



Understanding digital bubbles amidst the COVID-19 pandemic: Evidence from DeFi and NFTs^{☆,☆☆}

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ABSTRACT

This paper investigates digital financial bubbles amidst the COVID-19 pandemic. Using a sample of 9 DeFi tokens, 3 NFTs, Bitcoin, and Ethereum, we detect several bubbles overlapping the examined cryptoassets. We also uncover DeFi and NFT-specific bubbles in Summer 2020 suggesting distinct driving factors for this class of assets. We document that DeFi and NFTs bubbles are less recurrent but have higher magnitudes than cryptocurrencies' bubbles. We also find that COVID-19 and trading volume exacerbate bubble occurrences, while Total Value Locked (TVL) is negatively associated with cryptoassets' bubbles. Our results suggest that TVL can be used as a tool for market monitoring.

1. Introduction

Despite still being a niche in the digital finance industry, Decentralized Finance (DeFi) and Non-Fungible Tokens (NFT)¹ are attracting a wide media coverage and a growing number of investors. The speed and magnitude of capital flows to DeFi and NFTs are reminiscent of cryptocurrencies, and bubble formation observed in these markets (Kyriazis et al., 2020). Given DeFi and NFTs prices dynamic, and the increase of their share in the cryptocurrencies world,² it is of prime importance for current and potential users and investors, as well as policy makers to investigate the price behavior of these new markets.

[☆] DeFi refers to Decentralized Finance and NFTs to non-fungible tokens.

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¹ DeFi and NFTs expand the use of the blockchain technology from simple value transfers (as in the case of Bitcoin and most original cryptocurrencies) to more complex financial cases. The novelty of DeFi and NFTs applications is to directly link market participants using smart contracts. This approach allows to bypass traditional centralized intermediaries, such as banks, brokers, insurance companies, cryptocurrencies exchanges and other trusted third parties (Harvey et al., 2021; Schär, 2020).

² The Total Value Locked in DeFi surged by 12763% from USD 677 million in 2020 to USD 87.05 billion in May 2021. The market capitalization of the Top 100 DeFi tokens, and NFTs markets increased from around USD 3.5 billion to USD 170.3 billion between 2020 and May 2021 (authors calculation).

Compared to the wide literature on Bitcoin and other cryptocurrencies, studies on DeFi and NFTs markets are scanty. Some of the few existing studies include Corbet et al. (2021) who investigate whether DeFi tokens should be regarded as a separate asset class, and Dowling (2021a,b) who investigates NFTs pricing and their relationship with cryptocurrencies.

Moreover, while several empirical studies have investigated bubbles in a variety of financial markets (Ghosh et al., 2021), commodity markets (Figuerola-Ferretti et al., 2015; Caspi et al., 2018), exchange rates (Hu and Oxley, 2017), and real estate markets (Deng et al., 2017) and more recently in cryptocurrencies markets,³ to the best of our knowledge there is no prior work exploring bubbles in DeFi and NFTs markets and investigating the factors that can help predict these bubbles.

In this paper, we contribute to fill this gap in the literature by investigating the existence of bubbles in DeFi and NFTs markets. This new class of digital financial assets is usually thought to be substantially different from traditional cryptocurrencies. Second, we contribute to the cryptocurrency price formation literature by exploring whether the COVID-19 pandemic, the Total Value Locked (TVL), along with a set of internal, sentimental and traditional financial and macroeconomic variables can predict bubbles formation in DeFi and NFTs markets. Indeed, DeFi and NFTs rapid growth coincided with the height of the pandemic. This period was characterized by stay-at-home orders throughout the globe with several governments making direct stimulus payments to households which lead to a documented surge in cryptocurrencies retail trading (Zimmerman and Divakaruni, 2021; Guzmán et al., 2021). Our results provide DeFi and NFTs actors and investors with a better understanding of the dynamics of this new assets class, particularly during extreme events, such as pandemics.

The rest of the paper is organized as follows. Section 2 describes the data and the methodology. Section 3 presents the characteristics of the cryptoassets investigated, and discusses our results. Finally, Section 4 concludes.

