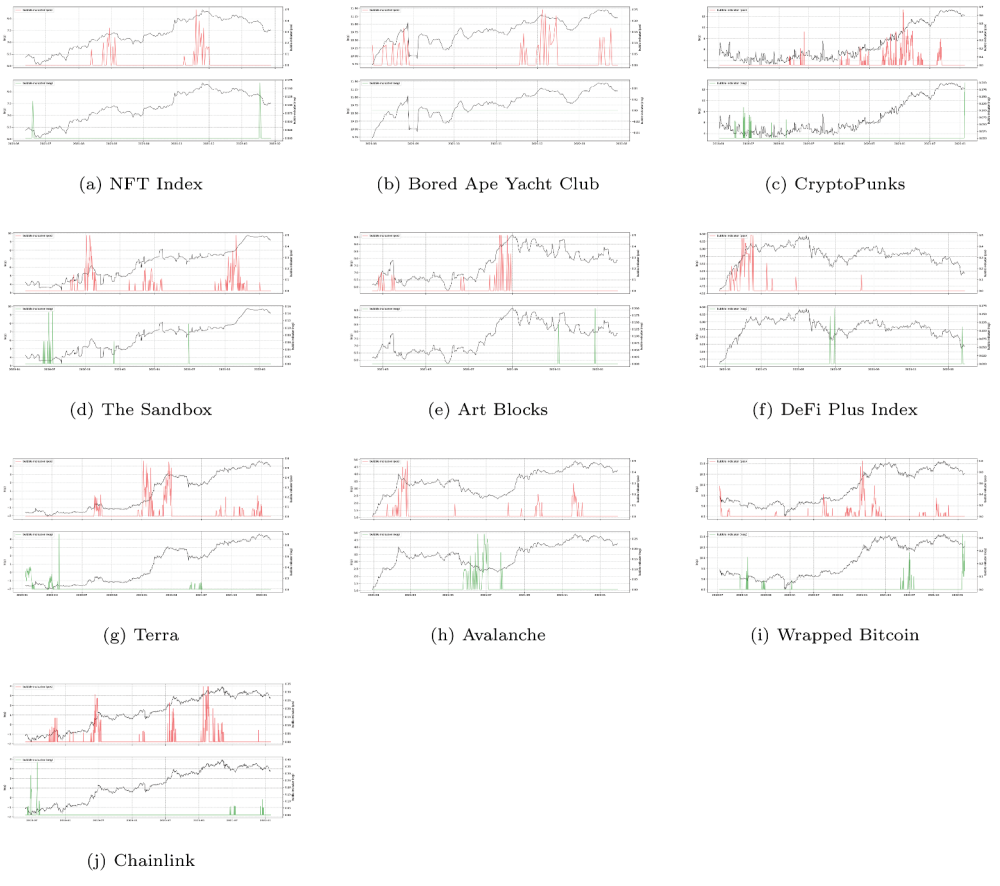

Figure 3. Date-stamping bubble periods in the NFT and DeFi assets: the LPPLS test. Notes: These plots display the LPPLS confidence indicator results. The positive (resp. negative) price bubble periods are tagged in red (resp. green).

55.05% for SADF and GSADF, separately. When media coverage and market growth led to a boom in NFTs (i.e. NFTs $2.5 billion sales volume (2021-July-07); Stephen Curry $180k NFTs purchase (2021-Aug-28); NFTs 315% increase month-on-month (2021-Sep-09); $24.4 million new record selling price for NFTs (2021-Sep-10); The Sandbox reaches market cap of $648.35 million (2021-Oct-13); Bored Ape Yacht Club 58,118% ROI (2021-Oct-13); NFTs $3 billion sales volume (2021-Oct-26), among others), these market hypes of the NFT market promotes considerable demand for NFT assets, triggering a continuous rise in NFT prices. When NFT owners sell NFTs in large quantities to arbitrage, the scale will also stimulate the bursting of the price of the NFT assets.

