Physica A 653 (2024) 130103

Contents lists available at ScienceDirect

Physica A

journal homepage: www.elsevier.com/locate/physa

Stylized facts of metaverse non-fungible tokens

Stephen Chan [a], Durga Chandrashekhar [a], Ward Almazloum [a], Yuanyuan Zhang [b], Nicholas Lord [b], Joerg Osterrieder [c,d], Jeffrey Chu [e,*]

[a] *American University of Sharjah, PO Box 26666, Sharjah, United Arab Emirates*
[b] *Center for Digital Trust and Society, Department of Criminology, University of Manchester, Oxford Road, Manchester, M13 9PL, UK*
[c] *University of Twente, Hallenweg 17, 7522 NH Enschede, Netherlands*
[d] *Bern Business School, Bern University of Applied Science, Brückenstrasse 73, 3005 Bern, Switzerland*
[e] *Center of Applied Statistics, School of Statistics, Renmin University of China, No. 59 Zhongguancun Street, Haidian District, Beijing 100872, China*

ARTICLE INFO

Keywords:
Metaverse
Non-fungible tokens
Stylized facts
Market efficiency
Volatility

ABSTRACT

Non-Fungible Tokens (NFTs) within the metaverse represent a rapidly emerging sector in the digital asset space. This paper provides a comprehensive review of the metaverse's history and an analysis of the stylized facts of five metaverse NFTs: Axie Infinity, Decentraland, Enjin Coin, Theta Network, and The Sandbox. We examine market efficiency, volatility clustering, leverage effects, and the return-volume relationship. Our key findings show that all NFT returns exhibit kurtosis values significantly exceeding the standard value of three, indicating more peaked and heavier-tailed distributions than a normal distribution. Autocorrelation analysis reveals statistically insignificant results, suggesting minimal influence of past returns on current returns. The Hurst exponent fluctuates between 0.3 and 0.8, indicating relative inefficiency in log returns with varying degrees of trend reinforcement and anti-persistence. The GARCH(1,1) model confirms the presence of volatility clustering, with high persistence of volatility shocks over time, and most NFT returns exhibit a negative leverage effect, where negative returns decrease volatility. These findings provide critical insights for investors, content creators, and policymakers, emphasizing the need for innovative strategies and regulatory considerations in this evolving ecosystem. A comparative analysis using alternative metaverse-related assets from Bloomberg and Yield Guild Games enhances the robustness of our findings, enriching the academic discourse on digital assets and laying the groundwork for future research in metaverse NFTs.

1. Introduction

1.1. Background

History has shown that every year, technological innovations, breakthroughs, and discoveries push the boundaries of what is possible with technology. Every once in a while, these developments do not just represent a simple step but rather a big leap forwards. Over the past century, there have been three notable innovations: the introduction of personal computers, the creation

* Corresponding author.
E-mail addresses: schan@aus.edu (S. Chan), g00092128@aus.edu (D. Chandrashekhar), g00097286@aus.edu (W. Almazloum), yuanyuan.zhang@manchester.ac.uk (Y. Zhang), nicholas.lord@manchester.ac.uk (N. Lord), joerg.osterrieder@utwente.nl (J. Osterrieder), jeffrey.jchu@ruc.edu.cn (J. Chu).

https://doi.org/10.1016/j.physa.2024.130103

Available online 13 September 2024

of the Internet, and the development of mobile phones/devices. At present, the world is experiencing a fourth innovation — the “metaverse”, which constitutes “spatial, immersive technologies such as Virtual Reality (VR) and Augmented Reality (AR)” [1].

The boom in the development of the metaverse signifies an important shift in the digital strategies of companies, merging physical reality with virtual environments through advanced technologies such as VR, AR, and of particular interest, the blockchain. This shift is evidenced by the actions of many of the world’s largest technology companies, such as Meta, Apple, and Microsoft, pouring billions of Dollars of investment into shaping the metaverse landscape through VR and AR products and platforms [2]. Beyond the traditional technology sector, companies such as Tencent and McDonald’s are also exploring metaverse applications, ranging from gaming to virtual dining, highlighting the metaverse’s appeal across all different industries [3,4].

Although the concept and interpretation of the metaverse are constantly evolving, and despite the absence of a universally accepted definition, certain characteristics are commonly associated with the metaverse, including (but not limited to): a persistent virtual environment, a diverse content ecosystem, and a functioning economy. Meta’s definition highlights the metaverse as a collective virtual space for creativity and exploration, suggesting a broad vision for its potential to extend beyond physical limitations [5–7]. This is particularly evident in the post-pandemic era, where hybrid and remote working models are prevalent [8], the metaverse offers a seamless transition into virtual spaces that replicate real-world experiences, enabling shared interactions despite physical separation [7,9]. The metaverse can be realistic, such as virtual museum visits, or unrealistic, allowing experiences like exploring other planets free from physical constraints. A fused metaverse combines these elements, blending virtual experiences with physical settings through augmented reality [9].

The metaverse promises escapism, progression, and achievement with minimal risk [8], potentially leading users to increasingly rely on digital lives. Gartner [10] predicts that by 2026, a quarter of the population will spend at least an hour daily in the metaverse for work, education, or recreation, with 30% of global enterprises developing metaverse-compatible products and services. For example, banks are exploring augmented and mixed reality to replicate banking experiences or embed financial services within the metaverse, facilitating easier digital-non-digital financial asset exchanges [8].

It is clear that the metaverse aims to bridge the gap between virtual and real spaces, and in doing so achieve a number of goals including (i) the creation of immersive experiences through VR and AR; (ii) interconnect users and devices to perform tasks that can be done in the real-world; (iii) encourage a digital economy that runs on virtual commerce and transactions; (iv) revolutionize education and entertainment, especially in the post-pandemic era; (v) ameliorate collaboration and data sharing [11]; (vi) cater to personalized needs through effective customization facilities, with all these goals working towards ultimately “blur[ring] the boundaries between physical and digital realities” [12].

1.2. Metaverse and cryptocurrencies

Indeed, one of the earliest (and existing) concepts of a social metaverse is Linden Lab’s “Second Life” project, which was launched in 2003, six years prior to the first cryptocurrency Bitcoin and the blockchain as we know it today. In particular, users of Second Life are able to interact in a virtual world as if it were a replication of the real world, with the platform operating its own virtual currency, the Linden Dollar [13]. Although US Dollars can be exchanged for Linden Dollars and vice versa, and Linden Dollars can be used in transactions for virtual land, digital goods, and online services, the currency stops short of being a true fiat currency or cryptocurrency as it is only valid within the Second Life Metaverse. Therefore, it is defined as a closed-loop digital currency. In the context of virtual economies in metaverses, the connection between blockchain and cryptocurrencies cannot be denied.

Blockchain technology, also referred to as distributed ledger technology (DLT) [14], is “a non-convertible account book that allows decentralized transactions” [15]. The blockchain is essentially a database that stores verified transaction data in order to assist with securing and tracing digital assets. The blockchain consists of consecutive blocks that contain transaction data and are each linked via hash functions using data from the previous block header to ensure immutability and security. Additionally, the timestamp, nonce, and other related data are also present in each individual block, with specific consensus protocols playing the quintessential role of regulation and operation of the blockchain under consideration [14]. As a result, blockchains are decentralized and able to operate without a centralized authority. With respect to the metaverse, the blockchain is said to play two significant roles: (i) serve as a repository of data anywhere in the metaverse; (ii) provide an economic system to bridge the virtual metaverse and real world.