2. Data set and materials

2.1. Data description and sources

We use the daily closing price of 14 cryptoassets, which include 9 DeFi tokens (Chainlink [LINK], Maker [MKR], Ox [ZRX], Ren [REN], Terra [LUNA], Synthetix [SNX], Fantom [FTM], Reserve Rights [RSR], THORChain [RUNE]), 3 NFTs (THETA [THETA], Enjin Coin [ENJ] and Decentraland [MANA]), in addition to Bitcoin [BTC] and Ethereum [ETH]. The selection of these 14 cryptoassets was based on the following. First, the choice of including the two largest cryptocurrencies markets, Bitcoin and Ethereum is motivated by (i) Bitcoin's dominance of the cryptoassets markets and the fact that it is considered as one of their main drivers, and (ii) Ethereum representing the backbone of DeFi and NFTs protocols. Most of the smart contracts used in these markets are powered by the Ethereum blockchain. In addition, the 9 DeFi coins and tokens and 3 NFTs were selected based on their market capitalization rank and data availability (the length of their time series). A further presentation is provided in Section 3.1. Moreover, we use the number of global COVID-19 cases, and a set of internal, sentimental and financial factors as potential bubbles predictors. As internal variables to the cryptoassets markets, we use the traded volume and the Total Value Locked (TVL) expressed in ETH.⁴ To measure the investors' sentiment, we use Google Trends searches for the different cryptoassets tickers. Moreover as robustness check we use the keywords "Bitcoin", "Ethereum", "DeFi" and "NFT". Regarding economic and financial conditions, we use the economic policy uncertainty (EPU) index and the CBOE Volatility Index (VIX). Finally, we use the gold and Brent crude oil prices as indicators reflecting traditional financial markets.

We collected our data from different sources. The daily closing prices and the internal variables for the cryptoassets were collected from coinmarketcap.com, except for the TVL which was retrieved from defipulse.com. The EPU Index was extracted from the policyuncertainty.com page. The VIX, gold, and Brent prices were collected from the St. Louis Fed's website. The number of global COVID-19 cases was retrieved from the COVID-19 Data Repository of the Center for Systems Science and Engineering at Johns Hopkins University.⁵ Moreover, as a robustness check of our results for the COVID-19 pandemic measure, we use a dummy variable taking the value 0 if the number of COVID-19 cases is 0 and 1 otherwise. This dummy variable takes the value 0 before January 22nd, 2020 and the value 1 for the rest of the sample period.

The starting dates in our sample vary depending on the first trading day for each cryptoasset. However, the last date, March 15, 2021, is the same for all the cryptoassets. A detailed presentation of the cryptoassets price series time-frame, their characteristics and descriptive statistics are provided in Section 3.1 and Tables 1 and 2.

2.2. Materials and methods

We follow Phillips and Shi (2020) (PS hereafter) and define a bubble as an explosive behavior of an asset price, representing exuberance in the speculative behavior driving the market. This definition helps identify bubbles by their time series characteristics, where the price of an asset follows a mildly explosive or random-drift martingale process as opposed to the martingale behavior observed during normal market conditions (Phillips and Shi, 2020).

³ Geuder et al. (2019), Cheung et al. (2015), Corbet et al. (2018), Enoksen et al. (2020), and Montasser et al. (2021) detected multiples bubbles in Bitcoin, Ethereum and several other leading cryptocurrencies. See also Anastasiou et al. (2021) who document a positive relationship between cryptocurrencies price crash with investors sentiments and Charfeddine and Maouchi (2019), Charfeddine et al. (2020) who investigate the dynamics and inefficiencies of the main cryptocurrencies markets.

⁴ The TVL represents the number of digital assets that are committed to a specific protocol or project.

⁵ <https://github.com/CSSEGISandData/COVID-19>

Table 1
Overview of the cryptoassets examined.

	Ticker	Type	Issue date	Rank	Max. S.	T. S.	% of C.S.	# of pairs
Bitcoin	BTC	Cryptocurrency	Jan 2009	1	21M	18M	89%	+5000
Ethereum	ETH	Cryptocurrency	Jul 2015	2	–	115M	100%	+5000
Chainlink	LINK	DeFi	Sep 2017	10/1	1B	414M	41%	461
Maker	MKR	DeFi	Dec 2017	47/10	appr. 1M	995K	99%	186
0x	ZRX	DeFi	Aug 2017	75/17	1B	760M	76%	257
Ren	REN	DeFi	Feb 2017	79/10	appr. 1B	appr. 1B	100%	116
Terra	LUNA	DeFi	Apr 2019	14/3	–	404M	–	37
Synthetix	SNX	DeFi	Sep 2017	43/9	appr. 0.21B	114M	54%	155
Fantom	FTM	DeFi	Dec 2019	78/19	3.175B	2.545B	80%	40
Reserve Rights	RSR	DeFi	May 2019	77/18	100B	13B	13%	62
THORChain	RUNE	DeFi	Jul 2019	15/69	–	238M	47%	27
THETA	THETA	NFT	March 2019	15/1	1B	1B	100%	45
Enjin Coin	ENJ	NFT	Nov 2017	52/3	1B	0.834B	83%	115
Decentraland	MANA	NFT	Sept. 2017	61/4	–	1.578B	–	125

The **Rank** is based on the total Market Capitalization. Each asset is ranked across all the cryptoassets as well as within its category, e.g. Chainlink is ranked 10 across all cryptoassets, and 1 within DeFi. **Max. S.** is the maximum supply which represents the maximum amount of coins that will ever exist. **T.S.** is the total circulating supply. **% of C.S.** is the percentage of the circulating supply from the total supply. **# of pairs** is the total number of listed crypto and fiat currencies exchangeable with each asset.

