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Time and frequency dynamics between NFT coins and economic uncertainty

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Abstract

Non-fungible tokens (NFTs) are one-of-a-kind digital assets that are stored on a blockchain. Examples of NFTs include art (e.g., image, video, animation), collectables (e.g., autographs), and objects from games (e.g., weapons and poisons). NFTs provide content creators and artists a way to promote and sell their unique digital material online. NFT coins underpin the ecosystems that support NFTs and are a new and emerging asset class and, as a new and emerging asset class, NFT coins are not immune to economic uncertainty. This research seeks to address the following questions. What is the time and frequency relationship between economic uncertainty and NFT coins? Is the relationship similar across different NFT coins? As an emerging asset, do NFT coins exhibit explosive behavior and if so, what role does economic uncertainty play in their formation? Using a new Twitter-based economic uncertainty index and a related equity market uncertainty index it is found that wavelet coherence between NFT coin prices (ENJ, MANA, THETA, XTZ) and economic uncertainty or market uncertainty is strongest during the periods January 2020 to July 2020 and January 2022 to July 2022. Periods of high significance are centered around the 64-day scale. During periods of high coherence, economic and market uncertainty exhibit an out of phase relationship with NFT coin prices. Network connectedness shows that the highest connectedness occurred during 2020 and 2022 which is consistent with the findings from wavelet analysis. Infectious disease outbreaks (COVID-19), NFT coin price volatility, and Twitter-based economic uncertainty determine bubbles in NFT coin prices.

Keywords: NFT coins, Wavelets, Economic uncertainty, Bubbles, Network connectedness

Introduction

> *"There's virtually nothing humans can't turn into a market. But increasingly there are speculative bubbles in things with absolutely no fundamental value."*
>
> *John Hawkins, The Conversation (2022)*

Non-fungible tokens (NFTs) are one-of-a-kind (i.e., non-fungible) digital assets that are stored on a blockchain. Chalmers et al. (2022) define NFTs as "blockchain-enabled cryptographic tokens that represent ownership of unique digital objects (e.g., an image) though typically not the underlying asset". Examples of NFTs include art (e.g., image, video, animation), collectables (e.g., autographs), objects from games (e.g., weapons and poisons), items in the metaverse where people interact as avatars in an immersive three-dimensional virtual world, and legal documents such as property documents (Karayaneva 2021). A digital asset's ownership is determined by the owner encoding or *minting* the asset onto a blockchain which can then be sold or exchanged like any other digital currency and where the NFT value is determined by its individual characteristics (Chalmers et al. 2022). As the popularity of NFTs has grown so too has the popularity of NFT coins. NFT coins are cryptocurrencies that support the NFT economy. NFT coins can be used for trading NFTs and are used in the establishment and governance of the platforms that support NFTs. For example, the NFT coin MANA is used to conduct NFT transactions in the Decentraland virtual world. NFT coins are a sub-category of the broader cryptocurrency market and can be considered as an alternative investment.

Bao and Roubaud (2022), in their systematic review of the NFT literature, note that although NFTs caught our attention in 2017 when they were used by CryptoKitties (Bardhan 2021)—an Ethereum based game—it was not until the emergence of COVID-19 that an explosive growth in the NFT market was observed (Corbet et al. 2022). Why was this the case? The main argument given is that COVID-19 lockdown measures increased digital engagement (Bao and Roubaud 2022). Such engagement, especially for content creators and artists who sought a way to promote and sell their unique digital material online while avoiding costly intermediaries, made NFTs an attractive option.

As an early-stage market, NFTs were found to have price inefficiencies yet investments continue to increase (Dowling 2022a). Scholars have examined the relationship between NFTs and cryptocurrency markets (Dowling 2022b; Corbet et al. 2022; Karim et al. 2022), NFTs and traditional financial assets such as gold, oil, and equity stock indices (Aharon and Demir 2022; Umar et al. 2022), as well as the possible existence of bubbles in NFT markets (Maouchi et al. 2022; Vidal-Tomás 2022). While there is an extensive literature on the relationship between cryptocurrencies and economic policy uncertainty (EPU) (Demir et al. 2018; Ji et al. 2019; Bouri et al. 2019; Al-Yahyaee et al. 2019; Wang et al. 2019, 2020; Matkovskyy et al. 2020; Papadamou et al. 2021; Demiralay and Golitsis 2021; Jiang et al. 2021; Mokni 2021; Umar et al. 2021; Raheem 2021; Wu et al. 2022; Mokni et al. 2022; Elsayed et al. 2022) there is much less known about the relationship between economic uncertainty and NFT coin prices.

There are two main ways that economic uncertainty can affect cryptocurrencies and altcoins (like NFT coins) (Aharon et al. 2022). First, the initial cryptocurrency, Bitcoin, was created in response to the uncertainty and the lack of trust in traditional banking when the global financial crises of 2008–2009 erupted. Bitcoin and the ensuing cryptocurrencies were created as a digital cash system that removed third party intermediaries. During periods of economic uncertainty decentralized currencies like cryptocurrencies attract a lot of attention from investors and experience rapid price increases. Bitcoin for example experienced rapid price increases during the European sovereign debt crises of 2010 = 2013 and the Cypriot banking crisis of 2012–2013 as a flight from paper assets to digital assets occurred (Bouri et al. 2017). Second, when it comes to cryptocurrency investors, Twitter is a major source of information. The decentralized nature of cryptocurrencies and altcoins makes it harder to clearly identify the underlying fundamentals leaving room for non-fundamental factors like mood, uncertainty, and sentiment to be important drivers of these digital assets.[1]

This paper seeks to answer three important questions. What is the relationship between economic uncertainty and NFT coins? Is the relationship similar for different NFT coins? As an emerging asset, do NFT coins exhibit explosive behavior and if so, what role does economic uncertainty play in their formation? The answers to these questions will be of interest to retail investors, institutional investors, venture capitalists, and policy makers.

The analysis behind this paper uses several empirical approaches. Wavelet coherence is used for assessing the time and frequency dynamics between NFT coins and economic uncertainty. Economic uncertainty is measured using a new Twitter-based economic uncertainty (TEU) index (Baker et al. 2021). A closely related uncertainty measure, Twitter-based (equity) market uncertainty (TMU) is also included in the analysis. Wavelet coherence is a widely used method for detecting linear interactions between two data series. Wavelet coherence is based on the Pearson correlation coefficient but applied to the time and frequency domain. Wavelet analysis provides a richer understanding of the dynamics between two series than that provided by a pure time series approach (Özdemir 2022). Wavelet coherence has been used to measure the relationship between digital assets and other assets (Phillips and Gorse 2018; Mensi et al. 2019a, 2021; Goodell and Goutte 2021; Dowling 2022b; Umar et al. 2022; Vidal-Tomás 2022). In this present paper, wavelet coherence between TEU, TMU and NFT coin prices is calculated. Four NFT coins are analyzed (THETA, ENJ, XTZ, and MANA). Each of these NFT coins is widely traded, has a decent trading history, and has a large market capitalization. Further analysis on the time frequency relationship between TEU, TMU, and NFT coin prices is conducted using the time frequency connectedness methodology of Barunik and Krehlik (2018) which has been applied to cryptocurrencies (Mensi et al. 2019b; Wang et al. 2021). Wavelet analysis is a nonparametric method while time and frequency connectedness is a parametric approach. Using both of these methods helps to establish how robust the results are to the choice of estimation methodology. While wavelet and time and frequency connectedness can both establish periods and frequencies of high and low correlation, they are not able to detect periods of explosive price behavior (bubbles). Evidence of bubble activity in NFT coin prices has been found by Vidal-Tomás (2022) and Maouchi et al. (2022). To address the question of potential bubbles in NFT coin prices (periods of rapid asset price growth followed by sudden collapse), the empirical approach developed by Phillips et al. (2015) is used to identify episodes of exuberance and collapse in NFT coin prices. Additional regression analysis is conducted to study the determinants of bubbles.

[1] Examples of research that broadly looks at the relationship between tweets and cryptocurrencies includes the following. Lansiaux et al. (2022) study the relationship between Twitter tweets and Dogecoin and Litecoin activity. They find that Dogecoin transaction value is impacted by tweets but tweets are impacted by Litecoin transaction value. Ante (2023) finds that non-negative tweets from Elon Musk lead to significantly positive abnormal Bitcoin returns. Individual tweets do raise the price of Bitcoin by 16.9% or reduce it by almost 11.8%. Abraham et al. (2018) investigate whether Twitter data can be a useful predictor of Bitcoin and Ethereum price direction. They find that tweet volume rather than tweet sentiment is useful for predicting Bitcoin and Ethereum price direction. Beck et al. (2019) use machine learning models to predict cryptocurrency tweets from published news articles. Prediction accuracy is highest the closer the prediction start time is to the target time.

With regards to the relationship between economic uncertainty and NFT coins, this research finds that the relationship with each of ENJ, MANA, THETA, and XTZ is strongest for the periods January 2020 to July 2020 and January 2022 to July 2022. Over the regions of highest coherence, economic and market uncertainty has an out of phase relationship with NFT prices. Is the relationship similar for different NFT coins? The answer is yes. These relationships are consistent across all four NFT coins studied. Further analysis conducted using network connectedness finds that connectedness is highest during the periods of highest wavelet coherence. In answering the question as to whether bubbles occur in NFT coin prices, bubbles are observed for ENJ, MANA, and THETA but not XTZ. From regression analysis it is found that the NFT coin price volatility and the COVID-19 period are positively associated with NFT bubble activity while economic and market uncertainty has a negative relationship. No bubbles are observed for XTZ. The XTZ is an NFT coin that is also connected to real world utility in that it is used to build smart contracts and decentralized applications and, as a result, is less susceptible to herding behavior.