Thus, the blockchain’s decentralized and secure ledger system ensures the validity and immutability of transactions, which is essential for the functioning of cryptocurrencies. For instance, cryptocurrencies like Bitcoin rely on blockchain to maintain security and trust without the need for a central authority. The decentralized nature of blockchain enables peer-to-peer transactions, allowing direct exchange of value, and consensus mechanisms like proof of work (PoW) to validate and secure these transactions [16,17].

In the 20 years that have passed since the launch of Second Life, blockchain and cryptocurrency technology have emerged as frontrunners in supporting the payment systems in most metaverses. Two of the most popular examples are the SAND token and MANA token that operate as virtual currencies in the Sandbox and Decentraland Metaverses, respectively, accounting for around 30% of the metaverse market capitalization [13]. However, to function as a currency, such cryptocurrencies must satisfy the three key properties of: (i) store of value; (ii) unit of account; (iii) medium of exchange [13,18]. In reality, cryptocurrencies (and thus metaverse tokens) are hindered by their extreme volatility compromising their ability to act as a unit of account or medium of exchange due to the frequent adjustment of prices, and store of value due to the seemingly erratic behavior in their worth and performance [13,18].

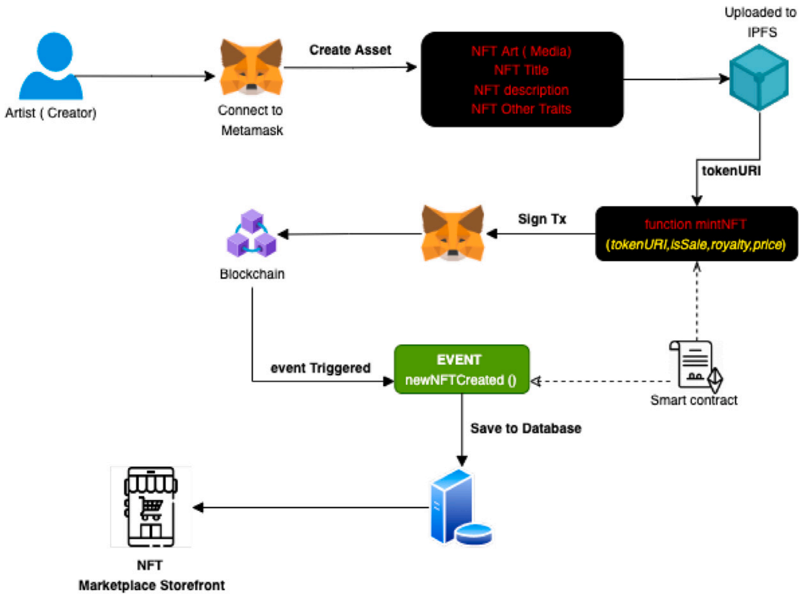

Fig. 1. An illustration of the NFT minting process [24].

1.3. Metaverse non-fungible tokens (NFTs)

As noted by Yilmaz et al. [19], the metaverse can also relate to "digital virtuality...in virtual asset trade". Whilst cryptocurrencies as virtual currencies represent the fungible (divisible and non-unique) side of metaverse economies, this is complemented by the non-fungible (unique and non-divisible) side of metaverse trading systems, giving rise to the concept of non-fungible tokens (NFTs).

NFTs can be defined as "a unique digital identifier that cannot be copied, substituted, or subdivided, that is recorded in a blockchain, and that is used to certify authenticity and ownership (as of a specific digital asset and specific rights relating to it)" [20], which is not interchangeable with other digital assets [21]. This is in contrast to fungible (identical) financial assets such as regulated commodities, stocks, money bills, or traditional cryptocurrencies — thereby leading to the concept of non-fungibility, or the ability to have an identity. In general, an NFT can be generated (or "minted") from any multimedia file such as a photo, text, audio, or video. This digital representation is then uploaded to an NFT marketplace, the pricing model selected, and the NFT is minted and validated on the blockchain [21]. A summary of the NFT minting process is illustrated in Fig. 1. The key properties of NFTs are that they are rare and unique making them irreplaceable and distinct from one another, and are not divisible such that only a single owner can own an entire NFT [22]. As Wang et al. [23] note, NFTs are ultimately a type of cryptocurrency derived by what is known as smart contracts, such that, using these contracts allows a creator to prove existence of ownership of the digital asset (regardless of form), and even earn royalties during trading or peer-to-peer exchange.

The most popular use cases of NFTs continue to be digital collectibles and art, as NFTs provide a solution to piracy, which negatively impacts artists in the art world, and digital trading cards and virtual pets have since become a niche [25]. However, NFTs continue to expand into other use cases such as "fashion, music, academia, tokenization of real-world objects, patents, membership sales and loyalty programs" [26]. Real world examples include tokenizing property deeds allowing for digital representations of property ownership, tokenizing individual identities to serve as verifiable proof of identity, selling music as NFTs, and a potential solution to protect intellectual property (IP) [25]. In addition, NFTs are playing a significant role in disrupting the gaming industry by offering "unique, tradable in-game items, combining aspects of art, collectability, and utility for players" [25].

Given the present focus on the metaverse and NFTs, the link or distinction between the two is that NFTs represent digital tokens and the metaverse represents a digital universe [27]. As mentioned above, items such as property deeds, identities, music, etc. can be NFTs but they can also be metaverse NFTs, where the latter focuses primarily on asset ownership within the metaverse, and are the predominant "building blocks of the metaverse economy" alongside other cryptocurrencies [9]. Metaverse NFTs can thus play a number of different roles such as representing ownership of virtual land in a metaverse, unique items in metaverse-based games, virtual avatars or characters in a metaverse, and even admission to virtual concerts or experiences [27].

The NFTs described above fall into the broad category of first generation NFTs, or NFT 1.0, consisting of static tokens that possess data that is immutable post-token creation, which reduces the ability to spread these tokens owing to lack of support for user interaction. As a result, this limitation has led to the evolution and development of second generation NFTs, or NFT 2.0, which are dynamic and encourage greater user interaction, therefore increasing the applications of these NFTs [28]. As highlighted by PrimaFelicitas [29], NFT 2.0 expand on the capabilities of basic NFTs to allow for abilities such as enhanced metadata — greater context and information content about an asset; nested NFTs — NFTs can own and be owned by other NFTs, which can be an infinite cycle; multiple resources — a significant departure from NFT 1.0, where NFTs can store multiple videos, images, etc. and choose which to show; rentals — renting or leasing of NFTs, allowing for financial gains without full ownership, reactive — a change in NFT resource conditional on some criteria, and more. A particular example in the metaverse is the "fractional ownership of high-value properties", where the property can have dynamic characteristics that showcase this dynamism based on real-time information within a metaverse.