In order to date-stamp bubbles, we use the real-time bubble detection method proposed by PS, which has the advantage of overcoming both unconditional heteroscedasticity and multiplicity problems encountered in other bubble identification procedures. Moreover, the PS method has been used by central bank economists, policy makers, and the financial industry (see Phillips and Shi (2020)). A full technical presentation of the PS method is provided in the supplementary document.

We investigate potential bubble predictors by considering several internal and external factors to the cryptoassets markets. For this purpose, we use four univariate models: logit, probit, tobit, and linear regression. The last three models are used for results robustness (see supplementary document). In the logit and probit models, the dependent variable is a dichotomous variable which takes the value 1 ($Bubble_t = 1$) if the calculated PS_t statistic is greater than the bootstrapped generated critical value and 0 otherwise. For the tobit model the dependent variable is a truncated $[0, 1]$ variable calculated based on PS's p -value where the truncation point is the 5% level of significance. For the linear regression model, the dependent variable is the calculated PS_t statistic.

The basic form of the two dichotomous probit and logit models is given by:

$$\begin{aligned}
 P(Bubble_t = 1) &= H(\mathbf{X}_t' \boldsymbol{\beta}) \\
 &= H(\beta_0 + \beta_1 Volume_t + \beta_2 TVL_t + \beta_3 Covid19_t + \beta_4 EPU_t \\
 &\quad + \beta_5 VIX_t + \beta_6 GTrend_t + \beta_7 Gold_t + \beta_8 Brent_t)
 \end{aligned}$$

where $H(\cdot)$ is the logistic function, $\boldsymbol{\beta}$ is the vector of parameters to estimate associated with the vector of regressors, \mathbf{X}_t' . This vector include the $Volume_t$, TVL_t , $Covid19_t$, EPU_t , VIX_t , $GTrend_t$, $Gold_t$, and $Brent_t$ variables that represent the traded volume, the TVL, the COVID-19 pandemic proxied by the global number of total cases, the EPU index, the VIX, Google Trend searches, gold, and Brent prices, respectively. All the explanatory variables are in logarithm form except the COVID-19 and GTrend as they contain zeros.

3. Results

3.1. Cryptocurrencies market characteristics and descriptive statistics

Tables 1 and 2 provide an overview of the 14 cryptoassets main characteristics. Table 1 shows that the selected cryptoassets are ranked in the top 20 of their categories in term of market capitalization. Specifically, 7 out of the 14 cryptoassets are ranked in the top 5 of their categories (BTC, ETH, LINK, LUNA, THETA, ENJ and MANA). In particular, Table 2 shows that, as of March 15th 2021, Bitcoin had a market capitalization of 1040B\$, representing a 60.4% market share of the 1722B\$ total market capitalization of the cryptocurrency market. ETH stood at 206B\$ which corresponds approximately to a 12% market share. The nine DeFi coins and tokens in our sample have an average market share of 65% from the total market capitalization of DeFi over our sample period. Finally, the three NFTs included in our sample have a market capitalization of 10.67 B\$ representing an average market share of 30% of the top 10 NFTs market capitalization.

3.2. Results discussion

3.2.1. Bubble detection results

Several conclusions emerge from the results of the date-stamping PS algorithm reported in Figs. 1–2 and Table 3. The results show that all the cryptoassets investigated experienced periods of price explosions. Particularly, we find that 34 out of the 47 months

