

Exploring efficiency and speculative behavior in the Metaverse economy: a comprehensive analysis

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Abstract

Purpose – The purpose of this paper is to explore market efficiency in the Metaverse economy by analyzing the behavior of major Metaverse tokens. This study examines how information diffusion, price discovery and systemic dynamics shape efficiency and speculative activity in this emerging digital ecosystem.

Design/methodology/approach – The methodology used in this paper, applied to five Metaverse tokens, is structured in three sequential phases. Firstly, the authors test the efficient market hypothesis in its weak form and the Random Walk Theory to assess the integration of historical information into prices. Secondly, the authors carry out Bubble Timestamping using explosive unit root tests (GSADF) and price/fundamental gap analysis. Thirdly, the authors quantify the magnitude of market inefficiency through the Adjusted Market Inefficiency Magnitude (AMIM), capturing its dynamic variations.

Findings – The results of this study reveal persistent inefficiencies and recurring speculative bubbles across all tokens. Explosive price trends often coincide with major announcements, amplifying volatility and distorting valuations. These patterns confirm the adaptive market hypothesis, showing that Metaverse markets evolve through adaptive cycles periods of speculation followed by phases of improved efficiency. Short-term price movements frequently overshadow fundamentals, creating systemic vulnerabilities and raising concerns about market integrity and investor protection. The findings of this study highlight the need for adaptive investment strategies and regulatory frameworks to manage systemic risks in rapidly evolving digital ecosystems.

Originality/value – This study offers a detailed analysis of the efficiency of the Metaverse market, a field that remains largely unexplored. This study goes beyond traditional approaches by examining speculative dynamics, responsiveness to global shocks and adaptability through the adaptive market hypothesis. By incorporating AMIM, a tool designed for emerging markets, into efficiency tests, this paper provides a dynamic interpretation of bubbles and inefficiency. AMIM also serves as a practical monitoring tool for regulators and helps investors anticipate risks in volatile virtual environments.

Keywords Metaverse, Tokens, Speculation, AMIM

Paper type Research paper

1. Introduction

The Metaverse is an emerging concept that describes a virtual reality-based, immersive digital space where individuals can engage with each other and digital environments in real time using three-dimensional graphics (Park and Kim, 2022; Wang *et al.*, 2022). This environment incorporates real-world metaphors without physical constraints. Following Facebook's rebranding to Meta, attention on the development of the Metaverse has significantly increased because of advancements in virtual reality, augmented reality, artificial intelligence, blockchain technology and related fields. Several companies and technology giants have shown interest and invested in constructing the Metaverse, as they envision it as the next stage of internet evolution (Sparkes, 2021). Understanding the economic perspective of the Metaverse is crucial, as it directly impacts user behavior, value creation and economic transactions within the virtual environment. The behavior of



Metaverse tokens, which function as the medium of exchange in this space, is key to comprehending the dynamics of the Metaverse economy (Akkus *et al.*, 2022). These tokens represent a convergence of blockchain technology and the gaming industry, harnessing decentralized and secure attributes to empower a resilient virtual economy (Vidal-Tomás, 2022). Exploring how these tokens are acquired, traded and their valuation mechanisms is essential to grasp their impact on the overall economy. Recent studies have unveiled a positive long-term performance association between play-to-earn and Metaverse tokens (Christodoulou *et al.*, 2022). Metaverse tokens are the main local currencies in this realm and play a crucial role in facilitating transactions.

Building in these insights, our study aims to deepen our understanding of these dynamic behaviors, with the primary objective of analyzing the market dynamics and broader economic activities within this virtual realm. By uncovering the movements and trends of these local currencies, we seek to shed light on the complex workings of this digital economy. The literature has previously focused on the technical characteristics of the Metaverse (Dwivedi *et al.*, 2022) and has proposed various definitions (Sparkes, 2021). However, the economic aspects, the current adoption of the technology and the potential business models within the Metaverse are still in their early stages (Parcu *et al.*, 2023). Notably, until 2022, no study had explored price bubbles in Metaverse token cryptocurrencies. Empirical studies indicate that cryptocurrencies often generate speculative bubbles because of their asset-like nature rather than functioning solely as currency. This tendency is compounded by their rapid price escalation and high volatility (Godsiff, 2015; Umeh, 2016). Similarly, scholars have empirically revealed evidence of bubbles using various methodologies for bubble detection, highlighting the inefficiencies inherent in cryptocurrency markets (Nadarajah and Chu, 2017). The discussion about the efficiency of the Metaverse market is relatively scarce despite its increasing relevance among investors. This paper seeks to test whether speculative behavior plays an important role in the Metaverse market and whether this market follows the efficient market hypothesis (EMH). The majority of studies on the Metaverse economy claim that Metaverse tokens are a speculative bubble rather than a long-term investment (Akkus *et al.*, 2022). Shah and Bahri (2022) document that the efficiency of the Metaverse market closely aligns with the observed efficiency in real-world cryptocurrency and equity markets. This research seeks to fill a critical gap in the existing literature by providing a comprehensive analysis of the dynamic landscape of efficiency within the Metaverse. By focusing on the most capitalized tokens in the Metaverse, our aim is to unveil their market behaviors, highlighting both efficiency patterns and potential bubble phenomena. We give priority to fungible tokens, recognizing that each digital asset represented by a non-fungible token (NFT) may have distinct characteristics (Shah and Bahri, 2022), similar to the uniqueness observed in physical assets.

To the best of our knowledge, no prior research has examined time-varying efficiency in the Metaverse market. This study seeks to address this gap by investigating market efficiency pattern and bubble risk among the five largest Metaverse tokens. We use two complementary approaches: the Adjusted Market Inefficiency Magnitude (AMIM) and the Generalized Supremum Augmented Dickey–Fuller (GSADF) test. AMIM, an innovative dynamic metric, quantifies deviations from informational efficiency and is particularly suited for emerging and fragmented markets such as cryptoassets (Tran and Leirvik, 2019; Corbet *et al.*, 2022). Its ability to capture efficiency trends across assets and time periods provides a robust framework for analyzing the evolving Metaverse landscape. To detect speculative dynamics, we apply the GSADF test, a widely recognized method for identifying explosive price behavior across asset classes, including commodities, energy and virtual currencies (Enoksen *et al.*, 2020). GSADF is especially appropriate for Metaverse tokens because of its

capacity to uncover multiple episodes of exuberant price movements a critical feature in markets characterized by high volatility and rapid structural shifts. Empirical evidence confirms GSADF's effectiveness in detecting bubbles in cryptocurrencies and other digital assets, which share similar susceptibility to hype-driven surges and abrupt corrections (Li *et al.*, 2020; Yamaguchi, 2025). Furthermore, comparative studies highlight GSADF's robustness relative to alternative bubble detection techniques, reinforcing its reliability for assessing speculative risks in emerging financial ecosystems (Enoksen *et al.*, 2020). By integrating AMIM and GSADF, our methodology enables a comprehensive assessment of both efficiency dynamics and bubble episodes. This dual approach reveals significant fluctuations in informational efficiency and frequent speculative phases within Metaverse token markets. These findings challenge the static assumptions of the EMH, instead supporting the adaptive market hypothesis (AMH). The observed alternating pattern periods of speculative dominance followed by temporary phases of improved efficiency suggests that Metaverse markets operate as complex adaptive systems shaped by investor behavior, competitive dynamics and rapid technological innovation. This study offers an initial step toward understanding the economic dynamics of the Metaverse. Our findings offer actionable insights for investors, policymakers and stakeholders, emphasizing the need for robust risk management, cautious engagement with speculative trading and strategies that prioritize diversification and long-term valuation metrics.