This paper is organized as follows. Section "Related literature" provides a short discussion on the related literature. Section "Methods" describes the methods used to study NFT coin prices. Section "Data" provides a description of the data. The empirical results are reported in section "Results". Section "Discussion and implications" presents a discussion of the results and some implications while section "Conclusions" concludes the paper.

Related literature

During periods of high economic uncertainty, investors reduce their holdings of risky assets (like stocks) and increase their holdings of less risky assets (like government bonds). Since Bitcoin was created in response to the global financial crisis, it is natural to conduct analysis to see how Bitcoin and other cryptocurrencies respond to economic uncertainty. The relationship between economic policy uncertainty (specifically focused on uncertainty regarding monetary policy, fiscal policy, and regulatory policy) and cryptocurrencies has attracted the attention of many scholars (Haq et al. 2021).

The relationship between economic policy uncertainty (EPU) and Bitcoin has attracted the most amount of attention. Some authors find a strong relationship between EPU and Bitcoin. Matkovskyy et al. (2020) find that the relationship between EPU and Bitcoin volatility is greater than the relationship between EPU and Bitcoin returns. Increases in EPU are associated with a decrease in Bitcoin volatility. Wang et al. (2020) find that Bitcoin returns around the highest EPU days are significantly greater than those around the lowest EPU days. The United States (US) EPU increases the volatility and trading volume of BTC after days when EPU spikes. Umar et al. (2021) find that during times of high economic policy uncertainty, EPU has a positive relationship with Bitcoin. During times of lower economic policy uncertainty, however, the relationship can be negative. Wu et al. (2022) find that EPU has a positive impact on Bitcoin returns but a negative impact on Bitcoin volatility. In examining the risk transmission between Bitcoin and other financial assets Elsayed et al. (2022) find that EPU is the only global factor that causes higher volatility in Bitcoin. In contrast to the above mentioned studies, Wang et al. (2019) study the relationship between Bitcoin and uncertainty and find that the risk spillover from EPU to Bitcoin in most conditions is negligible.

Some authors find the relationship between Bitcoin and EPU to be more complicated in that it varies by quantiles or has time and frequency effects. Demir et al. (2018) study the impact of economic policy uncertainty (EPU) on Bitcoin price returns. They find that EPU has a mostly negative relationship with Bitcoin, but the relationship is positive at the lower and upper quantiles. Al-Yahyaee et al. (2019) find that the relationship between EPU and Bitcoin depends upon the time and frequency. Mokni (2021) finds that EPU has a causal impact on Bitcoin returns during extreme market conditions. Causality from EPU to Bitcoin volatility is established during normal or bullish conditions.

In studying the network connectedness between six large cryptocurrencies (Bitcoin, Ethereum, Ripple, Litecoin, Stellar, and Dash) Ji et al. (2019) find the EPU has a significant impact on net directional spillovers. Bouri et al. (2019) estimate the herding behavior of 14 cryptocurrencies. They find that EPU has a positive and significant impact on herding behavior of cryptocurrencies. Demiralay and Golitsis (2021) find that the linkages between cryptocurrencies increased significantly during the COVID-19 pandemic. EPU is an important determinant of market linkages. Papadamou et al. (2021) find that half of the cryptocurrencies they study are strongly linked to EPU during bull markets.

There is also a developing literature on how useful cryptocurrencies are for hedging against EPU. Jiang et al. (2021) find that cryptocurrencies are good hedging assets for high values of EPU but not so useful for periods of low or moderate EPU. Raheem (2021) finds that Bitcoin was a safe have against EPU in the pre-COVID-19 period but not during. Mokni et al. (2022) explore how useful some major cryptocurrencies are for hedging against economic policy uncertainty. Their analysis reveals that cryptocurrencies cannot act as a strong hedge or safe haven against EPU before and during the COVID-19 pandemic. During COVID-19 cryptocurrencies act as a weak safe haven.

Most of the research on economic uncertainty and cryptocurrencies has focused on the more narrowly defined notion of economic policy uncertainty and used the EPU indices developed by Baker et al. (2016). These indices are constructed using key word searches of “monetary policy”, “fiscal policy”, and “regulatory policy” from major newspapers. Recently, Baker et al. (2021) have developed the Twitter-based Economic Uncertainty (TEU) and the Twitter-based market uncertainty (TMU) indices. These indices are designed to more generally measure economic uncertainty and market uncertainty. The TEU is a Twitter based index of economic uncertainty constructed from the total number of daily English language tweets containing terms with words for “uncertainty” and “economy”.[2] TMU is constructed in a similar way using keywords like “equity markets” and uncertainty. The TEU captures perceptions of economic uncertainty based on the views of social media users. The TMU captures perceptions of equity market uncertainty based on the views of social media users. The relationship between these new indices and cryptocurrencies has been studied by several authors. Wu et al. (2021) investigate the relationship between TEU, TMU, and four cryptocurrencies (Bitcoin, Ethereum, Litecoin, and Ripple). They find that the T EU has a mostly positively effect on the returns of the related cryptocurrencies. Aharon et al. (2022)

[2] https://www.policyuncertainty.com/twitter_uncert.html.

explore the dynamic relationship between TEU, TMU, and four cryptocurrencies (Bitcoin, Ethereum, Bitcoin Cash, Ripple). They find a causal link from the uncertainty indices and cryptocurrencies returns and the effect is strongest for Bitcoin. Bashir and Kumar (2022) study the relationships between TEU and 20 cryptocurrencies and find that the relationship between TEU and returns is negative while the relationship between TEU and volatility is positive. French (2021) studies the relationship between TMU and Bitcoin prices and finds that TMU has a much larger impact on Bitcoin following the onset of COVID-19. These studies establish that TEU and TMU have an impact on cryptocurrency prices.

The analysis in this paper extends the above streams of research that focus on TEU and cryptocurrencies by providing empirical evidence on how TEU and TMU interact with NFT coin prices. NFT coins, like cryptocurrencies, are based on blockchain technology but whereas cryptocurrencies are primarily used to conduct digital payments, NFT coins are used primarily for supporting the NFT ecosystem. Since the functionality of NFT coins differs from that of cryptocurrencies there is no reason to expect that the impact of economic uncertainty on NFT coins should be the same as that on cryptocurrencies. It may be the case that NFT coins respond to Twitter based economic uncertainty in a similar way as cryptocurrencies. Or it may be the case that NFT coins respond to Twitter based economic uncertainty in a different way. It is only through empirical analysis that the relationship between NFT coins and Twitter based economic uncertainty can be discovered.

Methods

The analysis in this paper uses three different empirical methods: wavelet coherence, time and frequency connectedness, and explosive behavior tests. A short description of each of these methods follows.

Wavelet coherence

Wavelets are used to transform signals into time and frequency components (Torrence and Compo 1998). Wavelets are a form of bandpass filter where only specific components of a time series are allowed to pass through. A wavelet can be written as:

$$\psi_{u,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right) \tag{1}$$

The width of the wave is defined by the scale parameter, s, and u specifies the location of the wave. A continuous wavelet transform can be written as:

$$W_x(u,s) = \int_{-x}^{+x} x(t)\frac{1}{\sqrt{s}}\psi^*\left(\frac{t-u}{s}\right)dt \tag{2}$$

The variable ψ^* is the complex conjugate of ψ. There are many wavelets but the Morlet wavelet has been used in previous financial applications (Phillips and Gorse 2018). The Morlet wavelet is basically a sine wave multiplied by a Gaussian distribution.

$$\psi^M(t) = \frac{1}{\pi^{1/4}}e^{iw0t}e^{-t^2/2} \tag{3}$$

The value of w0 is set at 8. When analyzing similarity between two time series, a cross wavelet function can be used to determine similar correlations for a particular wavelet.

The cross wavelet transform for two continuous wavelet transforms $W_x(u,s)$ and $W_y(u,s)$ is:

$$W_{x,y}(u,s) = W_x(u,s)W_y^*(u,s) \tag{4}$$

where * denotes the complex conjugate.

Wavelet coherence measures the cross-spectral density between two data series (Torrence and Compo 1998; Rua and Nunes 2009).

$$R^2(u,s) = \frac{|S(s^{-1}W_{x,y}(u,s))|^2}{S(s^{-1}|W_x(u,s)|^2)S(s^{-1}|W_y(u,s)|^2)} \tag{5}$$

where S is a smoothing operator. The wavelet coherence is the ratio of the cross-wavelet power to the product of the individual power. Notice the similarity to the squared coefficient of correlation. Wavelet coherence is useful for determining regions in time and frequency space where the two series move together.

In the wavelet coherence plot, warmer colors (red) indicate stronger coherence while cooler colors (blue) indicate weaker coherence. The wavelet coherence plots include black arrows indicating the phase relationship between the two series. Arrows pointing to the right indicate that the two series are in phase. Arrows pointing to the left indicate the two series are out of phase. In phase indicates positive correlation while out of phase indicates negative correlations. Arrows pointing upwards indicates the first series leads the second series by π/2. Downward pointing arrows indicate the second series leads the first series by π/2. A zero phase difference means that the two series are moving together simultaneously. Statistically significant regions (at 5% level) are indicated by solid loops. These confidence regions are calculated using 1000 Monte Carlo simulations. Wavelet coherence plots also show a cone of influence where the wavelet power spectrum is distorted at its end points due to the finite length of the data. A Morlet mother wavelet function was used with 8 scales which is common for analyzing wavelet coherence between financial assets measured at a daily frequency (Mensi et al. 2021).