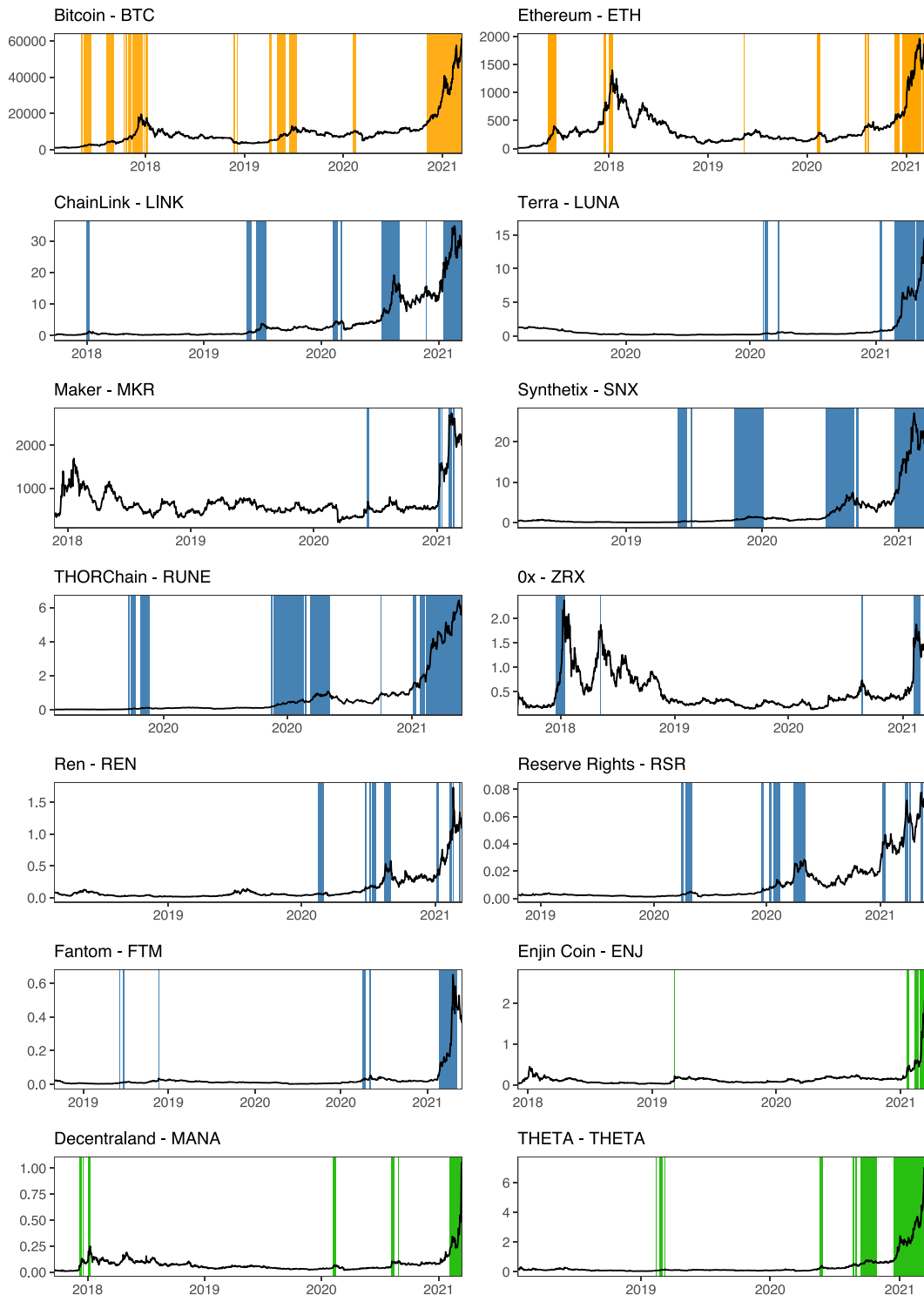


Fig. 1. Bubble Periods in the Cryptoassets. The colored areas in the figure highlight the explosive periods identified by the PS framework for the cryptocurrencies (BTC and ETH) in orange, the 9 DeFi tokens and coins in blue, and 3 NFTs in green. The black line represents the cryptoasset price in USD. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

in our sample are characterized by the existence of at least one bubble with up to six-fold price increases. The results reveal three main periods of exuberance during which the prices of the different cryptoassets experienced bubbles.