The remainder of this paper is organized as follows: Section 1 presents the literature review on market efficiency and speculative behavior. Section 2 outlines the empirical methodology and describes the data. Section 3 reports the empirical results and provides a discussion, and finally, Section 4 concludes the paper.

2. Literature revue

The EMH has long proven valuable in understanding traditional financial markets and has recently been applied to assess the impact of major global events such as the COVID-19 pandemic and the Russia–Ukraine conflict (Mensi *et al.*, 2022; Gaio *et al.*, 2022; Aliu and Nuhui, 2025). However, our understanding of how EMH applies to emerging and rapidly evolving markets such as cryptocurrencies and the Metaverse remains limited (Liu *et al.*, 2020; Mokhtarian and Lindgren, 2017). Since the introduction of Bitcoin in 2008, the cryptocurrency ecosystem has expanded exponentially, with thousands of new digital assets entering the market (Corbet *et al.*, 2019). This rapid proliferation of cryptocurrencies has significantly heightened global interest and attention toward these digital assets. While cryptocurrencies hold considerable potential for integration into the global financial system, their value remains highly volatile (Bouri *et al.*, 2019). A substantial driver of this volatility is speculative demand, which has been closely linked to the frequent emergence of price bubbles (Corbet *et al.*, 2018). The speculative nature of cryptocurrencies has raised concerns about their stability and long-term sustainability. In response, academic research has increasingly focused on understanding the causes of this volatility and the formation of bubbles, using established financial theories like the EMH to assess whether these new digital markets operate efficiently or are mainly driven by speculation. Zhang *et al.* (2018) assessed the efficiency of nine cryptocurrencies and concluded that all were inefficient. Similarly, Al-Yahyaee *et al.* (2018) compared Bitcoin's efficiency with gold, stocks and currency markets, finding Bitcoin less efficient than these traditional assets. Chaim and Laurini (2018) examined whether Bitcoin exhibited bubble characteristics and presented evidence supporting speculative bubbles in Bitcoin prices. Urquhart (2016) also found Bitcoin inefficient over the full sample period; however, a split-sample test indicated improved efficiency in later periods, suggesting a trend toward market development.

Consistent with this, [Vidal-Tomás and Ibañez \(2018\)](#) and [Sensoy \(2019\)](#) argued that Bitcoin has become more efficient over time, in line with findings by [Nadarajah and Chu \(2017\)](#) and [Khuntia and Pattanayak \(2018\)](#). [Groby and Sapkota \(2019\)](#) extended this analysis to 143 cryptocurrencies, concluding that this emerging digital market appears more efficient than traditional markets. Conversely, other studies observed that return predictability among cryptocurrencies decreases when market liquidity is high ([Brauneis and Mestel, 2018](#)). Using the Log-Periodic Power Law model, [Geuder et al. \(2019\)](#) analyzed Bitcoin prices from 2016 to 2018 and found frequent signs of bubble-like behavior, highlighting the cryptocurrency's repeated exposure to speculation and price volatility. These findings are supported by other studies ([Philippas et al., 2019](#); [Baur and Dimpfl, 2018](#); [Bouri et al., 2019](#)), which also point to Bitcoin's vulnerability to speculative dynamics. Similarly, [Bianchetti et al. \(2018\)](#), applying both the Log-Periodic Power Law model and the PSY test, confirmed that cryptocurrencies are highly prone to speculation and face significant risks of forming bubbles. In line with this, [Aliu \(2024\)](#) compares the sharp rise in Bitcoin prices during the COVID-19 pandemic to a case of explosive market behavior, showing how global crises can trigger rapid and extreme price movements in crypto markets.

The Metaverse market is one of the most emerging and dynamic digital ecosystems. It is characterized by price discovery mechanisms that are often opaque, unstable and heavily influenced by non-fundamental factors such as speculation, network effects or social dynamics specific to virtual environments ([Lee et al., 2025](#); [Basty and Abidly, 2025](#)). This complexity poses significant challenges for the valuation of digital assets and understanding their valuation. Similar to real world, the Metaverse economic system is a complex economic system composed of large, heterogeneous, adaptable individual actors whose interactions contribute to shaping emerging overall behavior ([Arthur, 1994](#)). Metaverse fungible token, NFTs, DeFi and cryptocurrencies exhibit distinct traits because of their novelty and ongoing development. Their returns and volatility are significantly influenced by the asymmetrical sentiment of a relatively small group of traders as well as the success or failure of underlying protocols and products ([Ghosh et al., 2023](#)). Moreover, behavioral biases, including the popularity of artists, herd behavior, overconfidence and overreaction can influence asset prices in ways that are not reflected in the underlying EMH ([Chowdhury et al., 2023](#)). [Kang and Lee \(2025\)](#) emphasize the decisive role of liquidity, the activity of dominant traders and royalty dynamics in price formation in NFT markets linked to the Metaverse. The Metaverse ecosystem has the potential to generate higher profitability compared to traditional physical events because of its broader accessibility and lower associated costs. Its expanding global reach includes consumers in emerging and frontier economies and may reduce vertical agency costs through Decentralized Autonomous Organizations ([Vidal-Tomás, 2022](#); [Bellavitis et al., 2023](#)). Furthermore, the Metaverse operates with its own virtual currency system, providing an economical platform for various activities. However, as noted by [Wang et al. \(2022\)](#), the Metaverse still lacks a strong economic engine, cannot fully replicate real-world economic scenarios and does not support scientific economic decision-making. The decentralized nature of blockchain enhances transparency and enables transactions without intermediaries ([Xu et al., 2023](#)). In this context, [Nakavachara and Saengchote \(2022\)](#) examined price appreciation in The Sandbox Metaverse. They argue that The Sandbox functions as an open economy with no capital controls and a fully flexible exchange rate, as the permissionless convertibility of blockchain tokens allows perfect capital mobility. Moreover, a medium of exchange that cannot restrict secondary transactions means that virtual currencies can be easily substituted or "dollarized," as demonstrated by The Sandbox's OpenSea auction and sales.

Although research on Metaverse token price predictability and efficiency remains limited, a few empirical studies have explored market efficiency and speculative behavior using models applied to cryptocurrency markets. The adoption and success of fungible tokens as investment assets in the Metaverse depend significantly on market efficiency and volatility patterns (Shah and Bahri, 2022). Dowling (2022) investigated Decentraland pricing and found that the NFT market remains inefficient, reflecting its early stage of development. Similarly, Knowles and Castronova (2016) observed that sudden wealth injections – such as real-money transactions for in-game items can disrupt economic balance, increase prices and negatively affect incentives and user experience. According to Akkus *et al.* (2022), no prior study examined price bubbles in Metaverse token cryptocurrencies. As a pioneering effort, they applied the GSADF test developed by Phillips *et al.* (2015) to MANA coin and identified 14 distinct bubble periods within the sample timeframe. These findings indicate that MANA prices are highly susceptible to speculation, suggesting that investors should exercise caution when considering investments in this cryptocurrency. In summary, most existing research focuses on bubble pricing in cryptocurrency and fiat currency markets. However, studies specifically addressing bubbles in the Metaverse economy remain scarce.