The shift towards NFT 2.0 is evident in a number of metaverses, as they look to expand on originally issued NFTs. Although they are not commonly described as NFT 2.0, they encompass the main properties and advantages. Prominent examples include Decentraland, who have developed an on-chain NFT rental solution to work with virtual land in the Decentraland Metaverse. Renters can rent virtual land through doNFT smart contracts, which generate a doNFT token featuring start and end times that specify permissions and usage for a specified time period. During this rental period, renters gain rights such as subleasing and developing the rented virtual land [30]. Axie Infinity has also introduced an evolution system for their Axie trading card NFTs, allowing for evolving or dynamic NFTs through the evolution of "parts" (characteristics). This allows the digital collectibles to evolve as players play, and allows for new content to be developed without the significant minting of new NFTs [31]. However, the transition towards NFT 2.0 has not been plain sailing. Some platforms have noted that metaverses require virtual or 3D worlds, especially in gaming, which rely on huge computing power in terms of graphics engines such as Unreal and Unity. These are closed applications that require software downloads, which limit access and accessibility, reducing the interoperability of NFT assets at scale [32].

From an economic perspective, such digital assets, which include any item created and stored digitally, play an essential role in the foundation and functioning of the metaverse economy. In these virtual environments, where users can engage in a wide array of activities including interaction, work, leisure, and socializing, NFTs play the critical role of representing unique digital assets, such as real estate, and in-game items or collectibles, on the blockchain. This allows for the digital metaverse economy to facilitate the buying, selling, and trading of these assets as if they were actual physical assets. Although they can be traded using virtual currency, NFTs are not generally exchanged for one another. However, since these assets are simply data and information, the problem of valuation and pricing is complex, although studies have shown that their value may be influenced by their uniqueness and scarcity, in addition to their functions within the respective metaverses [13].

As mentioned above, uniqueness and scarcity form two key properties of NFTs. It is during the minting process that NFTs derive their uniqueness, as once an NFT is minted it is assigned a unique non-transferable identifier that links it to a blockchain address. Therefore, even if multiple NFTs of the same item are minted, each NFT will possess a unique identifier that will distinguish it from another. NFTs were first introduced with the ERC-721 standard, as opposed to the Ethereum Requests for Comment-20 (ERC-20) standard used for initial coin offerings (ICOs), ensuring that NFTs are unique due to their non-fungibility [33]. Scarcity is related to the limited number of a particular NFT available. In general, only a fixed number of NFTs are created and traded, after which no further creation takes place [34], and in most cases this means for a single asset there will only ever be one NFT. Similar to pieces of art, the value of an NFT is thus derived from owning or having access to this one of a kind item — one that the owner knows no one else will have access to or be able to recreate.

The importance of understanding the metaverse and NFTs is becoming increasingly critical as these technologies demonstrate the potential to significantly impact various aspects of daily life and societal functions. The metaverse, with its capacity to offer precise and graphic online self-representation, holds the promise of transforming workplaces, enhancing social interaction, and fostering economic growth. It enables cross-cultural exchanges in environments that closely mimic physical reality, which potentially increases the amount of time people spend online. Drawing parallels with the internet's revolutionary impact in the 1990s, the metaverse's versatile nature allows it to permeate almost every facet of life, from socializing and work to gaming and education, indicating a profound potential to alter both professional and personal spheres. Instances of marriages and office campuses within the metaverse underscore its transformative capabilities. Thus, understanding the metaverse provides insights into future life changes, as it could reshape every aspect of our existence [35].

The growing interest and awareness in the metaverse and NFTs, in particular, is reflected in Fig. 2.[1] NFTs have become increasingly popular primarily due to their non-fungibility, their technical properties, and their profitable transactions, unlike traditional cryptocurrencies (such as Bitcoin or Ethereum). Although there is a clear variation in the public awareness of the three topics, it can be observed that within the seven-month period between 2021 and 2022, there is a significant surge in the interest in NFTs with search interest peaking in January 2022. While cryptocurrency and metaverse interest are relatively stable, the interest for the two appears to peak around the fourth quarter of 2021. In general, the greater level of public interest in the metaverse and, in particular, NFTs, asserts the importance of this research study.

Fig. 3 plots the daily market capitalization of five popular metaverse tokens: Axie Infinity (AXS), Decentraland (MANA), Enjin Coin (ENJ), Theta Network (THETA), and The Sandbox (SAND), for the same sample period as for the price and volume data. It can be observed in Fig. 3 that there is a significant increase in the market capitalization value of all five tokens within the considered time frame, which further asserts the implications of performing extensive stylized facts analyses on these tokens.

[1] As per the information provided by Google Trends, the plot displays the overall interest over time, where the y-axis signifies the search interest, relative to the highest point on the chart for the chosen time range and region (in this case, worldwide). If the interest value is 100, this signifies peak popularity whereas a value of 50 would imply that the term is half as popular, for instance. At any instance, if the value is 0, this would imply that there is not enough data for the term at that point in time.

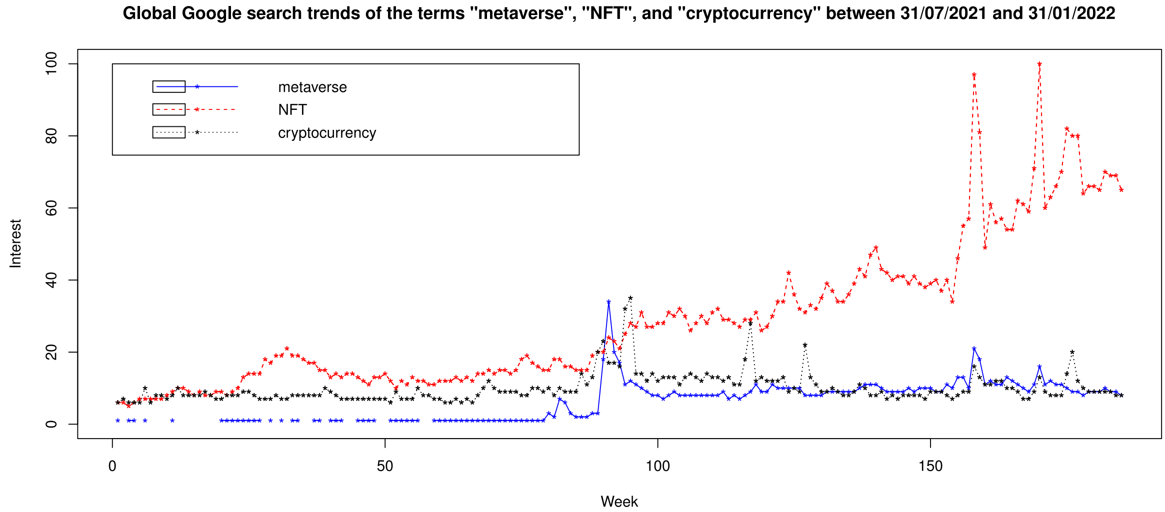

Fig. 2. Plot of the weekly global Google search trends for the terms 'metaverse', 'NFT', and 'cryptocurrency', for the period of July 2021 and January 2022, inclusive, measured in terms of number of weeks since the beginning of July 2021.