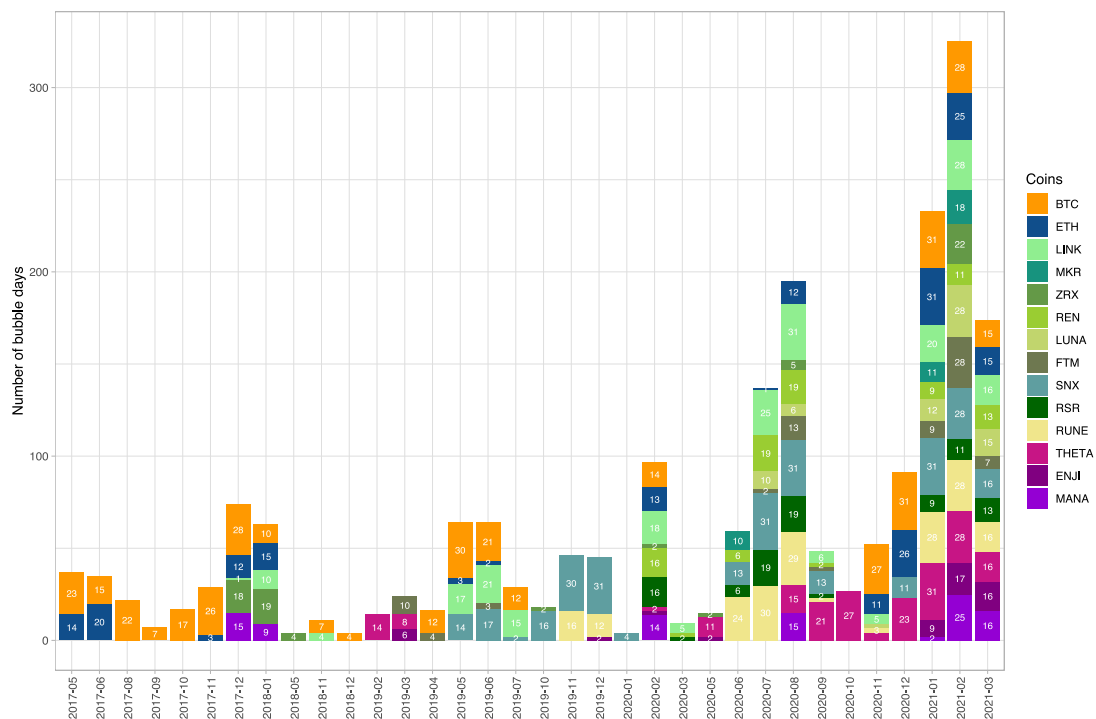


Fig. 2. Monthly Detected Bubble Days Per Cryptoasset. The figure reports the total detected number of bubble days per month for each cryptoasset. DeFi and NFTs are represented by the purple and green color palettes, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The first period corresponds to the end of 2017 and the start of 2018 where an explosive price was detected for BTC, ETH, ZRX and MANA. These results are inline with the previous literature on bubble detection in pure cryptocurrencies (Kyriazis et al. (2020)). The highest bubble magnitudes were detected between November 14, 2017 and December 21, 2017 for Bitcoin, between December 2017 and the end of February 2018 for Ethereum. The DeFi coin 0x (ZRX) experienced its highest bubble period between mid-December 2017 and mid-January 2018 (see Table 3).

The second period corresponds to June–September 2020, where DeFi coins and tokens have experienced a real price boom and a substantial increase in their TVL. This period corresponds to what is known within the crypto-community as the DeFi Summer 2020 during which DeFi saw a surge in TVL and market capitalization. Its main catalyst seems to be the launch of the liquidity mining program of the COMP token by Compound in May 2020. This introduction is considered as the real starting point of decentralized lending applications which led to the popularization of the so called “liquidity mining” and “yield farming”. These arbitrage practices consist in investors actively shifting their cryptoassets between different decentralized lending pools and platforms to maximize their return.

Finally, the third period spans from mid-December 2020 to March 2021. During that time all 14 cryptoassets exhibited price explosive behaviors. However, the bubble duration is more pronounced for the case of Bitcoin, Ethereum, ChainLink, Terra, Synthetix, THORChain, Fantom and THETA when compared to the rest of the cryptoassets. Our results show that February 2021 is the single month during which all 14 cryptoassets saw bubbles occurring with a full month bubble for BTC, five DeFi tokens: LINK, RUNE, LUNA, FTM, SNX, and one NFT: THETA. During this period several companies and institutional investors, such as Tesla, Mastercard or Bank of New York Mellon, announced their interest or involvement in investing or using cryptocurrencies. These results suggest that there are common factors driving both markets and worth investigating, which is inline with the conclusion of Dowling (2021b) for NFTs.

Considering the results from Table 3 and Fig. 2, we find that the average magnitude, measured as the price increase per bubble day, is much higher for DeFi and NFTs (0.67% and 0.769% of price increase per day, respectively) compared to pure cryptocurrencies (0.154% increase per day). However, DeFi and NFTs experience less bubbles compared to pure cryptocurrencies (with an average of 19%, 14%, and 9% bubbles days for cryptocurrencies, DeFi and NFTs, respectively).