Referring to the magnitude of price bubbles in Table 3, we can find that the DeFi markets have a more substantial, higher bubble magnitude than the NFT markets when we compare to NFTI with DPI. This result could be caused by the high volatility and uncertainty of cryptocurrency markets (Urquhart 2016) and (Lucey et al. 2022) because DeFi assets are more closely related to cryptocurrencies. The periods of occurrence of the highest bubble magnitude have been bolded in the Table 3. The highest price

bubble magnitude periods in the DeFi and NFT markets broadly correspond to the periods of 'DeFi summer 2020', 'NFT Spring 2021' and '2021 Q4 NFT bull markets'. The positive news such as PieDAO DEFI++ market capitalisation reaches $2.34 million in 2021, NFTs sales volume surges to $2.5 billion in the first half of 2021, NFT markets have a 315% increase in total sales volume month-on-month, Bored Ape Yacht Club 58,118% return of investment in 2021, among others, could significantly heat the DeFi and NFT markets. Motivated by these positive events related to DeFi and NFTs, more investors join these two emerging markets and look for speculative opportunities, which could cause explosive speculative bubbles in the DeFi and NFT assets. However, when we pay attention to the average bubble magnitude (AM) and the absolute value of average price bubble percentage change (APC), the statistical results reveal that NFT markets have a higher average bubble magnitude and a higher average price bubble percentage change than the DeFi markets. This finding can confirm that NFT assets have the attributes of works of art, which are traded infrequently, and in terms of their quality and scarcity. Especially, some NFT assets may only be popular among specific cultural circles. Under this condition, the transactions of NFT assets are more prone to unexpected high price bubbles. Tapping the existing literature related to identifying price bubble in the cryptocurrency markets (Corbet, Lucey, and Yarovaya 2018) and (Maouchi, Charfeddine, and El Montasser 2021), we can clearly find that both the highest bubble magnitudes and the average bubble magnitudes of DeFi and NFT markets are significantly higher than that of cryptocurrency markets, indicating that there are more and stronger price explosive behaviours in the DeFi and NFT markets. This finding also could prove the inefficiency of the price mechanism in the DeFi and NFT markets, which could be in line with the findings of (Dowling 2022a).

5.1. Robustness test

The main findings of this paper are the price bubble periods captured above. As a robustness test, this study uses an alternative econometric model. The LPPLS method can infer the timing of a bubble burst, as discussed above, and could show stable results, essentially the same as the SADF and GSADF tests. LPPLS models have been used extensively as robustness checks for G/SADF tests. The LPPLS model allows quantification of the extent of growth in price beyond exponential growth under positive feedback, so it can also be applied to price bubble detecting in financial markets. Furthermore, many studies have proven that the LPPLS model can precisely identify the termination time of price bubbles and measure the risk of bubble crash in stock markets (Zhang et al. 2016; Filimonov, Demos, and Sornette 2017; Li 2017), futures (Zhou, Huang, and Chen 2018), and cryptocurrency (Wheatley et al. 2019; Gerlach, Demos, and Sornette 2019; Shu and Zhu 2020; Yao and Li 2021), among other financial markets. The LPPLS model $LPPLS(\Phi, t)$ can be expressed as Equation 11:

$$E_t[lnp(t)] = A + B(t_c - t)^m + C(t_c - t)^m cos[\omega ln(t_c - t)] - \phi], \tag{11}$$

where, $E_t[lnp(t)]$ is the expected logarithm of the asset price at the date of the termination of the bubble. t_c is the critical point, and it can be interpreted as the date of termination of the bubble and transition in a new regime. A represents the expected value of the $lnp(t)$ when the bubble at the critical point t_c, $A = ln[p(t_c)] > 0$. B is the amplitude of the power