3. Empirical methodology

3.1 Methodology

Our methodology consists in three pivotal stages. Initially, we delve into establishing evidence of inefficiency within Metaverse market by testing for the weak form of the EMH and validating the principles of the Random Walk theory. This foundational step seeks to elucidate the degree to which market prices reflect historical information, laying the groundwork for subsequent analyses. The second phase of our methodology delves into the exploration of bubble occurrence within the Metaverse market. Here, our focus sharpens on identifying and understanding the dynamics of speculative bubbles that may manifest in this new economy. The aim of this section is to capture the distinctive features and occurrence of bubbles within the Metaverse. Building upon our findings from the second phase, the third and final part of our methodology examines market behavior specifically during periods characterized by the presence of bubbles. This critical examination aims to unravel the nuanced responses, trends and fluctuations exhibited by the Metaverse market in the wake of speculative bubbles, providing valuable insights into the dynamics and resilience of this emerging economic landscape.

3.2 Efficient market hypothesis and random walk theory

To examine the efficiency of the Metaverse market, returns for the variables are computed as the natural logarithm of the ratio between two consecutive daily prices of each variable. This transformation serves to mitigate fluctuations within the data set. The analysis starts with the description of the data's characteristics followed by the Jarque–Bera test of normality to assess the data's adherence to a normal distribution. Autocorrelation is examined through the Autocorrelation Function (ACF), Partial Autocorrelation Function (PACF) and the Ljung-Box Q-Statistic (Ljung and Box, 1978). These tests aim to evaluate the overall randomness of the data across various lag intervals. Additionally, the variance ratio test (Lo, 2004) is applied to test random walk of token prices and the ARCH-LM test examine the presence of autoregressive conditional heteroskedasticity (ARCH) in a data set. The ACF offers insights into the degree of association between a time series and its past values by providing the autocorrelation values at various lags. It essentially quantifies the relationship between a time series and its historical data.

3.3 Bubble timestamping

Following [Akkus et al. \(2022\)](#), we adopt the generalized Sup ADF (GSADF) test developed by [Phillips et al. \(2015\)](#) to assess the extent to which Metaverse tokens can be considered as a bubble. Also named the PSY test, the GSADF frequently used in finance literature to identify explosive behavior in various asset prices, including commodity, energy, real estate and virtual and digital currencies, and is able to give indications about the initial and final dates of a period of exuberance ([Li et al., 2020](#)). The hypotheses of the GSADF test are shown as follows:

$H0$. $\delta = 1$ (bubble has not formed).

$H1$. $\delta > 1$ (multiple bubbles have formed).

The following recursive sliding regression equations are used to detect the presence of price bubbles in GSADF tests ([Phillips et al., 2015](#)):

$$\Delta y_t = \hat{\alpha}_{r1,r2} + \hat{\beta}_{r1,r2} y_{t-1} + \sum_{i=1}^k \hat{\psi}_{r1,r2}^i \Delta y_{t-i} - \hat{\epsilon} \quad (1)$$

The GSADF statistics calculated based on [equation \(1\)](#) are shown as follows ([Phillips et al., 2015](#)):

$$GSADF(r_0) = \sup \{ADF_{r_2}^{r_1}\} \quad (2)$$

$$r_2 \in [r_0, 1]$$

$$r_1 \in [0, r_2 - r_0]$$

The starting and the ending of a bubble are estimated by rejecting the null hypothesis of this test. The beginning and ending point of each bubble at the time T_{r2} are determined by comparing each calculated value of ADF_{r2} with its critical values. The point of bubble emergence (r_{start}) is when ADF_{r2} is greater than the critical value ($ADF_{r2} > CV$) and the ending point (r_{end}) is when ADF_{r2} is lesser than the critical value ($ADF_{r2} < CV$).

3.4 Adjusted market inefficiency magnitude (AMIM)

Following [Tran and Leirvik \(2019\)](#), we use the AMIM to examine the existence of inefficiency during bubble periods. The AMIM is a market efficiency assessment tool developed by [Tran and Leirvik \(2019\)](#). This tool is designed to capture the changing characteristics of efficiency in various asset classes and regions over time. Furthermore, the AMIM provides a direct way to quantify the importance of efficiency in a market during a specific time period. Starting with an autoregressive AR(q) return equation as given in [equation \(3\)](#), the EMH mandates that the beta coefficients in this equation should not deviate significantly from zero. This implies that past returns are not a reliable predictor of future returns:

$$rt = \alpha + \beta_1 rt - 1 + \dots + \beta_q rt - q + \epsilon t \quad (3)$$

The extent of inefficiency within the market, quantified by the Market Inefficiency Magnitude (MIM), is determined based on the standardized beta coefficients obtained from [equation \(1\)](#). However, it is important to note that MIM requires an adjustment, as it has a tendency to produce elevated values because of its positive correlation with the number of lags in the base AR(q) equation. This adjustment is achieved through the AMIM at a specific time (t), and it can be expressed as follows:

$$AMIM_t = \frac{MIM_t - R_{CI}}{1 - R_{CI}} \quad (4)$$

where MIM_t represents the MIM at time t , and R_{CI} is the range of confidence intervals for the MIM. A detailed derivation of [equation \(4\)](#) and the associated range of confidence intervals is provided in the work by [Tran and Leirvik \(2019\)](#). The denominator in [equation \(4\)](#) serves as a common reference point that facilitates comparisons across different time periods, assets and regions. In interpreting the model, when $AMIM_t$ is less than or equal to 0 ($AMIM_t \leq 0$), it signifies that the market is efficient. Conversely, when $AMIM_t$ is greater than 0 ($AMIM_t > 0$), it indicates inefficiency within the asset or market being evaluated.

4. Empirical findings

4.1 Data description and descriptive statistics

The data set we investigate consists of daily closing price values of five meta coins: MANA coin, SAND coin, ENJIN coin, THETA coin and AXIE coin. We selected these tokens based on their market capitalization. Time spans from November 04, 2020 to October 07, 2023. As the Metaverse market is relatively new, the choice of the period in our paper was based on the availability of the data. Given that the USD is the most commonly used fiat currency in cryptocurrency trading pairs, we focus on prices quoted in USD ([Krištoufek and Vošvrda, 2019](#)). For each time series, we have 1,069 daily observations. We use daily closing prices obtained from Yahoo Finance website [\[1\]](#).