Overall, our empirical results show that while DeFi and NFTs experienced bubbles overlapping the pure main cryptocurrencies, specific bubbles to DeFi markets were detected during the summer of 2020. Moreover, the characteristics of bubbles are different between DeFi and NFTs on the one hand, and pure cryptocurrencies on the other hand. This result suggests that DeFi and NFTs’ price dynamics are distinct from pure cryptocurrencies. This is inline with studies by Corbet et al. (2021) and Dowling (2021b).

Table 2
Descriptive statistics of the considered cryptoassets.

	From	To	Price	Max P.	Min P.	High	Low	Market Cap.	# of Obs.
BTC	22/4/17	15/3/21	55907.2	61243.08	919.5	61683.86	65.53	1.04 T	1424
ETH	22/4/17	15/3/21	1791.7	1960.16	10.48	2036.29	0.42	206 B	1424
LINK	4/12/17	15/3/21	27.92	34.72	0.131	36.83	0.126	11.3 B	1198
MKR	16/1/18	15/3/21	2067.21	2743	24.31	3041.57	21.06	2.05 B	1155
ZRX	1/11/17	15/3/21	1.33	2.37	0.137	2.53	0.104	1.01 B	1231
REN	2/5/18	15/3/21	1.1	1.73	0.015	1.83	0.015	1.08 B	1049
LUNA	13/9/19	15/3/21	16.34	16.34	0.125	22.33	0.119	6.54 B	550
SNX	22/5/18	15/3/21	18.9	27.07	0.032	28.77	0.032	2.17 B	1029
FTM	29/12/18	15/3/21	0.37	0.65	0.001	0.871	0.001	1.03 B	808
RSR	14/7/19	15/3/21	0.08	0.081	0.001	0.099	0.001	1.06 B	611
RUNE	10/9/19	15/3/21	5.68	6.42	0.01	6.76	0.007	1.35 B	553
THETA	29/3/18	15/3/21	6.76	7.39	0.041	10.74	0.039	6.75 B	1083
ENJ	12/2/18	15/3/21	2.7	2.7	0.022	3.05	0.015	2.25 B	1128
MANA	2/12/17	15/3/21	1.06	1.06	0.008	1.19	0.007	1.67 B	1200

The Price and Market Capitalization (**Market Cap.**) are as of March 15. **Max P.** and **Min P.** are the maximum and minimum prices, respectively over our period of analysis. **High** and **Low** are the respective all time high and all time low prices since July 05, 2013.

3.2.2. Bubbles prediction results

The results of bubbles prediction are reported in Table 4 for the logit model and in Tables S1, S2, and S3 in the supplementary document for the probit, tobit, and linear regression models, respectively.

The COVID-19 pandemic is positively and significantly associated with the probability of bubbles occurring for all cryptoassets at the 1% significance level, except for REN and SNX for which the relationship is negative. This result is in line with the findings of multiple studies. Zimmerman and Divakaruni (2021) highlight the impact on Bitcoin of the monetary transfers made by governments to citizens to alleviate the pandemic effects. Guzmán et al. (2021) show that cryptocurrencies' investors became more active during the pandemic due to the free time on their hands caused by home-confinements. Finally, our results are consistent with the herding behavior observed during extreme times such as COVID-19 (Rubbiani et al. (2021)). The negative and significant effect of COVID-19 on the probability of bubble occurrences in the case of REN (which holds in robustness checks) could be explained by the introductions of a new protocol by Ren in 2020; the RenVM Mainnet. Similarly, the results for SNX could be due to its nature, as it provides exposure to various assets such as Bitcoin, US Dollar, or various stocks traded on traditional equity markets, and the fact that it is used by advanced and sophisticated users different from the above highlighted investors.

For the TVL, we find that it is negatively correlated with bubbles for all cryptoassets, except for SNX, THETA, and ENJ for which the relationship is positive. TVL represents the total amount of underlying cryptoassets supply being secured by a specific application and/or by DeFi as a whole. In a sense it represents the confidence level of users and investors in the protocol. The higher the TVL, the higher the investors' confidence in the protocol. Overall, the TVL can be seen as a gauge of the fundamental value of DeFi. The positive relationship with bubble occurrences for SNX and two NFTs, THETA and ENJ, is however interesting and suggests the need for further investigation of NFTs prices behavior compared to other NFTs and DeFi tokens. This conclusion is similar to Dowling (2021b) who show that NFTs have a distinct behavior from pure cryptocurrencies, and that NFT markets might even contain multiple asset classes. As for SNX, and similar to the results of COVID-19, the inverted sign of the relationship suggests that SNX might have a different behavior than other DeFi tokens which warrants further investigation.