Time–frequency connectedness

Wavelet coherence is useful for analyzing the time and frequency relationship between a pair of variables. It does not, however, control for additional factors. Consequently, the approach developed by Barunik and Krehlik (2018) is used to estimate connectedness in the time and frequency space. Their methodology builds on the variance decompositions derived from a vector autoregression (VAR) moving average representation (Diebold and Yilmaz 2009, 2012). Connectedness is important for understanding the spillovers between variables (Diebold and Yilmaz 2009, 2012). The Diebold and Yilmaz approach is based on generalized impulse responses and captures both directional and net spillovers. The Barunik and Krehlik approach uses the spectral representation of the variance decompositions over frequencies in the range of – π to π. This can be used to calculate connectedness indices for different frequencies. The derivations of these indices are provided in Barunik and Krehlik (2018). The total directional connectedness to is the proportion of a shock that a variable transmits to the other variables. The total directional connectedness from is the share of a shock that a variable received from the remaining markets. The net directional connectedness is the difference between the to and from directional connectedness values. Pairwise and net pairwise connectedness indices can be computed to isolate the relationships between two specific variables. The total connectedness index (TCI) shows the degree of network connectedness. It shows how the mean impact of a shock to one variable impacts the other variables. Higher values represent a larger shock while lower values indicate a smaller shock. The connectedness indices are easily summarized in graphical form.

In this paper, connectedness was analyzed using frequency bands for 1 to 7 days, 7 days to 28 days, and 28 days and longer. The VAR was estimated with three lags (as chosen by the HQ criteria). The rolling window length was set at 350 days (approximately one year of daily NFT coin price data) and the forecast horizon set at 100 days. The results reported in this paper are not sensitive to small changes (plus or minus 50 on the window length, plus or minus 20 on the forecast horizon) in either of these two values.

Testing for explosive behavior

Phillips et al. (2011) construct tests for explosive behavior (bubbles) using the supremum augmented Dickey–Fuller test (SADF). The basic idea is to apply a series of right tailed unit root tests to expanding windows of data where all windows have the same start date (r_0) but the length of each window increases sequentially.

$$SADF(r_0) = \underset{r_{2\in[r_0,1]}}{sup} ADF_0^{r_2} \tag{6}$$

The SADF locates the largest ADF statistic from all the windows. The null hypothesis of no explosive behavior is rejected if a test statistic is found to exceed a critical value. This test is useful for detecting single bubbles but may be less accurate if there are more than one bubble. Phillips et al. (2015) extended the analysis to allow for multiple bubbles. They introduced the generalized supremum augmented Dickey–Fuller test (GSADF) which allows both the start date and endpoints to vary. This modification is useful for detecting multiple bubbles. Phillips et al. (2015) also found that improved test statistics could be obtained by using a backwards expanding window known as the BSADF. The BSADF test uses a fixed endpoint and backwards expanding window. A GSADF version of this test can be constructed by allowing the fixed endpoint to vary while using a backwards expanding window. In the calculation of these tests, the ADF lag length is determined from a maximum lag length set at int($4^*(t/100)^{0.25}$) and the window size set at $0.01 + 1.8/\text{sqrt}(T)$ where T is the sample size. These data driven processes are widely used for ADF and rolling ADF calculations (Phillips et al. 2011).

Data

The main data for this study consists of daily data for four NFT coins (THETA, ENJ, XTZ, and MANA) and two Twitter-based uncertainty indices, TEU and TMU. The THETA coin is used for the governance of the THETA decentralized video streaming platform.[3] The ENJ coin is associated with a for-profit company responsible for the Enjin gaming software. ENJ is used by developers to create and manage virtual goods on the

[3] https://www.kraken.com/en-gb/learn/what-is-theta#:~:text=THETA%20allows%20nodes%20to%20validate,for%20sharing%20a%20video%20stream.

Ethereum blockchain and by gaming participants to trade in-game NFTs.[4] The XTZ is a coin for the Tezos open source blockchain used to build smart contracts and decentralized applications that is backed by a global community of validators, researchers, and builders.[5] The MANA coin is associated with the Decentraland software running on the Ethereum blockchain network that allows global users to conduct transactions in a virtual world.[6] These four NFT coins were chosen because they have large market capitalization and a long (for NFT coins) trading history (Yousaf and Yarovaya 2022).

Economic uncertainty is measured using TEU and stock market uncertainty is measured using TMU. These are Twitter-based measures of uncertainty. The Twitter-based economic uncertainty index is based on tweets about the words "economy" and "uncertainty" (Baker et al. 2021). The Twitter-based market uncertainty index is constructed from tweets containing "uncertainty" and "equity markets". Higher values of these indices reflect greater uncertainty while lower values indicate lesser uncertainty.

The NFT coin data are collected from Yahoo Finance. The Twitter-based uncertainty indices are obtained from https://www.policyuncertainty.com/twitter_uncert.html. The data set covers the period February 6, 2018 to December 31, 2022. The starting date for this data set is determined by the start date of THETA.

The patterns for THETA, ENJ, and MANA are fairly flat until January 2021 after which time there was a dramatic increase in the prices of these NFT coins (Fig. 1). After January 2021, XTZ, ENJ, and MANA show similar patterns (double peak formation although it is not as pronounced for MANA) indicating some common co-movement between these NFT coins. THETA experienced a large increase in early 2021 and trended downwards afterwards. The TEU and TMU show some similarities, especially the large increases in March of 2020. The World Health Organization (WHO) declared COVID-19 a global pandemic on March 12, 2020 and this announcement had a pronounced impact on both TEU and TMU. As of December 2022, the values of TEU and TMU remain elevated relative to their pre-COVID values. TMU recorded a huge spike on November 4, 2020 depicting the significant uncertainty associated with the outcome of the US presidential election.

Summary statistics for the continuously compounded returns for TEU, TMU and the NFT coins are presented in Table 1. Three of the NFT coins (THETA, ENJ, MANA) have positive mean returns while one (XTZ) has negative mean returns over the sample period. Amongst THETA, ENJ, and MANA, THETA is the least variable because it has the smallest coefficient of variation. TEUI and TMU also have positive mean returns and according to the coefficient of variation, TMU is the most variable. The W statistics show that each of the data series display evidence of non-normality.

Additional data are used to study the drivers of bubbles in NFT coins. The choice of explanatory variables used to study the drivers of NFT bubbles is similar to that used by Maouchi et al. (2022) and consists of NFT coin specific volatility (volatility), the

4 https://www.kraken.com/learn/what-is-enjin-enj.

5 https://tezos.com/nftgallery/.

6 https://www.kraken.com/learn/what-is-decentraland-mana.

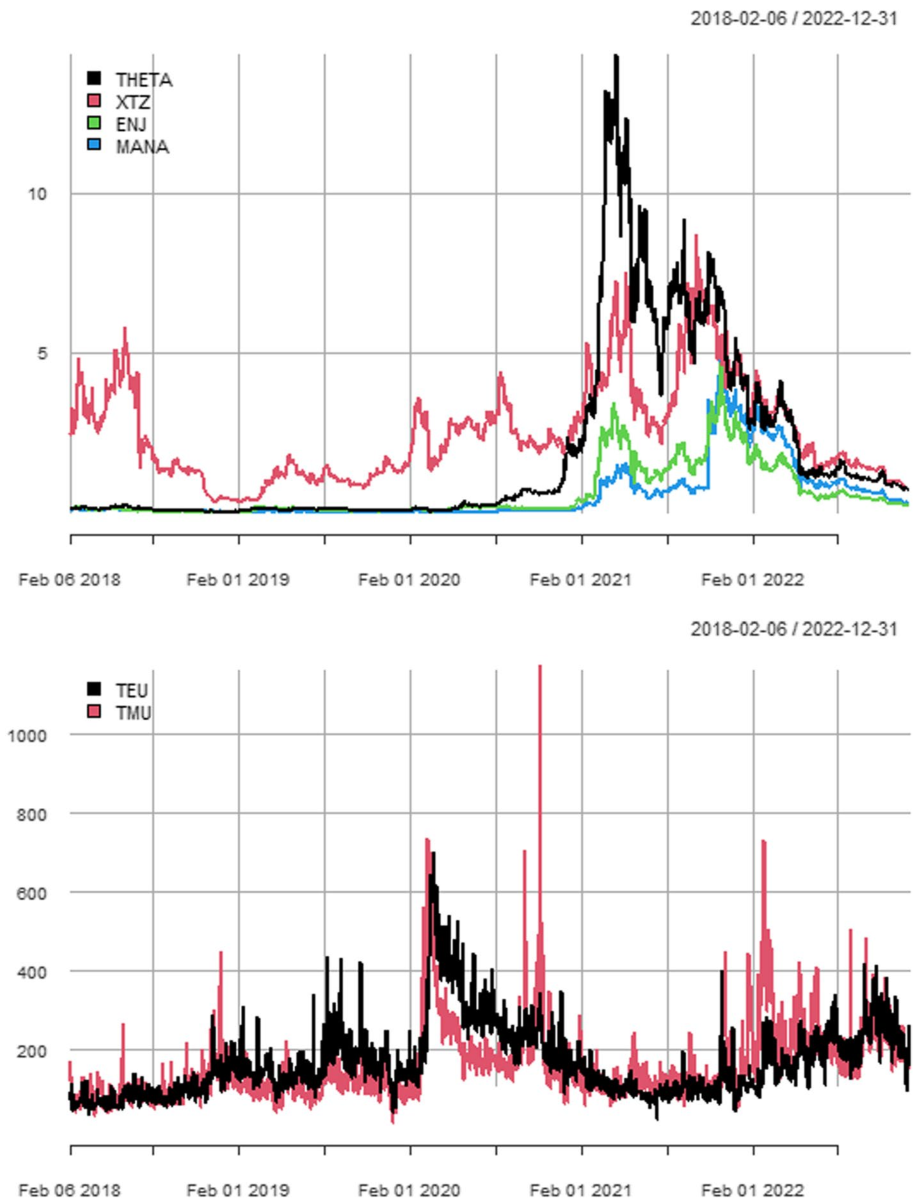

Fig. 1 Time series plots of the data

Table 1 Summary statistics for returns

	Median	Mean	Std.dev	coef.var	Skewness	Kurtosis	W	W(p)
TEU	− 0.878	0.058	23.732	406.954	0.231	1.553	0.987	0.000
TMU	− 0.440	0.011	26.978	2396.518	0.244	2.043	0.982	0.000
THETA	0.006	0.093	7.216	77.722	− 0.070	7.379	0.934	0.000
XTZ	0.032	− 0.069	6.501	− 94.263	− 0.667	7.764	0.934	0.000
ENJ	− 0.110	0.024	7.464	310.090	1.180	17.793	0.869	0.000
MANA	0.052	0.067	7.365	109.849	1.317	21.289	0.870	0.000