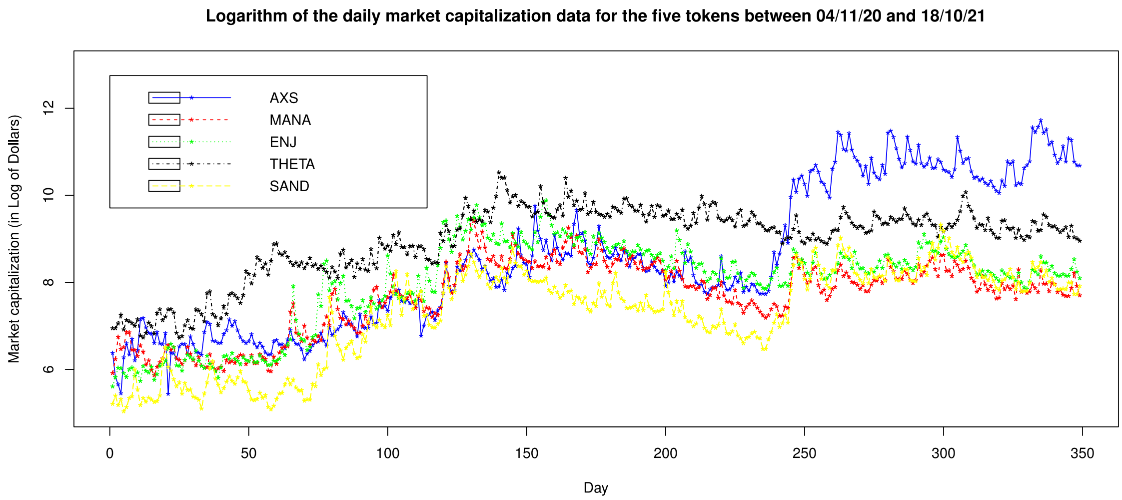

Fig. 3. Plot of the logarithm of daily market capitalization of AXS, MANA, ENJ, THETA, and SAND, for the period of 4th November 2020 to 18th October 2021, inclusive. Dates are indicated by the number of days since (and including) the 4th of November, 2020.

1.4. Crime and risks in metaverse NFTs

As the metaverse evolves into an investment hub owing to its multitudinous uses, it is key to consider the security and privacy aspects of the metaverse due to it being prone to cybersecurity issues [9]. As Di Pietro and Cresci [36] note, if "social network users are the product of today's Internet, in the metaverse literally everything and everyone will be the product".

At the metaverse level, one issue concerns the architectural security and insecure designs, with the latter not being resolvable by mere implementation of security systems. Another issue is the technological complexity of the metaverse, which combines methods of AR, VR, artificial intelligence (AI), and/or machine learning (ML), that are pillars of an effective metaverse and hence unavoidable — this complexity amplifies the vulnerability to cybersecurity threats. There is also the issue of amplified technical impacts, which refer to the grave consequences of privacy violations that occur as a result of the multisensory, sophisticated features of the metaverse that can be intrusive to end-users. With the metaverse requiring supporting technology, such as VR headsets or eye-tracking equipment, businesses can capitalize on the collected consumer data, that can potentially be sold to third parties, without the users being aware [9]. Casey et al. [37] highlight another key issue that they term the "Human Joystick Attack" which signifies the ability of external attackers to exploit and take control of VR systems and their users without their knowledge. While there exist a number of proposed countermeasures in the literature, such as masking avatars making re-identification of an user harder, there are issues of radicalization where the centralized nature of the metaverse can lead to specific groups of users negatively targeting those of other groups [36].

Focusing on metaverse gaming, in particular, NFTs empower players with true ownership of diverse in-game assets, including skins, characters, and virtual land. While this innovation offers unprecedented opportunities, it also introduces substantial risks and the potential for crime, exacerbated by the current lack of regulation in digital asset markets [38]. Over $100 million in fraud and scams associated with metaverse NFTs have been reported, which highlights the urgent need for scrutiny [39].

Some key issues include market manipulation, which involves coordinated activities such as "pump and dump" schemes [40,41], and manipulation of NFT prices, undermining market integrity. Moreover, insider trading by developers or testers who leverage confidential information to trade NFTs poses a serious challenge to fairness. Intellectual property theft occurs when individuals frequently counterfeit digital artwork or game assets of legitimate creators [42,43], which thereby infringes on intellectual property rights and flooding the market with unauthorized replicas [44]. Privacy concerns arise from extensive data collection and data retention within metaverse platforms, including biometric data, which poses significant privacy risks [38]. Additionally, the potential for invasive surveillance by platform operators or third parties remains a critical concern. Harassment and abuse in the immersive and persistent nature of the metaverse may replicate and amplify real-world social issues [45], necessitating stringent, enforceable policies to safeguard users. Cybersecurity threats including vulnerabilities in smart contracts can lead to theft of NFTs or funds, while account hacks and phishing attacks remain prevalent, targeting players' NFTs through compromised security practices [46].

Effective mitigation of these risks requires robust security protocols, legal regulations, and ethical guidelines, collaboratively developed by game developers, platform providers, and regulatory bodies [47]. Raising awareness and educating players about the potential pitfalls of NFTs is crucial for ensuring a safe and fair gaming environment. NFTs are susceptible to various forms of fraud, including tokenization, wash trading, insider trading, and even money laundering [48]. This underscores the importance of educating the public on these and other associated risks. A study by Vigderman [49], which surveyed over 1000 American consumers about their awareness of NFTs and their sentiment towards trading them, revealed that familiarity with NFTs increased significantly from 2021 to 2022. Despite this growth, 7% of respondents who do not currently own NFTs indicated they might purchase one in the next year, suggesting a persistent gap in understanding the risks and benefits associated with NFT trade. This highlights the ongoing need for public education on NFTs to ensure informed decision-making and protect consumers.

1.5. Motivation

Given the rising prominence of NFTs in the digital asset landscape and the corresponding increase in associated risks such as hacks and fraud, understanding their stylized facts are essential not only for leveraging their potential but also for mitigating the vulnerabilities that these digital assets introduce. These facts, which are consistent empirical findings observed across various assets and markets, provide valuable insights into asset behavior and returns. Key examples of stylized facts in financial markets include heavy-tailed distributions, autocorrelation, volatility clustering, long-range dependence, leverage effects, and the relationship between returns and trading volume. Recognizing these characteristics is crucial for effective analysis and forecasting in the NFT market. For instance, understanding heavy-tailed distributions helps manage risks associated with extreme price variations, while identifying autocorrelation improves the accuracy of price prediction models based on past trends. Volatility clustering informs the timing of market entries and exits by anticipating periods of high risk and potential returns. Long-range dependence enhances long-term investment strategies and trend predictions, and acknowledging leverage effects enables better risk estimation and strategic adjustments in response to market downturns. Lastly, understanding the relationship between returns and trading volume assists in predicting market sentiment, aiding in the identification of bullish or bearish trends.

In the literature, these stylized facts have been extensively researched for traditional financial markets and assets. Examples include studies on asset returns [50], high-frequency data in foreign exchange [51], financial transaction taxes [52], precious metals [53], and floating exchange rates [54]. These stylized facts have also been examined in traditional cryptocurrencies. Zhang et al. [55] highlighted several key characteristics, including heavy tails for all cryptocurrency returns, the rapid decay of return autocorrelations contrasted with the slow decay of autocorrelations for absolute returns, strong volatility clustering, leverage effects, and a power-law correlation between price and volume. Furthermore, Phillip et al. [56] discussed Bitcoin's diverse stylized facts, such as long memory and heteroskedasticity, demonstrating the complex dynamics within cryptocurrency markets.