In [Table 1](#), we can observe that the mean returns for all five tokens are approximately close to 0. The standard deviation of returns for each token is notably away from 1, substantially exceeding the mean, signifying a significant level of volatility. The return series for THETA exhibit negative skewness, indicating a tendency for more frequent negative returns. As a result of this negative value, we can deduce that the distribution is left-skewed, signifying that the tail of the distribution extends to the left side. In contrast, MANA, SAND, ENJIN and AXS returns series displays positive skewness, suggesting more frequent positive returns. Given the positive nature of this value, it signifies that the distribution is right-skewed, indicating that the tail of the distribution extends toward the right side.

Furthermore, the kurtosis of returns for all five Metaverse tokens is remarkably high, indicating that these return series are leptokurtic, or in other words, they exhibit fat-tailed distributions with more extreme observations. In addition, the Jarque–Bera statistic rejects the null hypothesis of a normal distribution for the returns of all five Metaverse tokens, further supporting the notion that the distribution of Metaverse tokens' returns deviates from a normal distribution. Consequently, it can be inferred that the returns of these Metaverse tokens exhibit all the typical characteristics associated with financial asset returns. As depicted in [Figure 1](#), notable price spikes within the Metaverse tokens price series are evident. Particularly, during the third quarter of 2021, there were significant price fluctuations. [Figure 2](#) illustrates the returns for MANA token, SAND token, ENJIN token, THETA token and AXS token spanning from November 05, 2020 to October 07, 2023. The

Table 1. Summary of descriptive statistics

Statistics	MANA	SAND	ENJIN	THETA	AXS
Mean	0.00145	0.00210	0.00059	4.26E-05	0.00321
Median	0.00052	-0.00055	0.00059	0.00057	-0.00212
SD	0.07450	0.07735	0.06837	0.061770	0.08127
Skewness	2.28540	1.13423	0.41909	-0.571738	1.08917
Kurtosis	29.51564	14.38769	9.99205	9.07434	9.97237
Jarque-Bera	32186.56***	5994.116***	2204.751***	1698.541***	2372.261***
Probability (p-value)	0.000	0.000	0.000	0.000	0.000
Augmented Dickey-Fuller test results	-31.3196***	-14.1036***	-34.3578***	-35.9770***	-32.6889***
Probability (p-value)	0.000	0.000	0.000	0.000	0.000
Phillips-Perron test results	-31.3002***	-33.1728***	-34.3202***	-35.8393***	-32.9481***
Probability (p-value)	0.000	0.000	0.000	0.000	0.000
Observations	1,067	1,067	1,067	1,067	1,067

Note(s): Authors' calculations; This table reports descriptive statistics for daily returns of five metaverse-related cryptocurrencies. All series exhibit positive skewness and high kurtosis, indicating leptokurtic distributions. The Jarque-Bera (JB) test rejects the null hypothesis of normality at the 1% significance level (***). The Augmented Dickey-Fuller (ADF) test rejects the null hypothesis of a unit root, indicating that the series are stationary. The Phillips-Perron unit root test results indicate that all series are stationary

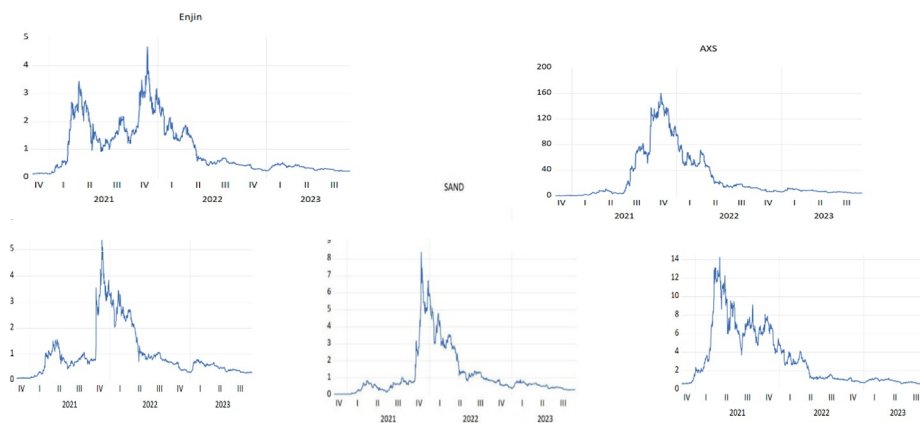


Figure 1. Price chart of metaverse tokens

Note(s): Authors' illustration; this figure shows the evolution of five metaverse-related cryptocurrencies (MANA, SAND, ENJIN, THETA and AXS) over time, revealing strong volatility and repeated explosive upward swings

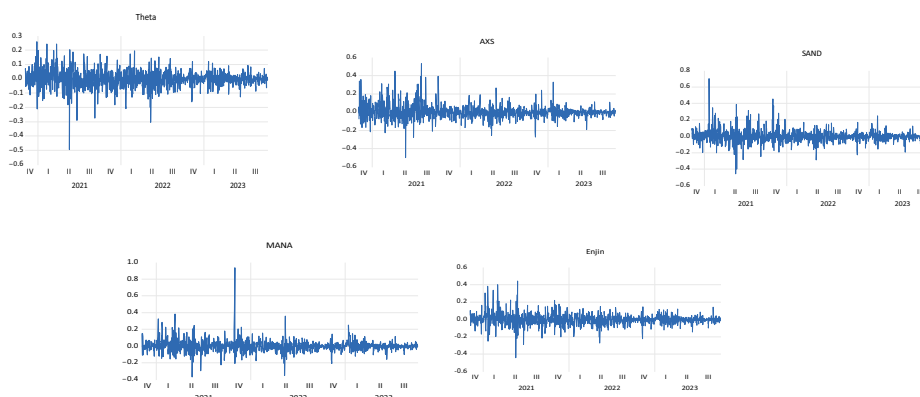


Figure 2. Line graph of tokens' returns

Note(s): Authors' illustration; this figure depicts the daily return dynamics of five metaverse-related cryptocurrencies (MANA, SAND, ENJIN, THETA and AXS) over the sample period. The series exhibit high volatility and frequent fluctuations, reflecting the speculative nature of digital asset markets

visual representation reveals that all five-return series exhibit characteristics of mean reversion and display signs of volatility clustering.

The results of the Augmented Dickey–Fuller (ADF) test, as displayed in [Table 1](#), reveal that the computed t -statistic falls below the critical values at all significance levels. Additionally, the p -value is exceptionally low, registering as 0.0000, which is less than the conventional significance level of 0.05 for all five Metaverse tokens. These findings lead to the rejection of the null hypothesis, which posits that the return series contains a unit root, indicating a non-stationary time series. Consequently, it suggests that there is a memory

effect in the process generating return data, indicating that the cryptocurrency market lacks weak-form efficiency, as the returns are not entirely unpredictable and exhibit persistence over time. Likewise, the outcomes of the Phillips–Perron (PP) test, as illustrated in Table 1, indicate that the adjusted *t*-statistic falls below the critical values at all levels of significance. Additionally, the *p*-value is remarkably low, standing at 0.000, which is less than the customary significance level of 0.05 for all five Metaverse tokens. This, too, leads to the rejection of the null hypothesis that suggests the return series is non-stationary. Consequently, it suggests that there is no consistent, underlying structure in the return series, implying that the prices or returns of tokens can be predicted or forecasted to some extent.