Data for the period February 7, 2018 to December 31, 2022 (1789 observations). All data are measured in log returns. W is the Wilcox test for normality and W(p) is the associated p value

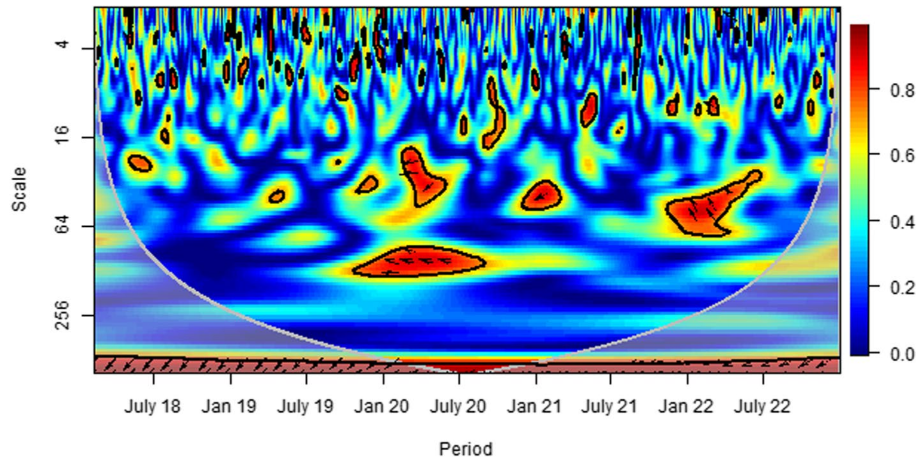

Fig. 2 Wavelet coherence between THETA and TEU

infectious disease equity market volatility tracker (IDT) which is a newspaper based infectious disease equity market volatility index that measures the volatility of infectious disease, the CBOE VIX (VIX) stock market volatility index, the oil volatility index (OVX), and the gold price volatility index (GVX). In addition, TEU and TMU are included as explanatory variables. Daily NFT coin volatility is constructed using the approach of Garman and Klass (Garman and Klass 1980). Each explanatory variable is smoothed using a 7-day moving average and the result is then lagged by one day. The variables IDT, VIX, OVX, and GVZ are available from the FRED database.

Results

The section reports results for wavelet coherence followed by results for time and frequency connectedness. Results on testing for explosive behavior in NFT coins and the determinants of bubbles follows.

Wavelet coherence

This section reports the results on wavelet coherence between NFT coin prices and uncertainty. Figure 2 shows a plot of wavelet coherence between THETA and TEU. There are several statistically significant large orange blobs indicating high coherence between the two series. Two blobs in particular stand out. For the period January 2020 to July 2020 (at just past 64 days), the arrows point to the left and slightly up indicating negative correlation and THETA leading TEU. The time period January 2020 to July 2020 is consistent with the onset of the COVID-19 pandemic. There is a similar THETA and TEU relationship between January 2022 and July 2022 at around 64 days.

A wavelet coherence plot for XTZ and TEU (Fig. 3), shows, as in the case for Fig. 2, two large dominant blobs. Between January 2020 and July 2020 there is a large region of coherence at the 64-day scale with the arrows pointing left and upwards. A large region of coherence is also observed between January 2022 and July 2022 at about the 64-day scale. The arrows point left and upwards indicating that XTZ leads TEU. The regions of coherence significance are not as large as those for THETA indicating that the coherence significance for XTZ and TEU is not as strong as that for THETA and TEU.

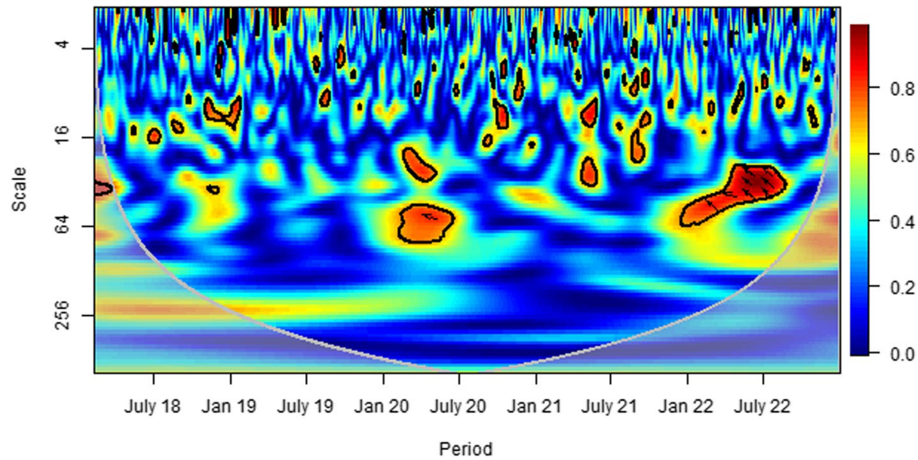

Fig. 3 Wavelet coherence between XTZ and TEU

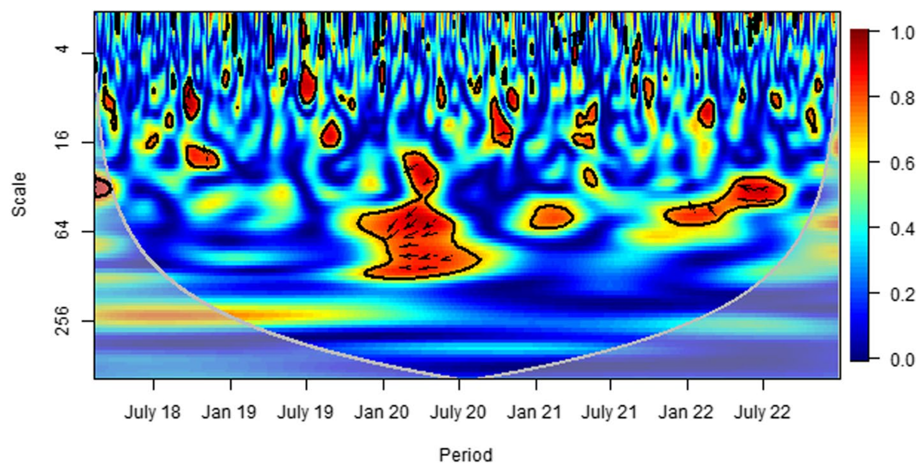

Fig. 4 Wavelet coherence between ENJ and TEU

The wavelet coherence between ENJ and TEU is dominated by a large region of significance covering January 2020 to July 2020 and another large region of significance covering the period January 2022 to July 2022 (Fig. 4). The largest region of significance (January 2020 to July 2020) covers the scale from 16 to 128 days and indicates an out-of-phase relationship with ENJ leading TEU. The second largest region of significance is located at about 64 days and covers January 2022 to July 2022. Here the relationship is out-of-phase with ENJ leading TEU.

There is a large out of phase region of significance between MANA and TEU (Fig. 5) for the 64-day to 128-day scale and the time period January 2020 to July 2020 with MANA leading TEU (upward pointing arrows). There is a smaller out of phase region between January 2022 and July 2022 with MANA mostly leading TEU.