law acceleration, and $B = -\kappa\alpha/m$. $B < 0$ represents a positive bubble and $B > 0$ a negative bubble. B can quantify if the asset price is growing (decreasing) super-exponentially as time moves towards t_c. m is a power exponent, and it represents the degree of the super-exponential growth and measures the acceleration of the asset price increase ($0 < m < 1$). $C = -\kappa\alpha\beta/\sqrt{m^2 + \omega^2}$ can quantify the proportional amplitude of the oscillations around the power law singular growth. ω is the scaling ratio of the angular log-frequency of oscillations during the bubble. $0 < \phi < 2\pi$ is a phase parameter, which can represent time scale of the oscillations. $t_c - t$ in Equation 11 represents a price dynamic and denotes a 'bubble'. The first component, $A + B(t_c - t)^m$, obeys the hyperbolic power law and can quantify the super-exponential growth. The second component, $C(t_c - t)^m$, controls the amplitude of the accelerating oscillation; it fails to zero at the critical time t_c. The third component, $cos[\omega ln(t_c - t)] - \phi]$, models the local frequency of the log-periodic oscillations, which approaches infinity at t_c.

Figure 3 presents the LPPLS confidence indicator results. The positive (resp. negative) price bubble periods are tagged in red (resp. green). The positive (negative) price bubbles indicate the process of upward (downward) accelerating prices. Moreover, the price bubble periods detected by the LPPLS model in Figure 3 match the main price bubble periods that are identified by the SADF and GSADF tests in Figure 1 and Figure 2. The matching of bubble periods from two sets of tests gives us confidence in our results

6. Conclusion

Motivated by the growth of the NFT and DeFi assets, this paper provides insight into the extent and timing of price bubbles. We have examined a total of 10 individual assets/indices that represent a relevant part of the markets.

From the perspective of individual assets, we find that although WBTC is the asset that exhibits the most price bubbles, the NFT market shows more price bubbles than the DeFi market in general. These findings are confirmed by the robustness test based on the LPPLS test. Generally, the two asset classes are constructed differently and therefore aim at different target groups. While DeFi Tokens are mainly targeted at payments and finance, NFTs map individual, heterogeneous assets and are especially related to the (digital) art market, the gaming industry or the growing metaverse. Accordingly, it is not surprising that NFTs, as an emerging, highly heterogeneous class with many potential use cases, are in this phase subject to greater volatility than DeFi tokens.

Regarding the timing of the bubbles, we could identify 3 outstanding periods. First, the DeFi summer 2020 already mentioned in the literature, second, a general bubble period in spring 2021 related to a general rise of cryptocurrencies and the first hype around NFTs ('NFT spring 2021') and third, the second, media-induced hype around NFTs later in 2021. The timing of the bubbles suggests that DeFi tokens are relatively strongly linked to general cryptocurrencies, while NFTs are driven more by specific, behavioural economic factors such as media coverage and NFT-specific herding. Considering the magnitude of price bubbles, we could identify that DeFi markets have a more substantial highest bubble magnitude than the NFT markets, but NFT markets have a higher average bubble magnitude and a higher average price bubble percentage change than the DeFi markets.

In addition, both the highest bubble magnitudes and the average bubble magnitudes of DeFi and NFT markets are significantly higher than that of cryptocurrency markets.