4.2 Autocorrelation functions, Partial autocorrelation functions and Ljung-Box Q-Statistics

The calculated values of ACFs, PACFs and Ljung-Box Q-statistics, along with their associated probability values at lags 1, 5 and 10, are presented in Table 2. The estimated values of ACFs, PACFs and Q-statistics at lags 1, 5 and 10 all exhibit statistical significance at a 5% level of significance.

This observation indicates the presence of autocorrelation within the return series, leading to the rejection of the null hypothesis that there is no serial correlation. Consequently, it implies that the prices of tokens do not adhere to a random walk pattern, as they are not independent of their past values. In essence, this finding suggests that the prices or returns of Metaverse tokens can be predicted or forecasted to some extent.

Table 3 presents the outcomes of the variance ratio test conducted on the returns of tokens. This test is designed to assess the null hypothesis that the returns adhere to a martingale model. Across all five Metaverse tokens, the “Joint Tests” z-statistics exhibit statistical significance at a 1% level, providing compelling evidence for the rejection of the null hypothesis. Furthermore, when examining the individual variance ratio z-statistics for time periods 2, 4, 8 and 16, these also reject the null hypothesis with *p*-values falling below 0.05. These results collectively suggest that the return series for all Metaverse tokens are not

Table 2. Results of ACF, PACF and Ljung-Box Q-Statistics

Returns	LAG	ACF	PACF	LQ-stat	Probability
Return MANA	1	0.042	0.042	1.9316	0.0165
	5	−0.041	−0.045	7.2472	0.0203
	10	0.008	0.005	11.888	0.0293
Return SAND	1	−0.012	−0.012	0.1597	0.068
	5	−0.011	−0.007	22.918	0.000
	10	−0.046	−0.055	27.719	0.002
Return ENJIN	1	−0.052	−0.052	2.8602	0.091
	5	−0.033	−0.028	7.6202	0.017
	10	0.001	−0.006	15.609	0.011
Return THETA	1	−0.097	−0.097	10.104	0.001
	5	−0.041	−0.026	19.865	0.001
	10	0.039	0.052	33.220	0.000
Return AXS	1	−0.002	−0.002	0.0030	0.095
	5	−0.017	−0.023	7.1526	0.021
	10	0.026	0.021	24.220	0.007

Note(s): Authors’ calculations; The table reports the autocorrelation (ACF), partial autocorrelation (PACF) and Ljung–Box Q-statistics for token returns at different lags. The Ljung–Box test checks for autocorrelation in the series. The *p*-values indicate the significance level of the test

Table 3. Variance ratio, ARCH-LM and GSADF test results for metaverse tokens

Token	Variance ratio (Period 2)	z-statistic	p-value	ARCH-LM (F-statistic)	p-value	GSADF test statistic	Critical values (90/95/99%)
MANA	0.532	−6.09***	0.000	26.304***	0.000	3.45***	2.11 /2.37/2.78
SAND	0.471	−6.86***	0.000	26.288***	0.000	7.18***	2.11/2.37/2.78
ENJIN	0.469	−7.99***	0.000	73.067***	0.000	5.05***	2.11/2.37/2.78
THETA	0.444	−8.28***	0.000	37.756***	0.000	6.35***	2.11/2.37/2.78
AXS	0.474	−9.04***	0.000	53.141***	0.000	5.28***	2.11/2.37/2.78

Note(s): Authors' calculations; the table reports the results of three diagnostic tests for each metaverse token. The variance ratio test examines the weak-form efficiency hypothesis (H_0 : price series follows a martingale). The ARCH-LM test detects the presence of heteroskedasticity in the return series. The GSADF test identifies explosive episodes indicating potential bubble behavior. *** denotes statistical significance at the 1% level

random, and having knowledge of past prices will indeed be beneficial in predicting future prices. In essence, there are discernible patterns or dependencies in the Metaverse tokens returns that can be used for forecasting purposes.

The outcomes of the ARCH-LM test with two lags (Table 3), which aims to investigate the null hypothesis stating. The ARCH-LM test was conducted on the daily tokens returns using a random walk model, and the outcomes are detailed in Table 3. The null hypothesis, indicating the absence of ARCH effects, was rejected across all return series at a 1% significance level. Likewise, the time-series plot of daily meta coins return (Figure 2) illustrates alternating phases of low and high volatility. This pattern, characterized by both tranquil and turbulent periods, strongly implies volatility clustering, confirming the existence of the ARCH effect.

3.4 GSADF test

In this section, we offer an in-depth exploration of our bubble detection findings. We use Figure 1 to visually depict the price chart of Metaverse tokens, providing valuable insights into their price movements. Additionally, we present the results of the GSADF tests for the daily observations both in Table 3 and graphically in Figures 3.

We direct our attention to the results of the GSADF test to explore the presence of price bubbles within the Metaverse tokens. Table 3 presents the GSADF test statistics. We follow the methodology outlined by Phillips *et al.* (2015) and set specific finite sample critical value thresholds at 90%, 95% and 99%. Additionally, the finite sample critical values are obtained through a Monte Carlo simulation involving 2,000 replications. The minimum window size is determined according to the rule proposed in Phillips *et al.* (2015):

$$r_0 = \left(0.01 + \frac{1.8}{\lambda T}\right)T, \text{ where : } T \text{ is the sample size and } r_0 \text{ is the minimum window.}$$

The GSADF statistics, with the respective sample critical values, are recorded in Table 3. The statistics of the test is 3.45 for MANA token, 7.18 for SAND, 5.05 for ENJIN, 6.35 for THETA and 5.28 for AXS which exceed their 1% right-tailed critical values, respectively.

According to the results, the null hypothesis is rejected at the 1% significance level, providing robust evidence that supports the hypothesis of explosive sub-periods and price bubbles in Metaverse tokens. Using the GSADF technique, we conclude that exuberance is

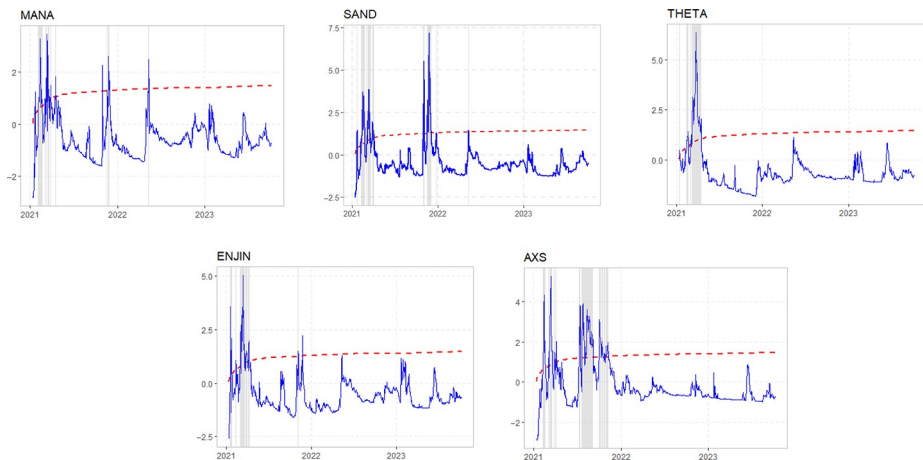


Figure 3. Date-stamping periods of exuberance in metaverse tokens

Note(s): Authors’ illustration; this figure illustrates the periods of exuberant behavior in metaverse token prices based on the GSADF procedure. The results indicate distinct phases of explosive price movements reflecting heightened speculative activity in the metaverse asset market. The shadows are bubbles’ subperiods. The red dotted line: critical value

prevalent in the Metaverse market, allowing us to investigate the potential presence of bubble episodes. Figure 3 presented below visually depicts the chronological periods during which bubble formations occurred, as determined by the GSADF test results. The vertical line in each figure corresponds to bubble occurrence.