In summary, the wavelet coherence plots between NFT coins and TEU shown in Figs. 2, 3, 4 and 5 show some similarities. The largest regions of wavelet coherence significance occur between January 2020 and July 2020 and January 2022 to July 2022. The relationship between NFT coins and TEU is out of phase with the coins mostly leading

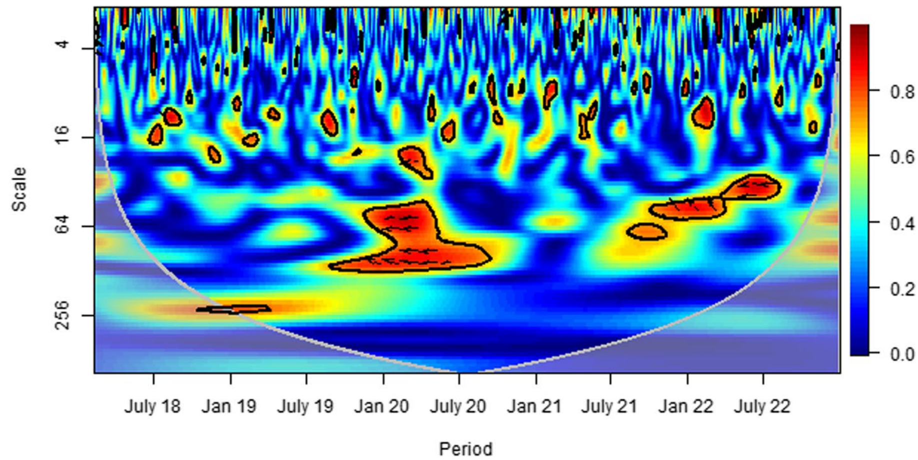

Fig. 5 Wavelet coherence between MANA and TEU

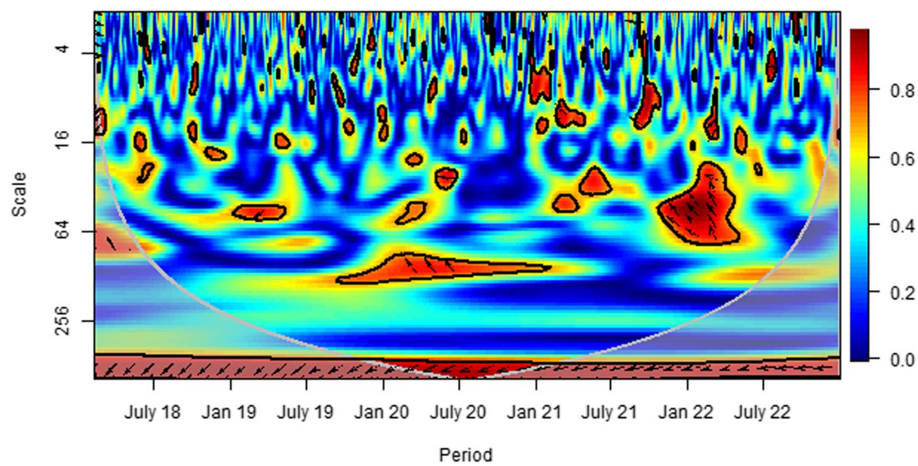

Fig. 6 Wavelet coherence between THETA and TMU

TEU. These results support the view that Twitter-based economic uncertainty and NFT coin prices are negatively correlated. Lower economic uncertainty correlates with higher NFT prices which is consistent with stylized facts about other financial assets like stocks.

Wavelet coherence between THETA and TMU show some large regions of out of phase coherence between January 2020 and July 2020 and again between January 2022 and July 2022 (Fig. 6). These regions are concentrated around the 128-day and 64-day scales respectively and show THETA leading TMU (arrows point up).

Wavelet coherence between XTZ and TMU (Fig. 7) show four significant regions of coherence either at or below the 64-day scale (July 2018 to January 2019 (TMU leading), January 2020 to July 2020 (simultaneous), January 2021 to July 2021 (simultaneous), January 2022 to July 2022 (XTZ leading).

There is one very large region of coherence between ENJ and TMU (Fig. 8). This region is located between January 2022 and July 2022 and covers the scale from 16 to 64 days. The phase arrows point left indicating an out of phase relationship. The arrows point up in the lower portion of the region (ENJ leads TMU) and down

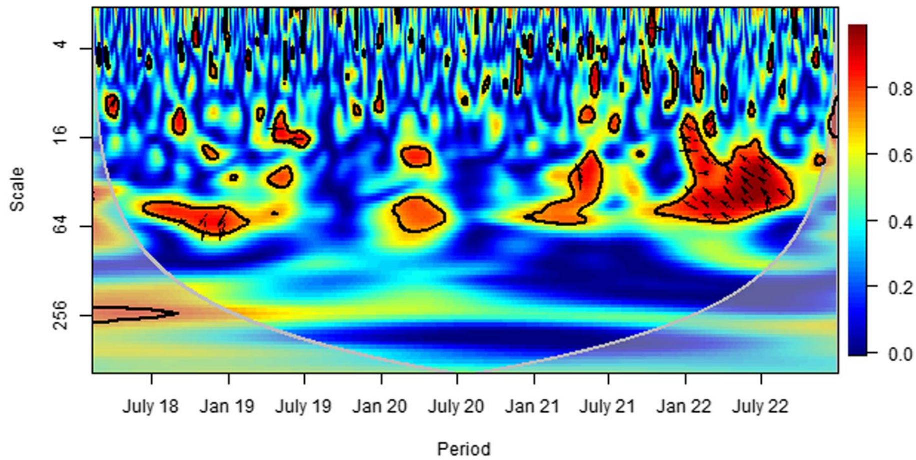

Fig. 7 Wavelet coherence between XTZ and TMU

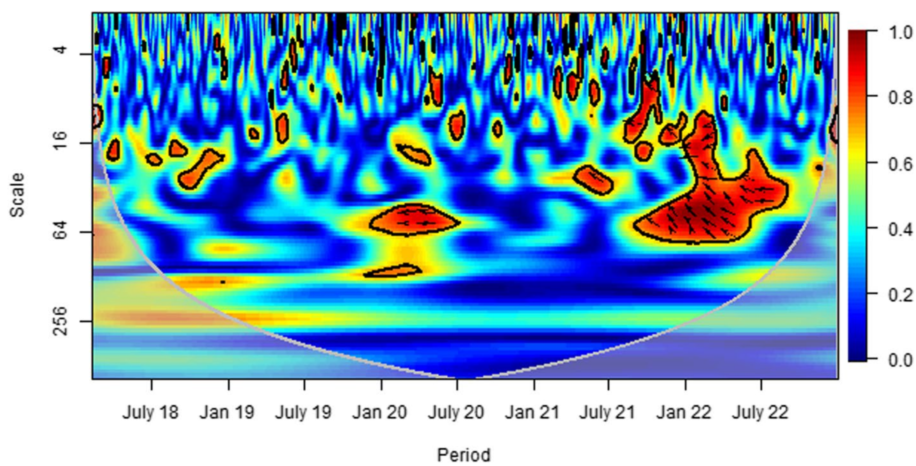

Fig. 8 Wavelet coherence between ENJ and TMU

(TMU leads ENJ) in the upper portion of the regions. The next largest region of significance is between January 2020 and July 2020, at 64 days, with an out of phase relationship with ENJ leading TMU.

There are two large areas of significance for the MANA and TMU coherence (Fig. 9). The first is between January 2020 and July 2022 and second is between January 2022 and July 2022. The phase arrows mostly indicate an out of phase relationship with MANA leading TMU.

In summary, the most prominent significant regions of coherence between the NFT coins and TMU are between January 2020 and July 2022 and between January 2022 and July 2022. For the January 2022 to July 2022 region the relationships are out of phase with the NFT coins mostly leading the TMU. The scale covers 16–64 days. The second largest significant region is between January 2020 and July 2022. Here again the relationship is out of phase with the NFT coins mostly leading TMU.

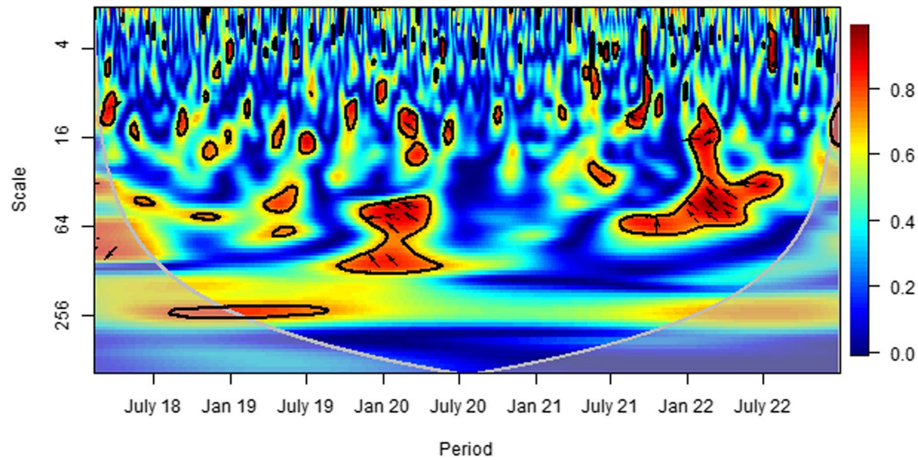

Fig. 9 Wavelet coherence between MANA and TMU

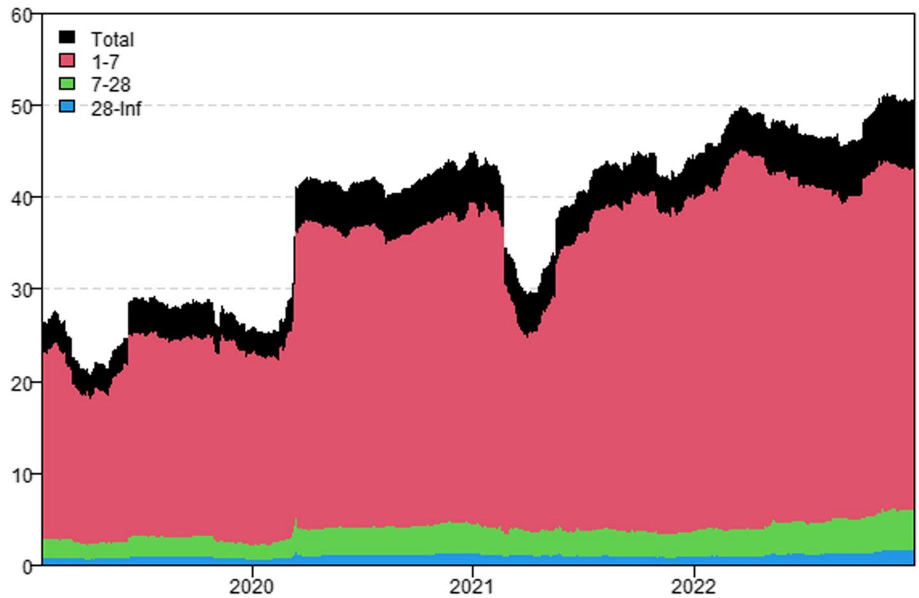

Fig. 10 Short-term (1–7), medium-term (7–28), long-term (28-inf), and total dynamic connectedness