With extensive studies of stylized facts in traditional financial assets and cryptocurrencies, it is crucial to extend this focus to the NFT markets. By identifying and understanding these properties in NFTs, researchers can establish a comparative framework that not only bridges the understanding between NFTs and established financial instruments, but also enhances our insights into how NFT markets operate. This comparative analysis is essential, as it enables a deeper understanding of market dynamics and can help in predicting future trends and behaviors in the growing NFT space. Focusing on the financial side of the metaverse can give insights into understanding market behavior and how NFTs are valued, traded, and used. This in turn can assist in developing measures to identify and mitigate financial risks such as market manipulation and fraudulent activities. In the context of regulators, this information may guide the development of future regulation in the digital asset space, as platforms and regulators understand whether these patterns and trends could be exploited for malicious use.

1.6. Aims and contributions

The current literature that explores the financial properties of NFTs remains relatively sparse with only a limited number of studies. Of the studies that do exist, the majority focus on investigating the importance of NFTs in the metaverse and Web3 systems [23,57,58], in particular relating to the field of the arts [59,60] and digital properties or ownership [61].

With respect to the economics of NFTs, Borri et al. [57] construct NFT indices and analyze their properties, and show that NFT returns are exposed to traditional cryptocurrency markets. However, NFT returns are found to have low exposures to other cryptocurrency and traditional asset market factors. Belk et al. [58] note that NFTs are likely to still be dominated by top-down ownership models, with those in the top two percent of Bitcoin owners owning 95% of all Bitcoin and the top nine percent of Web3 accounts owning around 80% of all NFT value. Wang et al. [23] also highlight that a major obstacle hindering the widespread adoption of NFTs is high gas prices incurred during the creation and trading of NFTs.

As noted by Wang et al. [23], high gas prices occur when minting NFTs at large scale, as metadata also needs to be uploaded and stored on the blockchain. As a result, NFT-related transactions are more expensive compared to simple cryptocurrency transfers and payments due to smart contracts requiring much greater computational resources and storage to process them. For example, a minimum of USD $60 is required to mine an NFT, while USD $60-100 is required to complete an NFT trade, due to complex operations and high levels of blockchain network congestion [23]. In addition, Kugler [59] discuss the "last mile" problem in the context of how NFTs interact and interface with the offline world. In the long run, the value of NFTs will be dependent on their link to the offline world. Furthermore, from a legal perspective, although NFTs share similar characteristics with personal property, laws have not kept up with the demand for unique digital property.

In light of the above, this manuscript aims to achieve three key objectives: first, to provide a comprehensive review of the development of the metaverse and the integration of NFTs within it; second, to analyze key stylized facts of NFTs—such as heavy-tailed distributions, autocorrelation, volatility clustering, long-range dependence, leverage effects, and the relationship between returns and trading volume—to understand their impact on market behavior; and third, to assess the consistency of these stylized facts across different NFT categories by comparing metaverse NFTs with the Bloomberg Metaverse Index and the Yield Guild Games token.

The contents of this paper are organized as follows. Section 2 provides a comprehensive review of the metaverse, from its benefits to the concepts of Web2 and Web3, through to comparisons and discussions between the past and present forms of the metaverse. Section 3 provides the methodology of the paper along with the key expressions utilized. Section 4 follows with details of the various datasets used and their summary statistics. Section 5 provides the results of the various tests for stylized facts, along with interpretations of the results and a discussion. An in-depth analysis of the robustness of the main results in comparison to metaverse indices from Bloomberg and Yield Guild Games is given in Section 6. Finally, Section 7 provides a holistic summary concluding with the key results and future implications of this paper.

2. A brief review of the metaverse

2.1. History and rise of the metaverse

The term "metaverse" itself is derived from two Greek words: "meta" which means "beyond-transcending" and "verse", which implies a universe [13]. However, there is currently no widely accepted definition to categorize what is constituted as the metaverse with definitions that range from "virtual socialization" to a "virtual collaboration and simulation platform". However, at a high level, it refers to the idea of bridging the physical reality with the virtual world.

The awareness of the metaverse surged following the announcement at the 2021 Facebook Connect conference that Facebook would change its name to Meta. This rebranding signaled a significant shift for the company and highlighted the growing corporate interest in the metaverse and a strategic pivot towards developing virtual spaces where work and leisure intersect, moving away from its social media roots. This name change, coupled with substantial investments in metaverse technologies, underscored the company's goal to pioneer integrated virtual environments, for example Horizon World [62]. The launch of advanced VR headsets and AR glasses further reflected these ambitions. However, this transition unfolded under significant scrutiny related to the company's internal practices and their broader social implications, including antitrust issues highlighted by Rodriguez [63] (see Fig. 4).

In recent years, the company NVIDIA introduced the deep learning super sampling (DLSS) technology that combines the techniques of deep learning (DL) and AI in line with enhancing the visual appeal of various aspects within the metaverse [64]. Apart from VR and AR, recent advancements in relation to game design [65,66] and metaverse security [67] include the utilization of ML and/or AI. For instance, as Ghantous and Fakhri [68] state, there are some virtual avatars rendered from real users using facial recognition technology which employs ML, while Wu et al. [69] suggest the use of AI in videogame visualization, and ML in "character animation, terrain generation and lighting effect". Additionally, as Xi [70] mentions, AI can be used to enhance the power of VR stating that AI can improve the game development, user experience, and game content of VR games.

The growing interest in the metaverse among technology companies signifies a major trend towards blending virtual environments with traditional digital platforms. Beyond Meta, the broader technology sector has significantly contributed to and demonstrated strong momentum in metaverse development. The rapid rise of initiatives like Decentraland and The Sandbox [71,72] highlights the growing interest in and investment in virtual real estate and decentralized virtual environments. Companies like NVIDIA have developed advanced graphics processing units (GPUs) specifically designed to handle the complex calculations required for highly immersive virtual reality experiences [73]. This momentum is further evidenced by the surge in venture capital investments in metaverse-related firms, which saw an influx of over $10 billion in 2021 alone [74]. Additionally, international events such as the virtual concerts hosted in Fortnite [75], which attract millions of viewers, illustrate how metaverse experiences are increasingly embraced and integrated into popular culture. As the metaverse continues to evolve, ongoing discussions and research into its applications, implications, and governance will be crucial to understanding and managing its potential future impact on society and industry practices.

Fig. 4. A screenshot from Meta's Horizon World, a virtual world utilizing VR for socializing [62].

2.2. Social and economic benefit of the metaverse

The metaverse, an expanding digital frontier, is increasingly recognized for its profound social and economic benefits, drawing attention from a diverse array of global participants. Companies like Warner Music Group are actively venturing into metaverse platforms, such as The Sandbox, to establish venues for musical performances, a move that has proven to be effective in increasing the value of the SAND token [76]. This collaboration exemplifies how incorporating the metaverse into the music industry can significantly boost both the metaverse economy and the music industry by opening new revenue streams. The potential of these virtual platforms is further evidenced by events such as the popular Korean band BTS's virtual concert, Bang Bang Con The Live, which earned $20 million and attracted 756,000 global viewers in 2020. Similarly, the Map of the Soul live stream sold 993,000 tickets across 191 countries [77]. These cases highlight the extensive reach and financial impact of metaverse-based events, demonstrating their effectiveness and underscoring the need for strategic planning to maximize their potential in the future. In addition, HSBC, which has invested in digital real estate within the metaverse to engage with sports, e-sports, and gaming enthusiasts [78], exemplifies the significant economic potential of these virtual environments. The collaboration between the Australian Open and Decentraland to host a major sporting event virtually [79] highlights the versatility and wide-ranging applicability of the metaverse in redefining traditional event hosting and viewer engagement. In the sports industry, this partnership exemplifies how leveraging blockchain technology can create highly immersive online sporting experiences. Not only do these virtual events enhance engagement, but they also allow viewers to collect and fully own digital memorabilia. For instance, during the Australian Open, fans had the opportunity to own an Art Ball NFT, a digital asset that cannot be taken away by any central authority [80]. This integration of blockchain and metaverse technology underscores the transformative potential of these platforms in creating new and secure avenues for fan interaction and ownership in sports.