As illustrated in Figure 3, the Metaverse tokens price series exhibits prominent price surges, with notably increased price movements, particularly noticeable after January 2021. The figure shows that bubble formations have occurred in all of the tokens listed, at various times of the period considered. This suggests that bubble formation is a common phenomenon in Metaverse markets.

The outcomes of the analysis regarding bubble formation for MANA and SAND are presented in the subsequent Table 4.

From Table 4, MANA prices have experienced 14 different price bubble periods in 2021 and 2022, making them susceptible to speculation. The first originates on January 23 and lasts for one day. The second bubble, which starts on February 5, 2021, and bursts on February 15, with a duration of fifteen days. Our results are in line with Akkus et al. (2022), who studied the behavior of MANA price and found that MANA is open to speculation, suggesting that investors should take this into account when making investment decisions. In this context, in January, TikTok’s owner, ByteDance, entered into the Metaverse with its first social app, Party Island. This app creates a virtual world where users can meet, chat and participate in real-time events. ByteDance, with a revenue of \$58bn in 2021, is quietly assembling a Metaverse ecosystem, similar to Meta’s, amid China’s tech regulation. While discreet, ByteDance is among the most ambitious Chinese companies in the Metaverse space. In December 2021, Baidu launched China’s first Metaverse platform, “Xi Rang” (Land of Hope). This diversification and competition in the Metaverse space can attract more attention and investment from global markets, fueling the demand for Metaverse tokens and contributing to the occurrence of bubbles.

Table 4. Display of MANA and SAND bubble

Display of MANA bubble					Display of SAND bubble				
N°	Start	Peak	End	Duration	N°	Start	Peak	End	Duration
1	23/01/2021	23/01/2021	24/01/2021	1	1	21/01/2021	22/01/2021	23/01/2021	2
2	05/02/2021	13/02/2021	20/02/2021	15	2	05/02/2021	05/02/2021	06/02/2021	1
3	21/02/2021	21/02/2021	22/02/2021	1	3	09/02/2021	14/02/2021	23/02/2021	14
4	04/03/2021	04/03/2021	05/03/2021	1	4	04/03/2021	04/03/2021	06/03/2021	2
5	08/03/2021	09/03/2021	10/03/2021	2	5	07/03/2021	13/03/2021	16/03/2021	9
6	11/03/2021	13/03/2021	16/03/2021	5	6	17/03/2021	18/03/2021	20/03/2021	3
7	17/03/2021	17/03/2021	20/03/2021	3	7	27/03/2021	28/03/2021	01/04/2021	5
8	21/03/2021	21/03/2021	22/03/2021	1	8	02/04/2021	02/04/2021	03/04/2021	1
9	28/03/2021	28/03/2021	31/03/2021	3	9	01/11/2021	02/11/2021	04/11/2021	3
10	16/04/2021	17/04/2021	19/04/2021	3	10	16/11/2021	25/11/2021	05/12/2021	19
11	20/04/2021	20/04/2021	21/04/2021	1	11	26/12/2021	26/12/2021	27/12/2021	1
12	30/10/2021	30/10/2021	31/10/2021	1	12	12/05/2022	12/05/2022	13/05/2022	1
13	19/11/2021	19/11/2021	20/11/2021	1					
14	25/11/2021	25/11/2021	30/11/2021	5					
15	11/05/2022	12/05/2022	13/05/2022	2					

Note(s): Authors' calculations; the table presents the identified bubble episodes for MANA and SAND tokens based on the GSADF date-stamping procedure. Each episode lists the start, peak and end dates, along with its duration in days

According to the findings extracted from [Table 4](#), a total of 12 periods of market have been identified within the SAND price series. Moreover, it is evident that some of these bubbles are of long duration. Notably, the presence of a price bubble that initiated on February 09, 2021 and persisted for 14 consecutive days strongly suggests a substantial speculative surge involving the SAND token. Furthermore, the continuity of the bubble activity for 19 days, commencing on November 16, 2021, further reinforces the notion of pronounced speculative activity in this context. In this context, November 2021 marked a significant milestone for the Sandbox as it expanded its horizons beyond gaming to build virtual worlds centered around fashion, architecture and virtual concerts. The overarching goal was to make the Metaverse more accessible to the general public. The company initiated a series of partnerships with celebrities, including the well-known rapper Snoop Dogg, who crafted a digital replica of his mansion within The Sandbox's Metaverse. The Sandbox has also collaborated with other prominent figures in the entertainment industry, such as the band Avenged Sevenfold, musician Richie Hawtin, Paris Hilton and Tony Hawk. According to the findings extracted from [Table 5](#), a total of ten bubble periods have been identified within the ENJIN price series. Moreover, it is evident that some of these bubbles are of long duration. Notably, the presence of a price bubble that initiated on March 07, 2021 and persisted for 13 consecutive days strongly suggests a substantial speculative surge involving the ENJIN token. According to the findings extracted from [Table 5](#), a total of four bubble periods have been identified within the THETA price series. Moreover, it is evident that some of these bubbles are of long duration. Notably, the presence of a price bubble that initiated on March 07, 2021 and persisted for 42 consecutive days strongly suggests a substantial speculative surge involving the THETA token.

Based on the findings presented in [Table 5](#), a total of 16 distinct bubble periods have been identified in the AXS price series. Notably, the analysis reveals the presence of extended, long-term price bubbles within this series. The price bubble that emerged on August 8, 2021 and lasted for 30 days points to a significant speculative surge associated