Regarding the control variables, we find that overall, the traded volume raises the likelihood of bubble states, as predicted by the rational bubbles and herding behavior theories (Barberis et al., 2018). Considering investors' sentiment, Google Trends searches have a positive effect on bubble occurrences for most cryptoassets except for RUNE and MANA for which the relationship is negative. The results for the variables representing economic (EPU) and financial (VIX) conditions are mixed and do not show a clear pattern confirming the results obtained by Enoksen et al. (2020) for eight major cryptocurrencies. Similarly, for gold and Brent oil we obtain mixed results.

Overall, we find that most of the factors used in this study help in predicting the realization of bubbles, and of these, COVID-19, Total Value Locked, volume and investors' sentiment appear to have the strongest connection with bubble occurrences. These findings are overall confirmed by the probit, tobit, and linear regression models results (see tables S1, S2 and S3). The results are also robust using a COVID-19 one-off dummy variable, and different keywords searches for Google Trend as highlighted above (The results are reported in the Tables S4-S7 in the supplementary document).

4. Conclusion

We detect several bubbles across the 14 cryptoassets, and identify three main persistent bubble periods: the turn of the year 2017/2018, the DeFi summer 2020, and the 2021 bubble. As predictors, we find that the COVID-19 pandemic exacerbated the last two series of bubbles. We also find that the trading volume and investors' sentiment are positively associated with bubbles, while the Total Value Locked is negatively linked with it.

The identified DeFi bubbles in summer 2020, as well as the difference in the average bubble frequency and magnitude, imply that DeFi and NFTs markets might have distinct price dynamics from pure cryptocurrencies. This result warrants a special attention

Table 3
Bubbles statistics.

	# of Obs.	# of bub. days	% of bub. days	Highest magnitude	Date of highest magnitude	ABM	Weighted ABM
BTC	1424	352	25%	194%	14 Nov - 21 Dec 2017	34%	66.08%
ETH	1424	186	13%	236%	23 Dec 2020 - 24 Feb 2021	49%	70.01%
LINK	1198	204	17%	235%	7 Jul - 2 Sep 2020	55%	81.09%
MKR	1155	33	3%	131%	4 Jan - 11 Jan 2021	41%	32.97%
ZRX	1231	64	5%	518%	16 Dec - 15 Jan 2018	75%	56.47%
REN	1049	82	8%	109%	13 Aug - 2 Sep 2020	25%	54.38%
LUNA	550	64	12%	552%	27 Jan - 27 Feb 2021	104%	90.68%
SNX	1029	279	27%	541%	18 Jun - 4 Sep 2020	155%	51.79%
FTM	808	65	8%	1143%	25 Jan - 5 Mar 2021	126%	183.67%
RSR	611	82	13%	109%	13 Aug - 2 Sep 2020	36%	80.43%
RUNE	553	176	32%	291%	21 Jan - 16 Mar 2021	86%	78.46%
THETA	1083	181	17%	916%	13 Dec - 16 Mar 2021	74%	117.78%
ENJ	1128	45	4%	399%	25 Feb - 16 Mar 2021	84%	126.02%
MANA	1200	82	7%	349%	28 Feb - 16 Mar 2021	79%	186.17%

The number of bubble days **# of bub.** is the sum of all the days when the cryptoasset was experiencing a bubble. The percentage of bubble days (**% of bub. days**) is the ratio of total bubble days to the total number of observations for each token. The **Magnitude of a bubble** is the percentage increase between the lowest and highest prices within each bubble. The **highest magnitude** represents the highest price change across all bubbles experienced by each token. The **ABM** is the average bubble magnitude which is the average price change across all bubbles experienced by each token. The **weighted ABM** is the ratio of the bubble magnitude to the total number of bubble days.

Table 4
Logit regression results.