Corporate adaptations to the metaverse, like Accenture's replicas of its offices [81], Microsoft's introduction of "Microsoft Mesh" for enhanced holographic collaboration [82], and Nvidia's "Omniverse" for real-time collaborative design [82], highlight the metaverse's role in transforming workplace dynamics and fostering innovation across industries. Meta's development of "Horizon World" [83] further demonstrates the metaverse's capacity to create immersive social experiences, illustrating the platform's potential to revolutionize personal and social interactions online. Gwaldis [84] argues that businesses stand to gain significantly from integrating the metaverse into their operations, as it can enhance internal processes, expand market reach, develop innovative marketing and revenue strategies, and improve customer relations while reducing friction between online and offline experiences. Furthermore, the metaverse offers opportunities for companies to implement more sustainable practices, protect intellectual property more effectively, and derive valuable insights from collected data [84].

The economic significance of the metaverse is also evident in forecasts by leading firms, with Accenture predicting a comprehensive transformation in business environments [85], JP Morgan estimating the market opportunity to exceed $1 trillion in annual revenue [86], PricewaterhouseCoopers projecting a substantial contribution to global GDP from VR and AR technologies [87], and Bloomberg anticipating significant market growth [88]. These projections highlight the metaverse's potential to enhance market accessibility, reduce operational costs through decentralized autonomous organizations (DAOs) [89], and create new avenues for economic activity and growth.

Table 1
A summary of the social and economic benefits of the metaverse.

Category	Benefits
Social Benefits	• Inclusivity: Users can create diverse avatars, overcoming physical world biases. • Educational Transformation: Immersive learning experiences, blockchain-enabled virtual campuses, customized learning pathways, and gamified education to improve engagement. • Enhanced Social Interactions: Immersive social experiences, transforming personal and social interactions online. • Skills Development: Growing demand for specific skills in 3D art, game design, and platform-specific expertise.
Economic Benefits	• New Revenue Streams: Integration into industries like music (e.g., virtual concerts) and sports (e.g., virtual events with digital memorabilia) boosts economic activity. • Market Growth: Significant economic opportunities with large potential market growth. • Business Innovation: Companies can enhance operations, reduce costs, protect intellectual property, and gain insights through data collection. • Sustainable Practices: Opportunities for implementing sustainable business practices. • Global Reach and Accessibility: Virtual platforms allow businesses to expand their market reach and engage with a global audience. • Job Creation: Significant potential for job creation in the metaverse. • Operational Efficiency: Reduction in operational costs through Decentralized autonomous organizations (DAOs).

Government initiatives, such as Spain's investment in Web3 and metaverse technologies through the Digital Spain 2026 strategy [90], acknowledge the metaverse's capacity for spurring technological innovation and generating employment opportunities. This evolving landscape indicates a growing demand for skills in 3D art, game design, and platform-specific expertise [85].

Socially, the metaverse will foster inclusivity, enabling users to overcome physical world biases by creating avatars that reflect a diverse range of identities [91]. It offers transformative educational opportunities, from immersive learning experiences that allow the practical application of theoretical knowledge [92] to blockchain-enabled virtual campuses that enhance university experiences [93]. Furthermore, the potential for online education to transcend traditional barriers to social interaction and informal learning in the metaverse [1] signifies a shift towards more accessible and engaging educational models. The technological prowess of the metaverse can be capitalized to allow for customized learning pathways that cater to individual student needs, making the experience of learning not only resemble physical learning, but also personal to the student [94,95]. The metaverse can also assist in "gamifying" the learning process, and this is considered to be one of the most effective uses of the metaverse in education [94]. The learning environment can also be pre-programmed using VR technology, leading to higher quality education being provided [95]. Furthermore, over 6000 students at the largest online schools in Japan currently use VR technology via the Meta Quest 2 headsets to learn, while also honing social skills, albeit virtually [96], showcasing that much of education can be transformed through the effective use of metaverse. A summary of the above social and economic benefits of the metaverse is provided in Table 1.

2.3. Web2 vs Web3

Although there is no exact definition of Web3, however, the stark difference between Web3, in which current metaverses operate within, as opposed to Web2, is the decentralization of the economy but this comes with the issue of unnecessary volatility for the users [13]. There is however, the incorporation of artificial intelligence in Web3 and a greater utility [97].

In comparing Web2 and Web3, a key distinction lies in their approaches to real-money trade (RMT) within virtual environments. Web2 primarily operates on virtual currency schemes with unidirectional flow, where users can purchase virtual items with real money but cannot convert virtual currency back into real money. This setup limits the economic scope of virtual transactions and maintains a clear boundary between virtual and real economies. In contrast, Web3 emphasizes bidirectional flow, which enables the conversion of virtual currency into real money and vice versa. This opens up possibilities for more complex economic interactions within virtual environments but also introduces legal and regulatory challenges regarding the legitimacy of online transactions, particularly within online gaming contexts. Thus, the classification of metaverses under development can be divided into two main categories: closed virtual schemes (no RMT) and virtual currency schemes with bidirectional flow, which align more closely with the principles of Web3.

The evolution of the metaverse is closely linked to the development of Web3, distinguished by two key factors that overcome the constraints of Web2, leading to a decentralized digital ecosystem that emphasizes user empowerment. The first factor addresses the metaverse's requirement for extensive data storage to accommodate digital assets, such as avatars and digital twins. The limitations of centralized cloud storage, as noted by Xu et al. [98], suggest that such a model may not effectively support the metaverse's expansive data needs. In contrast, blockchain technology offers a decentralized solution for data storage, allowing for the creation, validation, and recording of data in a distributed manner [99,100].

The second factor concerns the ownership and control of digital assets within the metaverse. Centralized digital economies, predominantly managed by large corporations, imply that the assets within the metaverse are owned by these operators rather than the users. To counteract this, blockchain technology is proposed to ensure decentralization and fairness within the metaverse, enabling the development of decentralized social ecosystems through the use of smart contracts [93,101]. NFTs are highlighted as a means to establish ownership of digital assets securely [102], while decentralized financial systems and tokens offer liquidity options for users [103]. Additionally, the adoption of DAOs could revolutionize the governance structures of virtual communities and businesses, moving away from traditional centralized models [104].

Table 2
A comparison between the properties of Web2 and Web3 technologies.