Table 5. Display of AXS, THETA and ENJIN bubble

N°	Start	Peak	End	Duration
<i>Display of AXS bubble</i>				
1	08/02/2021	14/02/2021	20/02/2021	12
2	04/03/2021	04/03/2021	05/03/2021	1
3	08/03/2021	14/03/2021	20/03/2021	12
4	29/03/2021	30/03/2021	31/03/2021	2
5	05/04/2021	05/04/2021	07/04/2021	2
6	09/07/2021	14/07/2021	17/07/2021	8
7	22/07/2021	27/07/2021	01/08/2021	10
8	02/08/2021	02/08/2021	03/08/2021	1
9	04/08/2021	04/08/2021	07/08/2021	3
10	08/08/2021	13/08/2021	07/09/2021	30
11	01/10/2021	03/10/2021	11/10/2021	10
12	12/10/2021	14/10/2021	18/10/2021	6
13	20/10/2021	20/10/2021	21/10/2021	1
14	22/10/2021	22/10/2021	24/10/2021	2
15	25/10/2021	25/10/2021	27/10/2021	2
16	29/10/2021	07/11/2021	10/11/2021	12
<i>Display of THETA bubble</i>				
1	13/01/2021	14/01/2021	16/01/2021	3
2	13/02/2021	19/02/2021	22/02/2021	9
3	04/03/2021	04/03/2021	06/03/2021	2
4	07/03/2021	25/03/2021	18/04/2021	42
<i>Display of ENJIN bubble</i>				
1	19/01/2021	20/01/2021	21/01/2021	2
2	22/01/2021	25/01/2021	27/01/2021	5
3	11/02/2021	12/02/2021	14/02/2021	3
4	02/03/2021	03/03/2021	06/03/2021	4
5	07/03/2021	15/03/2021	20/03/2021	13
6	21/03/2021	21/03/2021	23/03/2021	2
7	26/03/2021	28/03/2021	03/04/2021	8
8	07/04/2021	09/04/2021	12/04/2021	5
9	06/11/2021	06/11/2021	08/11/2021	2
10	25/11/2021	25/11/2021	26/11/2021	1

Note(s): Authors’ calculations; the table presents the identified bubble episodes for AXS, THETA and ENJIN tokens based on the GSADF date-stamping procedure. Each episode lists the start, peak and end dates, along with its duration in days

with the AXS token. Furthermore, we observed the emergence of a bubble on October 29, 2021, coinciding with the announcement of the rebranding of Facebook to Meta. In this context, Mark Zuckerberg emphasized his interest in the Metaverse, which explains the high movement observed in the AXS market. Our results are in line with [Saengchote \(2022\)](#), who observed that following Mark Zuckerberg’s announcement of rebranding Facebook as Meta, the prices of MANA and SAND tokens increased significantly. In particular, MANA prices increased by 28.6 times, while SAND prices skyrocketed by 287.5 times. The rebranding of Facebook can be seen as a significant catalyst that piqued the investment community’s interest in the Metaverse and has the potential to drive advancements in this emerging technology. The high movement observed in the Metaverse market can be attributed to the belief that the Metaverse represents the future of digital interactions and commerce.

Investors sought to capitalize on the growing interest in this futuristic concept and the associated technologies. The combination of Mark Zuckerberg's endorsement of the Metaverse and the market's speculative nature created a perfect storm, resulting in a notable price bubble. These findings are consistent with previous research showing that cryptocurrency markets are highly reactive to external events, both positive and negative. For instance, [Jo et al. \(2020\)](#) demonstrated that announcements such as regulatory changes, exchange listings or strategic partnerships can lead to abnormal returns and shifts in liquidity, with negative news often producing stronger market reactions. This supports the idea that speculative behavior is closely tied to information flows and investor sentiment. In the context of Metaverse tokens, our detection of multiple speculative bubbles aligns with this literature. The observed price explosivity following major announcements suggests that these markets, like broader crypto assets, are influenced by factors beyond fundamentals. [Shahzad et al. \(2022\)](#) linked bubble episodes in Bitcoin and Dogecoin to social media activity, particularly tweets from influential figures like Elon Musk, highlighting the role of public influence in driving speculative surges. Moreover, the presence of information leakage and delayed market reactions, as noted by [Yu et al. \(2021\)](#), reinforces the notion that Metaverse markets may not fully reflect information immediately, which is consistent with the adaptive cycles observed in our study. These external validations strengthen the credibility of our results and suggest that the speculative nature of Metaverse tokens is not an isolated phenomenon but part of a broader pattern seen across digital asset markets. Moreover, the mixed reactions to tech-related news such as [Azouzi and Echchabi \(2019\)](#) finding of no significant market response to Facebook's Libra announcement highlight that not all events generate speculative behavior. However, regulatory actions, as shown by [Yu et al. \(2021\)](#) in the case of China's ICO ban, can lead to short-term corrections, reinforcing the idea that Metaverse markets, like other crypto assets, are highly reactive to institutional signals. Taken together, these studies validate the relevance of our findings and suggest that the speculative episodes observed in Metaverse tokens are not isolated anomalies but part of a broader pattern of market behavior driven by external shocks, public influence and investor psychology.

3.4 Adjusted market inefficiency magnitude (AMIM)

We further apply the AMIM model to capture the time-varying level of market inefficiency during tokens' price bubbles. [Table 6](#) presents the Summary Statistics of AMIM for five Metaverse tokens: MANA, SAND, THETA, ENJIN and AXS. The AMIM is computed daily with one year overlapping data using simple return. The sample is from November 05, 2020 to October 07, 2023. Mean Amim is the sample average of AMIM, Stdev is the sample standard deviation of AMIM and min is the minimum AMIM, respectively. Also, skew is the skewness of AMIM, kurtosis measures the thickness of the tails of the AMIM distributions and SE Mean is the standard error of the mean.

[Table 6](#) shows that on average the prices for MANA, SAND, THETA, ENJIN and AXS are all inefficient (Mean AMIM > 0). This is statistically significant, as seen by the small size of the standard error. Similarly, positive median is noted for most variables, with exception for ENJIN.

[Figure 4](#) shows time series plots of the AMIM for all tokens. For a clearer illustration of the trend of AMIM, we present graphically the time series plot of AMIM for five Metaverse tokens. The AMIM is computed daily data using simple return. As one can see from the graph ([Figure 4](#)), we observe significant variations in the AMIM over time, indicating that the level of market efficiency varies substantially over time. In particular, in the early stage of the sample period, the prices of all tokens we analyze are relatively inefficient. However,

Table 6. Summary statistics of AMIM for five tokens

Token	Min	Quartile	Mean (AMIM)	Median	SE mean	Variance	SD	Skewness	Kurtosis
MANA	-0.2596	0.1882	0.0664	0.0689	0.0030	0.0185	0.1362	-0.1598	-0.8665
SAND	-0.2168	0.1575	0.1235	0.1222	0.0022	0.0054	0.0737	-0.9132	2.7823
THETA	-0.2972	0.1591	0.0578	0.0828	0.0036	0.0223	0.1494	-0.2262	-0.5381
ENJIN	-0.2236	0.0805	0.0062	-0.0123	0.0024	0.0129	0.1138	0.8420	1.1813
AXS	-0.3785	0.1896	0.0705	0.1223	0.0056	0.0217	0.1474	-1.4665	1.1318

Note(s): Authors’ calculations; [Table 6](#) reports the adjusted market inefficiency magnitude (AMIM) for the five metaverse tokens. The statistics capture the average level, dispersion and extreme values of market inefficiency over the sample period. Higher AMIM values indicate stronger deviations from informational efficiency