Time and frequency connectedness

This section presents results on the time and frequency connectedness between the NFT coins and the two Twitter-based uncertainty indices. Analysis is conducted using three frequency bands: short (1–7 days), medium (7–28 days), and long (greater than 28 days). The pattern of total connectedness indicates that total connectedness increased dramatically up until early 2020, fluctuated between 40 and 45% and then declined in early 2021. After this there was an increase in total connectedness and by the end of 2021 total connectedness was back around 45%. As of December 2022, total connectedness reached a new sample period high of 50% (Fig. 10). The total connectedness is primarily driven by the short-term dynamics. The contributions of the medium-term and long-term are slight. Connectedness was highest in 2020 and 2022

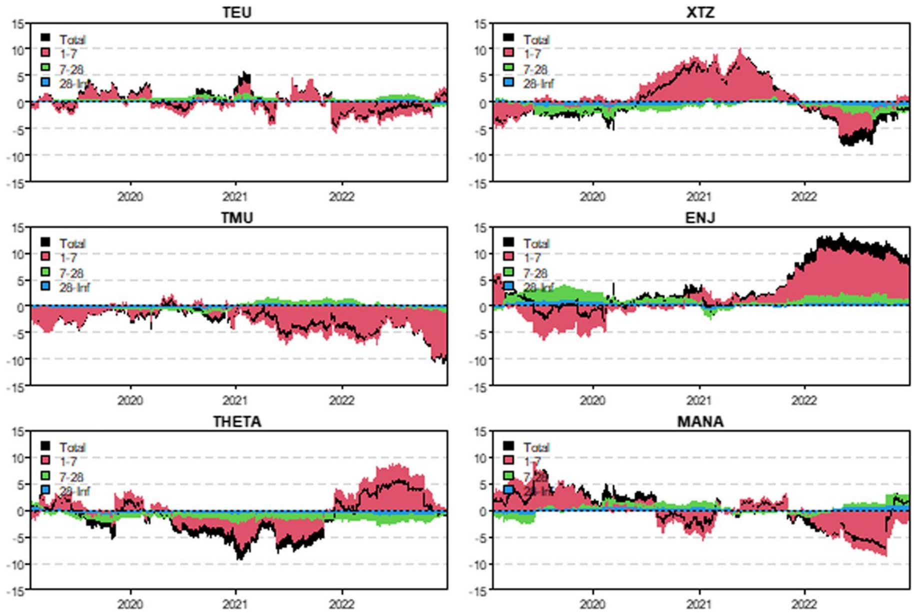

Fig. 11 Net total directional short-term, medium-term, and long-term connectedness

which is consistent with the findings of the wavelet analysis that found periods of high coherence between economic uncertainty and NFT coins occurred during these time periods.

Figure 11 presents the net connectedness of each of the variables. Positive values indicate that a variable is a net transmitter of shocks to the system while negative values indicate that a variable is a net receiver of shocks from the system. For TEU, the medium-term and long-term dynamics are mostly positive indicating TEU is a net transmitter of shocks for these frequencies. The short-term dynamics varies considerably between positive and negative values. Mid 2019 to early 2020 was the longest period of positive values while in 2022 TEU was mostly a net receiver of shocks. A different pattern is observed for TMU. TMU is mostly a net receiver of shocks across all of the frequency bands. Throughout 2021 the medium-term was a net transmitter of shocks. For THETA, the medium-term and long-term are net receivers for the sample period. In 2022, the short-term is a net transmitter of shocks. For XTZ, the medium-term and long-term are net receivers of shocks. The only period of net transmission is for the short-term over the period mid 2020 to late 2021. For ENJ, the medium-term is most a net transmitter of shocks. The short-term is a net receiver of shocks in 2020 and a net transmitter of shocks from the beginning of 2021 to the end of 2022. As in the case of ENJ, the medium-term dynamics for MANA are mostly net transmitters of shocks. The short-term MANA dynamics are net transmitters in 2020 but switch to net receivers in 2022.

A network diagram of average net pairwise directional connectedness can be used to summarize the pairwise connectedness relations (Fig. 12). Overall, THETA and TMU are net receivers of shocks and ENJ is an important transmitter. In the short-term, TMU is a net receiver of shocks with the largest impact coming from ENJ. In the medium-term and long-term a different pattern emerges. THETA and XTZ are net receivers of

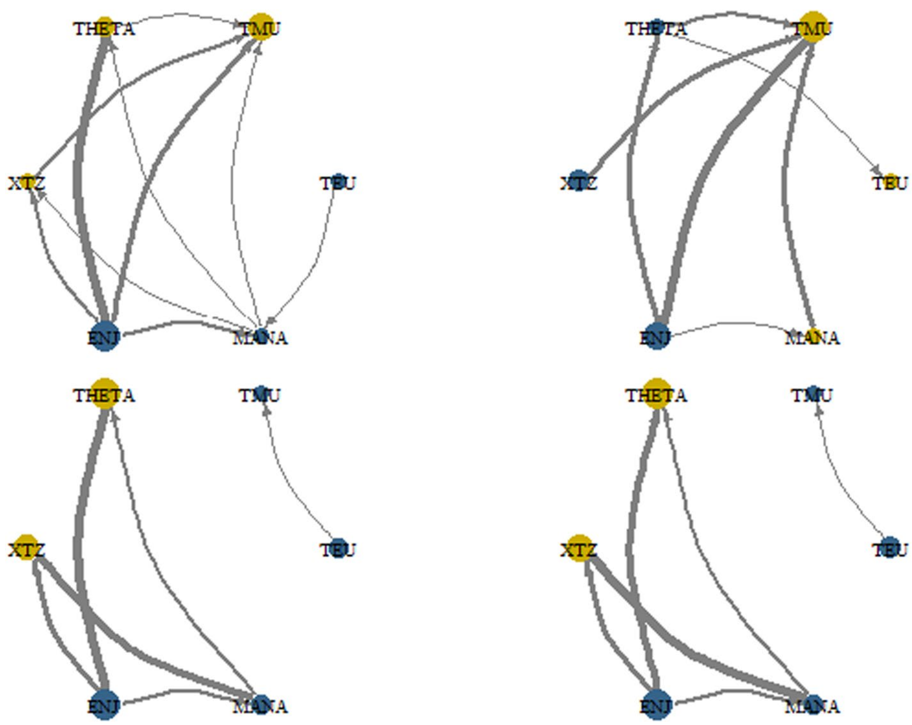

Fig. 12 Network diagram of average net pairwise directional connectedness. Top left total, top right short-term, bottom left medium-term, bottom right long-term

shocks while ENJ and MANA are net transmitters. TEU transmits shocks to TMU but both of these variables are now separated from the NFT coins.

Testing for bubbles in NFT coin prices

This section reports results from testing for bubbles in NFT coin prices. For ENG, MANA, and THETA, the SADF and GSADF tests indicate evidence of bubbles at the 1% level of significance (Table 2). Interestingly, XTZ does not show evidence of bubble activity. Plots of date stamping of the BSADF tests are shown for ENJ (Fig. 13), MANA (Fig. 14), THETA (Fig. 15), and XTZ (Fig. 16). The pattern of the BSADF tests for ENJ, MANA, and THETA show similar bubble behavior in early 2021.

Table 3 shows the dates of the bubbles. ENJ had one bubble between March 7, 2021 and April 11, 2021. MANA had a bubble between February 7, 2021 and May 9, 2021 and a very short lived bubble for the week of November 28, 2021. THETA had two bubbles with the first one occurring between August 23, 2020 and October 25, 2020. The second bubble occurred between December 20, 2020 and April 18, 2021. ENJ, MANA, and THETA each had bubbles between March 7, 2021 and April 11, 2021. The results for ENJ, MANA and THETA are broadly consistent with those of Maouchi et al. (2022) who, using the BSADF test, found a bubble for ENJ between February 25, 2021 and March 16, 2021, a bubble for MANA spanning February 28, 2021 to March 16, 2021 and a bubble for THETA occurring between December 13, 2020 and March 16, 2021. Vidal-Tomás (2022) tested the Metaverse Index for bubbles and found a cluster of bubbles in August and September of 2021 which differs from the results in our paper and those of Maouchi

Table 2 Tests for bubbles

	Test	CV 90	CV 95	CV 99
ENJ				
ADF0	− 2.490	− 0.448	− 0.095	0.552
SADF	4.637	1.111	1.400	1.950
GSADF	5.751	1.877	2.113	2.561
MANA				
ADF0	− 2.258	− 0.448	− 0.095	0.552
SADF	3.791	1.111	1.400	1.950
GSADF	4.753	1.877	2.113	2.561
THETA				
ADF0	− 2.020	− 0.448	− 0.095	0.552
SADF	8.841	1.111	1.400	1.950
GSADF	8.935	1.877	2.113	2.561
XTZ				
ADF0	− 2.857	− 0.448	− 0.095	0.552
SADF	− 0.835	1.111	1.400	1.950
GSADF	1.038	1.877	2.113	2.561