Property	Web2	Web3
Economy	Centralized, closed with no RMT	Decentralized, virtual
Currency Flow	Unidirectional: Real money to virtual currency	Bidirectional: Real money to virtual currency and vice versa
Data Storage	Centralized cloud	Decentralized storage using blockchain technology
Digital Asset Ownership	Owned by platform operators or corporations	Owned by users via blockchain and NFTs
Volatility	Less volatile due to centralized control	More volatile due to decentralization
Governance	Centralized management	Decentralized through smart contracts and DAOs
Utility	Limited by centralized control	Greater utility with support for complex applications

This shift towards a Web3-based meta-economy, or "metanomics", signifies a novel approach to virtual economies, leveraging Web3 infrastructure to foster a more equitable economic model within the metaverse. Although the concept of an economy within the metaverse predates blockchain technology, as evidenced by Bloomfield [105]'s exploration of "metanomics" through Second Life, the introduction of blockchain brings a new dimension to the economics of the metaverse. Bloomfield [105] conducted early research relating to a laboratory economy smaller in scale to those in the current metaverse. This was followed with exploring how controlled studies in larger economies could be conducted, of which one possibility would be a virtual world that consisted of "business-oriented serious games". Bloomfield [105] noted that this could bring changes to the education and research sectors, with goals that include incorporating in-world activities into traditional forms of education, while also assuring flexibility, and maintaining a focus on real-world business. Focusing on Second Life, Bloomfield [105] was particularly interested in its financial community that relied on the Linden Dollar exemplifying how the gaming dimension somewhat paralleled the business dimension. Notably, Bloomfield [105]'s work emphasized the complexity of virtual economies, considering their technical, legal, business, and gaming dimensions even before the advent of blockchain technology. Examples of these dimensions of virtual economies include the provision of business education relating to trade, inventory management, production, and more; the creation of custom legal institutions or property rights, contracts and voting abilities; the creation, trade, and use of game assets. Additionally, experimental research into participant behavior can be conducted and user-created production functions can be generated. Bloomfield [105] also asserted how business reporting systems and databases — both internal and external, "underl[ie] every virtual world", not unlike the blockchain as we know it today. Readers are directed to Bloomfield [105] for further details on early insights into the concept of metanomics. A comparison of the above properties of Web2 and Web3 is provided in Table 2.

2.4. Economic continuity and speculation

The metaverse holds significant potential to reshape future economic and social structures, but its development faces substantial technological and infrastructural hurdles. In December 2021, Koduri from Intel emphasized the necessity for a thousand-fold increase in computational efficiency to realize a fully immersive and accessible metaverse. This indicates a pressing need for advancements in both hardware and software [106]. Such a statement positions the metaverse as a dynamic entity within a context marked by intense anticipation and speculative investment. Critiques of the metaverse, such as those by Kim [107] and Jones [108], raise concerns about its current infrastructure and the concrete evidence supporting its utility, likening the excitement to "meta déjà vu". This skepticism is informed by the historical context of Linden Lab's Second Life, which offered a multi-user environment with its own economy and intellectual property rights for users [109].

However, the trend of investing in digital lands, as seen in platforms like Decentraland and Axie Infinity [110,111], echoes the earlier virtual real estate investments in Second Life, indicating sustained interest in metaverse economies. The involvement of major corporations in Second Life, such as Nissan, Disney, and Amazon, underscores early corporate engagement in virtual spaces [112–115], suggesting a long-standing interest in exploring these digital environments for commercial opportunities.

Comparing past and present metaverse initiatives shows a consistent focus on digital environments for user interaction and commerce. Despite challenges related to the visual quality and affordability of VR/AR technologies [116,117], Meta's decision to increase VR headset prices in 2022 signals a commitment to enhancing the metaverse experience. Moreover, concerns from the Council of the European Union [118] and other companies [119] about privacy, safety, and governance underscore the complexities of metaverse development. The transition from Second Life to current metaverse efforts highlights both continuity and change in the ambitions for virtual worlds, alongside ongoing debates about their feasibility and ethical implications.

The evolution of massively multiplayer online role-playing games (MMORPGs) into the modern metaverse represents a continuum of virtual economies, from traditional Web2 metanomics seen in Everquest (1999), EVE Online, and World of Warcraft (WoW) (2004), to the decentralized economies of Web3 platforms like Decentraland, The Sandbox, and Axie Infinity. This transition highlights the enduring nature of virtual economies, whether in "gaming" metaverses, where players engage in a cycle of activities to enhance their characters, or in "social" metaverses like Second Life, where the goals are less defined and participants engage in a broad range of virtual life activities. In early MMORPGs, the virtual economy was driven by players in completing tasks, earning in-game currency, and trading goods and equipment. This economic engagement led to the emergence of real-world transactions for in-game assets on platforms like eBay, creating underground markets [109,120]. Castronova's analysis of Everquest's "Norrath" revealed a virtual economy with real-world economic parallels, including a gross national product (GNP) per capita and currency valuation [109,112]. The phenomenon of RMT highlighted the challenges of balancing in-game economies with real-world economics, leading to efforts by companies to curb the sale of in-game items on external platforms [112,120].

Drawing parallels between Web2 and Web3 metaverses reveals consistent themes of speculative activity and the creation of virtual economies that extend beyond in-game worlds to real economic impact. Axie Infinity, for example, features virtual pets (via NFTs) that have seen substantial appreciation in value, illustrating the speculative nature that underpins both traditional and modern metaverses [121]. The platforms for buying and selling virtual goods have evolved from eBay to Web3 marketplaces like OpenSea, yet the fundamental dynamics of virtual economies and the opportunity for individuals to earn income through virtual worlds remain consistent.

This analysis demonstrates that while the technology underpinning virtual worlds has advanced from Web2 to Web3, the economic principles and speculative behaviors within these spaces have maintained a remarkable continuity. The transition from traditional MMORPGs to contemporary metaverses encapsulates a broader shift in digital culture and economics, highlighting the persistent allure of virtual worlds as spaces for economic activity, social interaction, and speculative investment.

3. Methodology

3.1. Volatility clustering - GARCH model

The GARCH $(1,1)$ model is a refined method by Bollerslev [122] of the earlier ARCH method by Engle [123]. Both methods study the heteroscedasticity or volatility of time series data [124], where Bollerslev [122]'s GARCH method also includes the lagged conditional variance [125]. In the context of GARCH (1,1), the notation (1,1) indicates the order of the GARCH model. Specifically, the first "1" denotes the number of lagged terms for the conditional variance (GARCH terms), while the second "1" represents the number of lagged squared residuals (ARCH terms). Therefore, GARCH (1,1) involves one lag of the conditional variance and one lag of the squared residuals in its formulation.