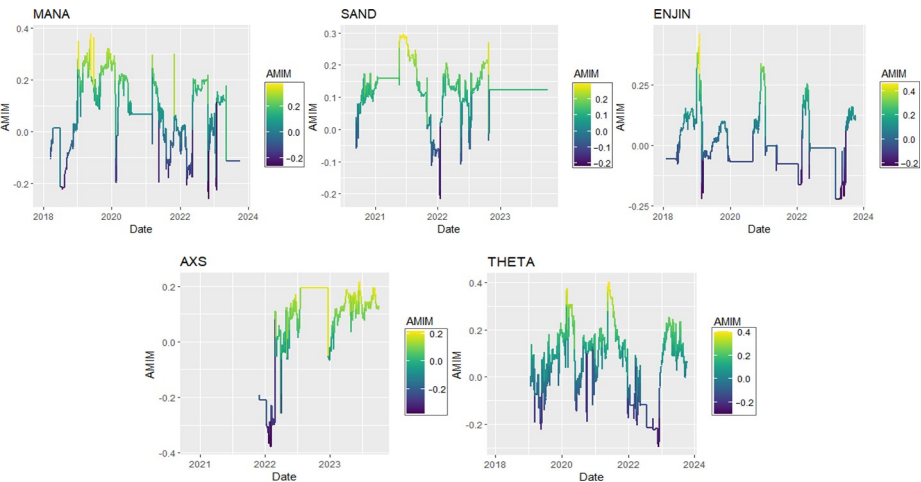


Figure 4. The time series plot of adjusted market inefficiency magnitude for five metaverse tokens
Note(s): Authors’ illustration; [Figure 4](#) illustrates the evolution of the adjusted market inefficiency magnitude (AMIM) for the five metaverse tokens over the sample period. The plot highlights pronounced fluctuations in inefficiency, with recurrent spikes that correspond to periods of intensified speculative activity

there are periods when the AMIM is negative, suggesting significant efficiencies in the performance of these tokens. In interpreting the results, the area of the graph above 0 represents inefficient periods within the market. Changes in the level of market efficiency can be observed in all tokens, which confirms that efficiency in the Metaverse market is time-varying and further lends support to the AMH.

In summary, the fluctuations in market inefficiency, depicted in [Figure 4](#), can largely be attributed to unique events. This is especially evident during the initial period of each token in our sample. As we move later into our sample duration, all tokens exhibit a notable enhancement in efficiency, indicated by a negative AMIM estimate, signifying significant efficiency. Nevertheless, toward the initial part of 2021, it appears that prices are becoming less efficient, but they return to an efficient state by the end of 2021. These findings align

with the central concept of the AMH proposed by Lo (2004), which posits that market efficiency evolves over time and responds to market events.

Clearly, we observe evidence of inefficiency that align with the bubble periods previously mentioned. A case in point is the prominent price surges of MANA token, characterized by significantly elevated price fluctuations, notably commencing after January 2021. Figure 4 visually illustrates the time-varying inefficiency of metacoins.

Starting with Mana coin, the AMIM value has increased steadily from around 0.2 in early 2021 to over 0.4 in late 2023, indicating the inefficiency of this token during this specific timeframe. These findings are in line with Dowling (2022), who conducted an analysis on the pricing dynamics of virtual real estate parcels in Decentraland, revealing that the price series of these NFTs exhibit inefficiency and demonstrate appreciation in value. This is the case for all Metaverse tokens considered. In fact, the time series plot of AMIM for the five studied Metaverse tokens indicates that these coins are clearly inefficient. However, we observe periods of efficiency when the plot is in the negative part, suggesting that the Metaverse market is time-varying and exhibits inefficiency.

Our study shows that the Metaverse market is highly vulnerable to speculation. Investors often focus on short-term price movements rather than fundamentals, creating opportunities for speculators to exploit inefficiencies. These inefficiencies lead to price distortions and increased volatility, which can either correct or worsen market imbalances. This interaction between inefficiency and bubbles adds complexity to the Metaverse economy and raises concerns about market integrity and investor protection. The AMH offers a useful framework for understanding these dynamics (Mokni *et al.*, 2024). Unlike the static assumptions of the EMH, AMH suggests that market efficiency changes over time as investors learn and adapt (Lo, 2004). Our findings support this view. The AMIM model reveals strong fluctuations in efficiency, while the GSADF test detects frequent speculative episodes. Metaverse token markets do not maintain constant efficiency; instead, they move through adaptive cycles periods dominated by speculation followed by phases of improved efficiency as participants adjust their strategies. These results align with recent studies showing bubble behavior in Metaverse tokens during times of heightened attention (Horky, 2024) and confirm similar patterns observed in cryptocurrency markets (Karasiński, 2023; Caporale *et al.*, 2018; Chu *et al.*, 2019; Khursheed *et al.*, 2020). Collectively, the evidence reinforces that Metaverse markets behave as complex adaptive systems shaped by investor learning, competitive pressures and rapid technological change.

Conclusion

Our study explores the efficiency of the Metaverse economy and evaluates the potential occurrence of a bubble within the Metaverse market. We focus on five Metaverse tokens selected by market capitalization and analyze 1,069 daily observations for each token from November 4, 2020 to October 7, 2023. The empirical methodology unfolded in three stages. Initially, we used various statistical tests to examine autocorrelation patterns within the time series data. Next, we used the GSADF test to investigate speculative bubbles in the Metaverse tokens. Finally, we used AMIM to dynamically assess market efficiency.

The results reveal multiple speculative bubbles in Metaverse token markets, often triggered by major announcements that amplify investor sentiment and drive short-term price distortions. This behavior aligns with prior evidence that both positive and negative news significantly influence cryptocurrency prices and liquidity. The detection of explosive episodes and fluctuating efficiency supports the AMH, indicating that Metaverse markets do not maintain constant informational efficiency. Instead, they evolve through adaptive cycles where investor behavior and market structure respond dynamically to changing conditions.

By integrating event-driven dynamics with time-varying efficiency analysis, this study provides a deeper understanding of how speculative bubbles form and dissolve in emerging digital ecosystems. It shows the balance between fair pricing and speculation, providing a useful way to understand price fluctuations in digital markets. These insights have practical implications for investors and regulators. For investors, the findings underscore the need for adaptive strategies that account for short-term inefficiencies and event-driven volatility, rather than relying solely on traditional valuation models. Investors should adopt flexible strategies such as dynamic portfolio rebalancing, diversification between digital and traditional assets and monitoring social media signals that often precede price movements. Such measures can strengthen risk management and improve timing decisions. For policymakers, the results emphasize the need of regulatory frameworks adapted to the unique characteristics of the Metaverse and cryptoasset markets. These markets are highly vulnerable to speculative bubbles, information leaks and social media manipulation, which threaten market integrity and investor protection. Policymakers should consider implementing measures that enhance transparency, improve information diffusion and monitor market manipulation risks. Adaptive rules that evolve with technological and behavioral changes are essential to ensure the stability and resilience of these rapidly changing ecosystems.

Finally, this research contributes to academic literature by offering a new perspective on the intersection of technological innovation, behavioral finance and market efficiency theory. It provides a practical reference for anticipating systemic risk by identifying patterns of time-varying efficiency and speculative bubbles in Metaverse token markets. These indicators can serve as early-warning signals for regulators and policymakers, helping them take proactive measures to reduce contagion effects and maintain stability in interconnected digital ecosystems.

Note

- [1.] Yahoo Finance provides publicly accessible financial and market data, including stock prices, returns and fundamental indicators for global listed companies. Data retrieved from <https://finance.yahoo.com>

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