	Dependent variable: <i>Bubble_{it}</i>													
	BTC	ETH	LINK	MKR	ZRX	REN	LUNA	SNX	FTM	RSR	RUNE	THETA	ENJ	MANA
Volume	0.1486*** (0.0143)	0.0662*** (0.0115)	0.1494** (0.0114)	0.0144** (0.0069)	0.0487*** (0.0048)	0.0692*** (0.0121)	0.0668*** (0.0086)	0.0310*** (0.0122)	0.0468*** (0.0083)	-0.0254 (0.0171)	-0.0419** (0.0179)	0.0751*** (0.0071)	0.0191*** (0.0039)	0.0621*** (0.0066)
TVL	- (0.0022)	-0.0119*** (0.0102)	-0.0463*** (0.0421)	-0.1455*** (0.0051)	-0.0161*** (0.0051)	-0.0233*** (0.0058)	-0.0724** (0.0363)	0.0643*** (0.0250)	-0.0428*** (0.0156)	-0.2018*** (0.0486)	-0.4081*** (0.0423)	0.0788*** (0.0166)	0.0277 (0.0178)	-0.0009 (0.0065)
Covid-19	0.1076*** (0.0075)	0.0352*** (0.0049)	0.0324*** (0.0051)	0.0841*** (0.0283)	0.0154*** (0.0035)	-0.0223*** (0.0005)	0.0836*** (0.00276)	-0.0351*** (0.0126)	0.0144*** (0.0023)	0.0362*** (0.0127)	0.0741*** (0.0138)	0.0114*** (0.0024)	0.0404*** (0.0025)	0.0407*** (0.0067)
EPU	-0.0546*** (0.0194)	0.0129 (0.0140)	0.1096*** (0.0200)	-0.0268*** (0.0110)	-0.0096 (0.0095)	0.0649*** (0.0244)	0.0307 (0.0128)	0.0874*** (0.0179)	-0.0155 (0.0349)	-0.0282 (0.0349)	0.0369 (0.0403)	-0.0133 (0.0178)	-0.0038 (0.0108)	-0.0151 (0.0134)
VIX	-0.6179*** (0.0502)	-0.4057*** (0.0496)	0.0043 (0.0399)	-0.0204 (0.0256)	-0.2660*** (0.0453)	0.0571 (0.0599)	-0.0233 (0.0546)	-0.0446 (0.2191)	-0.0879 (0.0566)	0.1681** (0.0708)	0.1824** (0.0926)	-0.0657 (0.0488)	-0.0075 (0.0257)	-0.2135*** (0.0514)
GTrend	0.0083*** (0.0018)	0.0023*** (0.0005)	0.0081*** (0.0010)	0.0042* (0.0025)	0.0093*** (0.0025)	0.0088*** (0.0027)	0.0016 (0.0009)	0.0015*** (0.0005)	0.0018*** (0.0004)	0.0015*** (0.0007)	-0.0036 (0.0025)	0.0021*** (0.0006)	0.0003 (0.0003)	-0.0004 (0.0007)
Gold	-1.9328*** (0.1950)	0.2614* (0.1581)	-0.8555*** (0.1938)	0.0389 (0.1356)	0.0203 (0.0984)	0.8337*** (0.2341)	0.2971*** (0.098)	1.5343*** (0.2459)	0.1989 (0.1778)	1.9990*** (0.3506)	1.454*** (0.4440)	-0.5544*** (0.16663)	-0.3543** (0.1520)	0.2848** (0.1418)
Brent	-0.2464*** (0.0503)	0.1169** (0.0584)	0.5705*** (0.0676)	-0.0936*** (0.0275)	-0.0790** (0.0340)	0.6442*** (0.1389)	0.0532 (0.0635)	0.9156*** (0.1243)	0.0483 (0.0807)	0.7758*** (0.1389)	1.3005*** (0.1305)	-0.0425 (0.0638)	0.0063 (0.0381)	0.0105 (0.0531)
Obs.	1412	1424	1198	1154	1231	1049	550	1029	805	611	553	1083	1128	1200
McFadden	0.359	0.620	0.463	0.637	0.665	0.207	0.735	0.327	0.489	0.227	0.413	0.665	0.695	0.588

The table reports the average marginal effects with their corresponding standard errors in brackets.

*Significance at the 10%.

**Significance at the 5%.

***Significance at the 1%.

from investors and policy makers, and underlines the need for future research on the nature and drivers of these nascent and rapidly evolving markets.

While DeFi and NFTs markets remain small and regulation would hinder their development and potential benefits, we believe that policy makers should closely monitor their expansion. The rapid growth of DeFi and NFTs can lead to potential spillovers to other cryptocurrencies and financial markets which might be a cause of concern. Our paper provides a blueprint informing policy makers and investors on the existence and nature of bubbles in these fast-changing ecosystems. Another area of focus should be the financial incentives and practices, such as liquidity mining and yield farming, and more recently the financialization of NFTs and NFTs mining. These mechanisms can generate unsustainably high returns due to massive new capital inflows, potentially distorting investors' expectations, and amplifying bubbles in these markets.

Finally, our results show that TVL represents a key tool for DeFi and NFTs markets players. TVL is already considered by the crypto-community as one of the main indicators of DeFi markets size and growth. Our results show that it can also be used for DeFi and NFTs markets monitoring.

CRediT authorship contribution statement

Youcef Maouchi: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing – original draft, Writing – review & editing. **Lanouar Charfeddine:** Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, Writing – review & editing. **Ghassen El Montasser:** Formal analysis, Writing – review & editing.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.frl.2021.102584>.

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