From the results, several policy implications can be derived. First, it is already apparent that DeFi- and NFT markets, although closely related, exhibit different bubble behaviour. Furthermore, the question arises whether with growing market maturity some NFT token use cases further differentiate, thus forming independent sub-markets, or whether NFTs can be continued to be treated as one common market. Date-stamping bubble behaviours identification in the DeFi and NFT markets can bring policymakers (e.g. China's central bank) an indicator and a window of opportunity to consider whether or not they should take action to adjust or control this market. Especially for China, as China's government banned cryptocurrency trading and mining. But at the same time, China's government is pursuing the uses of blockchain technology and NFTs – as long as these blockchain-based technologies are under its control. Accordingly, policymakers should seek to identify valuable use cases for DeFi- and NFT assets and tailor any regulations to these use cases. However, overly broad regulation can destroy market potential that could be of particular interest for developing economies in general (Zhao et al. 2021). The analysis of potential actions by policymakers in the occurrence of price bubbles in the DeFi and NFT markets is beyond the content of this study. Second, DeFi Token and NFT are high-risk assets, exhibiting strong bubble behaviour and the risk of substantial loss. These risks can be well illustrated by the example of the LUNA1 crash in 2022. In addition, these potential risks are significant for developing countries. As financial markets in these countries are not fully developed, the supply of alternative investment tools is limited. Investors in developing countries are prone to speculative investments with high risk and high returns, such as cryptocurrencies, P2P lending, and NFTs, among others. Given the proven evidence that the latest financial crises all originated from a bubble burst. Policymakers should seek to improve the financial literacy of the population as trading becomes more accessible to a broader segment of the population. Thirdly, although there are periods of significant bubbles, it should be noted that there are also calm periods. As these markets mature, it is expected that the price dynamics will settle to fewer bubbles and greater efficiency. However, this environment also offers profit opportunities for risk-seeking investors.

In the future, it will be necessary to examine the extent to which these markets continue to mature (e.g. price mechanism efficiency test). Another potential research direction is the investigation of risk transmission channels between cryptocurrency, DeFi and NFT markets, as these three digital asset markets share several common price bubble periods, and the flash events related to cryptocurrency markets can significantly stimulate DeFi and NFT markets to generate price bubbles. Although Karim et al. (2022), Yousaf and Yarovaya (2022b), Yousaf and Yarovaya (2022a) and Wang (2022) have discussed the risk spillover connectedness between the cryptocurrency, DeFi and NFT markets, the median transmission effects between these three markets also deserve to be explored. In addition, especially against the background of new possibilities, it is important to keep an eye on different use cases. These could, if sensibly regulated and after the initial market turbulence, offer an economic added value especially for developing countries. However, our analysis clearly shows that currently, these markets are still characterised by erratic bubbles and that caution should be exercised when operating in them.

Highlights

- NFT and DeFi markets price bubbles can be detected using SADF and GSADF tests.
- NFT and DeFi markets contain significant speculative components.
- NFT bubbles are more recurrent and have higher average explosive magnitudes than DeFi bubbles.
- Market hype and cryptocurrency market uncertainty are highly correlated with bubbles.
- There are certain periods where bubbles are not detected, suggesting that these markets do have some intrinsic values.

Notes

1. An NFT is a non-interchangeable and secure unit of data on a blockchain, and it is a type of digital ledger. An NFT can be associated with a piece of reproducible digital media, including but not limited to digital arts, texts, photos, videos, audio and even bits of code. DeFi assets are claims on companies that use the blockchain, primarily Ethereum, to facilitate decentralised peer-to-peer transactions. (More details can be found in (Wang 2022)).
2. NFT and DeFi market capitalisation data are obtained from https://coinmarketcap.com/
3. The NFTI is a capitalisation-weighted composite index designed to track the performance of the non-fungible token market. It is weighted based on each NFT asset's circulating supply value. Underlying NFT assets in the NFTI including Polygon (Matic), Enjin, Decentraland, Sand, Axie Infinity, Aavegotchi, Rarible, and Meme.
4. The DPI is a composite capitalisation-weighted index designed to track the performance of the decentralised finance market. It is weighted based on the value of each DeFi asset circulating supply. Underlying DeFi assets in the DPI includes Aave, Balancer, Compound, Cream, Farm, KNC, Loopring, Maker, meta, REN, Sushi, Synthetix, Uniswap, Yearn, Instadapp, Badger, Rari Capital, Vesper.
5. https://coinmarketcap.com
6. https://nonfungible.com

Disclosure statement

No potential conflict of interest was reported by the author(s).

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