ADF0, SADF, and GSADF tests for bubbles. Critical values (CV) shown for the 90%, 95%, and 99% levels

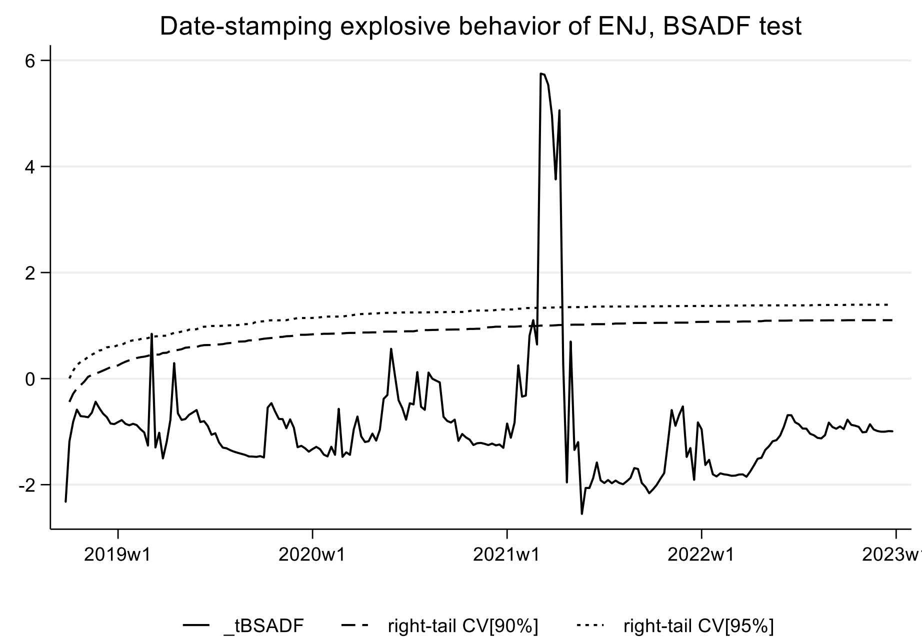

Fig. 13 BSADF tests for bubbles in ENJ

et al. (2022). The Metaverse Index is a market cap weighted index of 16 tokens from the entertainment and virtual reality space. This index, however, has a very short history as it only began trading on April 7, 2021.

The episodes of NFT coin explosive behavior (Table 3) shows that ENJ, MANA, and THETA share common time periods of bubbles. Thus, it is of interest to see if there are common features driving these bubbles. A logit model is used to examine the determinants of NFT coin bubbles. In the logit model, the dependent variable is a dichotomous

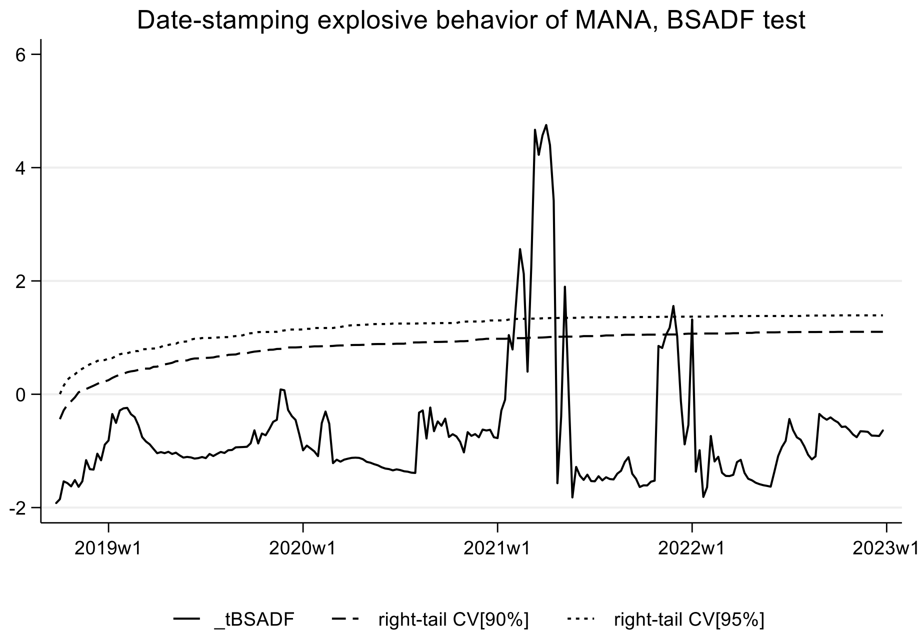

Fig. 14 BSADF tests for bubbles in MANA

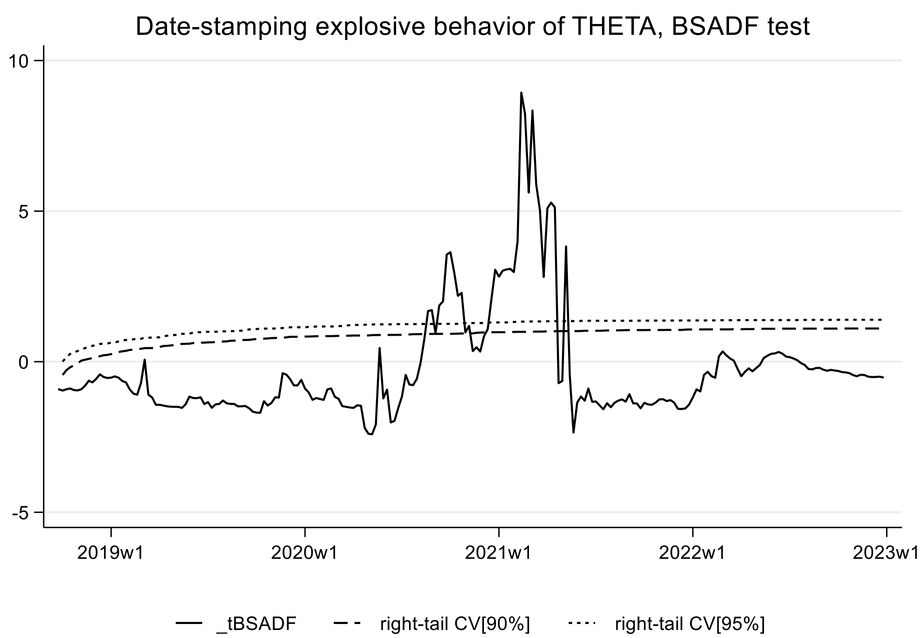

Fig. 15 BSADF tests for bubbles in THETA

variable which takes the value of 1 (bubble) or 0 (no bubble). The explanatory variables for the logit model are discussed in the data section.

The results show that NFT coin volatility and the period of COVID-19 are each positive and significant determinants of bubbles in ENJ, MANA, and THETA (Table 4). Higher coin volatility is associated with a higher likelihood of bubbles which is consistent with the literature on rational bubbles and herding (Brunnermeier and Nagel 2004;

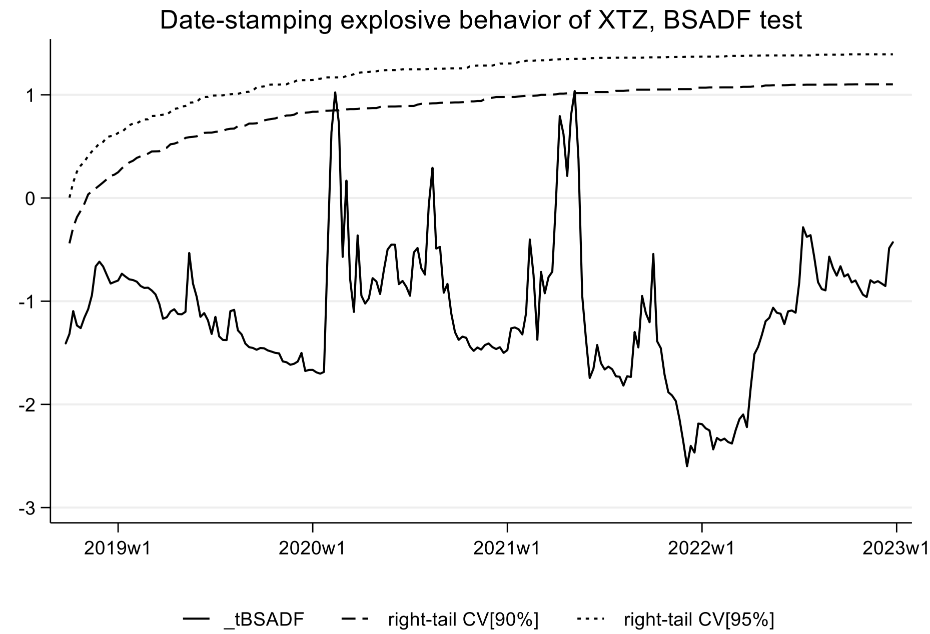

Fig. 16 BSADF tests for bubbles in XTZ

Table 3 Episodes of NFT coin explosive behavior

NFT	Significant regions
ENJ	March 7 2021 to April 11 2021
MANA	Feb 7 2021 to May 9 2021, November 28 2021
THETA	August 23 2020 to October 25 2020, Dec 20 2020 to April 18 2021
XTZ	None

Regions where the BSADF test indicates significance at 5%

Bekiros et al. 2017) and support the findings of Maouchi et al. (2022). The estimated coefficient on TEU is negative and significant indicating larger values of Twitter-based economic uncertainty decrease the probability of a bubble. Higher economic uncertainty may create incentives for investors to more carefully evaluate their asset holdings thereby making it less likely that herding and speculative activity lead to bubbles. Similarly, the estimated coefficient on TMU is negative and statistically significant. The estimated coefficients on VIX, OVX, and GVZ indicate that each of these variables are significant for no more than two NFT coins indicating these volatility measures have coin specific effects. THETA seems to be most affected by market volatility as VIX and GVZ each have positive and significant impacts while OVX has a negative and significant impact on the determinants of bubbles.

Discussion and implications

Wavelet coherence plots show some interesting commonalities between Twitter-based economic uncertainty and ENJ, MANA, THETA, and XTZ prices. Wavelet coherence plots show high coherence between January 2020 and July 2020 and January 2022 and July 2022 around the 64-day scale. In most of the largest regions of coherence

Table 4 Determinants of NFT coin bubbles

	(1) ENJ	(2) MANA	(3) THETA
Volatility(− 1)	1.941[a]	0.748[a]	0.678[a]
	(3.67)	(4.10)	(3.54)
TEU(− 1)	− 0.0506[a]	− 0.0205[a]	− 0.00923[a]
	(− 2.70)	(− 4.45)	(− 3.29)
TMU(− 1)	− 0.0926[a]	− 0.0330[a]	− 0.0162[a]
	(− 4.67)	(− 5.64)	(− 5.27)
IDT(− 1)	0.384[a]	0.208[a]	0.254[a]
	(6.26)	(7.20)	(10.10)
VIX(− 1)	0.0892	0.0671	0.0946[b]
	(0.72)	(1.45)	(2.32)
OVX(− 1)	0.112[a]	0.0141	− 0.143[a]
	(3.55)	(1.40)	(− 8.10)
GVZ(− 1)	0.130	0.158[c]	0.352[a]
	(0.55)	(1.80)	(6.07)
Constant	− 4.006[b]	− 3.817[a]	− 4.660[a]
	(− 2.02)	(− 3.94)	(− 6.07)
N	1783	1783	1783
AIC	167.6	472.3	668.3
Chi-squared	238.8[a]	336.6[a]	699.5[a]
Log-likelihood	− 75.78	− 228.2	− 326.2

t statistics in parentheses

[c] $p < 0.10$, [b] $p < 0.05$, [a] $p < 0.01$

there is an out of phase relationship and that movements in NFT coin prices occur before movements in economic uncertainty. Investors in these NFT coins need not be concerned that movements in Twitter-based economic uncertainty will affect their investments in ENJ, MANA, THETA, or XTZ. The results of this present paper are different from those of Wu et al. (2021), Aharon et al. (2022), and Bashir and Kumar (2022) who found a relationship from TEU to cryptocurrencies.

The wavelet coherence between the ENJ, MANA, THETA, and XTZ Twitter-based market uncertainty shows similar results. Prominent regions of coherence occur between January 2020 and July 2020 and January 2022 to July 2022. The coherence relationships in these regions are out of phase with NFT coins mostly leading Twitter-based market uncertainty. This result is important in establishing that neither TEU or TMU are likely important for forecasting the prices of ENJ, MANA, THETA, or XTZ.

Network connectedness analysis shows that connectedness was highest in 2020 and 2022. Thus, the network connectedness analysis agrees with the wavelet coherence analysis in establishing the time periods of strongest relationships between NFT coin prices and economic uncertainty. On average net pairwise connectedness shows that economic uncertainty has no direct impact on NFT coins for the medium-term and long-term.

There is evidence to support bubble behavior in ENJ, MANA, and THETA. These three NFT coins experienced a common period of bubble behavior from late March 2021 into April of 2021. THETA experienced the greatest bubble behavior as bubbles were detected between August 2020 to October 2020 and from December 2020 to April 2021.

Analyzing the determinants of ENJ, MANA, and THETA bubbles reveals that the COVID-19 period and NFT coin volatility are each positively correlated with bubble formation. These results are consistent with the findings of Maouchi et al. (2022). During the COVID-19 period individuals received monetary transfers from government, some of which were used to participate in the digital asset markets (Divakaruni and Zimmerman 2021). The lockdowns associated with COVID-19 also provided cryptocurrency investors more free time with which to increase their trading activity (Guzmán et al. 2021). COVID-19 also increased herding behavior (Rubbaniy et al. 2021). Increases in volatility are associated with herding that often occurs during turbulent times like the COVID-19 outbreak (Rubbaniy et al. 2021).

Interestingly higher Twitter-based economic uncertainty and Twitter-based market uncertainty are negatively correlated with the formation of bubbles in ENJ, MANA, and THETA. This may be because during times of heightened economic uncertainty, these NFT coins are viewed as useful diversification assets rather than speculative assets. Notice that the period of highest Twitter-based uncertainty occurred in early 2020 while NFT coin bubbles were most prominent in early 2021.

The results obtained from estimating NFT coin bubbles offer some practical implications. First, investors in ENJ, MANA, and THETA should monitor infectious disease outbreaks, individual NFT coin price volatility, and Twitter-based uncertainty. Second, the presence of bubbles in ENJ, MANA, and THETA raises questions for regulators (Chalmers et al. 2022). If NFT coin bubbles are being driven by clear intent to commit fraud, then regulators need to play a more active role in the NFT coin markets. However, bubbles by themselves do not necessarily represent fraud. They may be due to short term irrational exuberance. In this case, large short-term profits and losses may be realized but, over a longer term, the pricing dynamics becomes more rational. Thus, a pure price bubble is of less concern for regulators. The analysis conducted in this paper (and others) on the determinants of NFT coin bubbles indicates there are solid fundamental reasons for the formation of bubbles in the prices of ENJ, MANA, and THETA.

Interestingly, XTZ did not experience any periods of explosive behavior. This may be due to its type. XTZ is an NFT coin for Tezos which is a blockchain used to build smart contracts and decentralized applications. XTZ is more closely related to real world utility as opposed to a virtual world indicating that utility based NFT coins are less likely to experience explosive pricing behavior. Of the four NFT coins studied, NFT may be a better fit for risk adverse investors. The other NFT coins studied, ENJ, MANA, and THETA, are more closely related to the metaverse and thus subject to hype, fads and herding about the metaverse and virtual world related products.

It is also worth noting that in general, periods of high wavelet coherence do not coincide with bubbles. Wavelet coherence measures the strength of the relationship between two variables. Tests for explosive behavior are testing whether the unit root hypothesis is rejected. Thus, wavelet coherence and tests for bubbles provide useful but different information and need not be in agreement.

One limitation of the research reported in this present paper is that it was limited to four NFT coins. The reason for this was that these coins have the longest trading history and have a large market capitalization. As more data becomes available it would be interesting to see how a larger sample of NFT coins responds to changes in economic uncertainty.

Conclusions

NFT coins are digital assets that are stored on a blockchain. The prices of NFT coins experienced impressive growth during the COVID-19 period and questions arise as to what impact economic uncertainty has on NFT coin prices. This paper studies the relationship between four NFT coins (THETA, ENJ, XTZ, and MANA) and economic uncertainty. Economic uncertainty is measured using a new Twitter-based economic uncertainty index. A related Twitter-based stock market uncertainty index is also included in the analysis.

There are two periods of pronounced wavelet coherence between Twitter-based economic uncertainty or market uncertainty and ENJ, MANA, THETA, and XTZ prices. The first period is January 2020 and July 2020 and the second is between January 2022 and July 2022. In both cases, significant coherence is clustered around the 64-day scale. In most cases there is an out of phase relationship between NFT coin prices and the uncertainty indices. Based on the wavelet coherence analysis, Twitter-based uncertainty is not a good predictor of ENJ, MANA, THETA, and XTZ prices over these regions.

Wavelet coherence between Twitter-based uncertainty and NFT coin prices were highest in the periods January 2020 to July 2020 and January 2022 to July 2022. The period January 2020 to July 2020 coincided with the global outbreak of COVID-19 and the lockdowns that followed. The second period, January 2022 to July 2022 coincided with Central Banks raising interest rates to address inflation and the resulting drop in stock markets as a result of higher interest rates. Network connectedness analysis shows that the highest connectedness occurred during 2020 and 2022 which is consistent with the findings from wavelet analysis. In the medium-term and long-term, TEU and TMU are, on average, not connected to the NFT coins studied.

Bubble behavior is observed for ENJ, MANA, and THETA. A common period of bubble activity for these NFT coins was observed from March 2021 to April of 2021. THETA has the most bubble activity with two distinct bubbles (August 2020 to October 2020, Dec 2020 to May 2021). NFT coin volatility and the COVID-19 period are positively associated with bubble activity. Government COVID-19 relief stimulus and the lockdowns associated with COVID-19 provided cryptocurrency investors with more money, free time, and incentive to look for alternative assets like NFT coins. Twitter-based economic uncertainty and stock market uncertainty has a negative relationship with bubble formation as periods of high uncertainty occurred outside of the range of bubble formation. By comparison XTZ has no bubbles. This may be because XTZ is a utility based NFT coin and NFT coins associated with a real-world utility are more grounded in economic fundamentals and less likely to experience herding and explosive pricing than NFT coins associated with a virtual world. Future research would look at how the relationship between NFT coin prices and uncertainty evolves in the post COVID-19 period.

Abbreviations

BSADF Backwards expanding window SADF test
GSADF Generalized supremum augmented Dickey-Fuller test
NFTs Non-fungible tokens
SADF Supremum augmented Dickey-Fuller test
TEU Twitter-based economic uncertainty index
TMU Twitter-based stock market uncertainty index

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Author contributions
PS: Conceptualization, Data curation, Methodology, Software, Writing—original draft, revision. IH: Conceptualization, Methodology, Writing—original draft, revision. Both author(s) read and approved the final manuscript.

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Declarations

Competing interests
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