The GARCH $(1,1)$ model is applied to the data to test for volatility clustering, which suggests that large price changes tend to cluster together, resulting in continuous large price movements, and similarly, small price changes lead to small price movements. The implementation of the model to the returns of the tokens is specified as

$$X_t = \mu_t + \sigma_t \epsilon_t, \tag{1}$$

where μ_t denotes the conditional mean, σ_t denotes a volatility process, and ϵ_t denotes the innovation process such that $\epsilon_t = \sigma_t \mu_t$. It follows that the conditional variance of the GARCH $(1,1)$ model, σ_t^2, is given by

$$\sigma_t^2 = \tau + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2, \tag{2}$$

where $\tau, \alpha, \beta > 0$. The main component of this model is the "persistence" parameter, denoted by $\alpha + \beta$, which captures the amount of volatility clustering captured by the model. In terms of interpreting this value, a significantly positive value for $\alpha + \beta$ indicates the presence of volatility clustering; $\alpha + \beta < 1$ indicates weak stationarity; $\alpha + \beta = 1$ indicates the time series is stationary and has strong persistence to volatility shocks. Before applying the GARCH $(1,1)$ model, the existence of the ARCH (1) effect should be tested using a GARCH $(0,1)$ model form, which is identical to the ARCH (1) model. The testing for ARCH (1) effects is a diagnostic step. If significant ARCH effects are detected, it justifies the use of a GARCH $(1,1)$ model, which extends the ARCH model by incorporating both lagged returns and lagged conditional variances, allowing for a more accurate modeling of time-varying volatility.

3.2. Asymmetric volatility clustering - GJR model

The GJR model by Glosten et al. [126] addresses the case of asymmetric volatility clustering and the leverage effect in a time series. The leverage effect refers to the phenomenon where past returns are negatively correlated with future volatility, meaning that the variance of returns increases as prices decrease.

The GJR model acts as an extension of the GARCH model. Therefore, the GJR-GARCH $(1,1)$ model is applied, which includes the lagged conditional variance, the lagged squared innovations, and the lagged squared negative innovations as its main components. The conditional variance of the model, denoted as σ_t^2, is given by

$$\sigma_t^2 = \tau + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \xi_t I[_{\xi_{t-1}} < 0]\epsilon_{t-1}^2, \tag{3}$$

where ξ_t is the coefficient of the leverage component and $I[\cdot]$ is an indicator function. The leverage effect typically refers to the negative relationship between asset returns and their volatility, which is crucial for making justifiable inferences [127]. If $1 - \alpha - \beta - 0.5\xi > 0$, this indicates that the time series is stationary and the volatility is mean-reverting. For more complete details regarding this derivation, we refer readers to Appendix. The GJR-GARCH $(1,1)$ model is a special case of the GARCH $(1,1)$ model when $\xi = 0$.

3.3. Long range dependence - Detrended fluctuation analysis

The long-range dependence in the NFTs, is analyzed using the detrended fluctuation analysis (DFA) method to calculate the Hurst exponent. While there are alternative methods, such as the R/S analysis, the DFA method is preferred due to its suitability for non-stationary time-series data and its effectiveness in testing the random walk hypothesis. As noted by Zhang et al. [128], the first step in computing the Hurst exponent values is to create an integrated time series of length M:

$$Z_i = \sum_{t=1}^{i} [X_{(t)} - \bar{X}], \tag{4}$$

where $X_{(t)}$ is the ith element of the stochastic time series X_t, in this case NFT returns, and $\bar{X}$ denotes the mean of X_t. In addition, $Z_{(i)}$ is divided into M/m non-overlapping subsamples. Then, the local trend of each subsample can be determined by computing a polynomial fit $Z_{pol(i/m)}$. In this study, we follow the original DFA methodology proposed by Peng et al. [129] such that the order of the polynomial fit is one and thus the local trend is simply the estimate of the time series value obtained from performing a linear regression on the corresponding subsample (block) of the integrated time series.

The integrated time series $Z_{(i)}$ is then detrended by subtracting the local trend $Z_{pol(i/m)}$. The fluctuation function is defined as

$$F_{(m)} = \sqrt{\frac{1}{M} \sum_{t=1}^{M} [Z_{(i)} - Z_{pol(i/m)}]^2}. \tag{5}$$

After multiple iterations using various values of the block size m, it is observed that the fluctuation function is proportional to a power function of m, with the power being the Hurst exponent, H. Following Zhang et al. [128], we set the maximum block size used in partitioning the data to be half of the length of the time series vector. Therefore, by regressing $\ln F_{(m)}$ against $\ln m$, the Hurst exponent can be determined, and in this study we use six points for the regression estimation, which are m: 4, 8, 16, 32, 64, and 128. The Hurst exponent (α) ranges from 0 to 1, where a value of 0.5 indicates a random walk; a value between 0.5 and 1 (inclusive) suggests trend-reinforcing behavior; a value between 0 and 0.5 (inclusive) indicates anti-persistence behavior. In general, a non-zero value (different from 0.5) signifies evidence of long-term correlations.

3.4. Return-volume relationship - Quantile on quantile regression

The return-volume relationship is a well-documented stylized fact observed in various markets, including stock markets [130], interest rates and currency futures [131], commodities [132], and real estate [133]. Understanding the dynamic relationship between volume and returns can offer critical insights into market microstructure and provide valuable information about future price movements for market participants. From an economic and financial perspective, this relationship can shed light on how market information is conveyed and incorporated into the prices of financial instruments.

We use the quantile-on-quantile regression (QQR) method proposed by Sim and Zhou [134] to investigate the return-volume relationship. The QQR method enables the regression model to consider the quantiles of both the dependent and independent variables, allowing the relationship to vary at different points in their respective distributions. The QQR method is specified as follows.

Let the quantile of an NFT token's returns be denoted as the superscript θ. The regression model for the θ-quantile of the NFT token's returns (NFT_t) as a function of its lagged returns (NFT_{t-1}) and returns of its trading volume ($VOLM_t$) is

$$NFT_t = \beta^{\theta}\left(VOLM_t\right) + \alpha^{\theta} NFT_{t-1} + \epsilon_t^{\theta}, \tag{6}$$

where $0 \leq \theta \leq 1$, and ϵ_t^{θ} is an error term that has a zero θ-quantile.

As in Sim and Zhou [134], the link function $\beta^{\theta}(\cdot)$ is assumed to be unknown since it would be reasonable that we do not know exactly how NFT token returns and the returns of their trading volume are related prior to our analysis. To investigate the relationship between the θ-quantile of the NFT token's returns and some τ-quantile of the returns of its trading volume ($VOLM^{\tau}$), this function can be linearized by taking a first-order Taylor expansion of $\beta^{\theta}(\cdot)$ around $VOLM^{\tau}$, resulting in

$$\beta^{\theta}\left(VOLM_t\right) \approx \beta^{\theta}\left(VOLM^{\tau}\right) + \beta^{\theta}\left(VOLM^{\tau}\right)\left(VOLM_t - VOLM^{\tau}\right). \tag{7}$$

It can be seen that since $VOLM^{\tau}$ is a function of τ and $\beta^{\theta}(\cdot)$ is a function of θ, the link function of a particular quantile of volume returns, $\beta^{\theta}(VOLM^{\tau})$, is a function of both θ and τ. For convenience, Eq. (7) can be expressed as

$$\beta^{\theta}\left(VOLM_t\right) \approx \beta_0(\theta,\tau) + \beta_1(\theta,\tau)\left(VOLM_t - VOLM^{\tau}\right), \tag{8}$$

where $\beta_0(\theta,\tau) = \beta^{\theta}(VOLM^{\tau})$ and $\beta_1(\theta,\tau) = \beta^{\theta'}(VOLM^{\tau})$, respectively [134].

Substituting Eq. (8) back into (6) we obtain

$$NFT_t = \beta_0(\theta,\tau) + \beta_1(\theta,\tau)\left(VOLM_t - VOLM^{\tau}\right) + \alpha(\theta) TOKEN_{t-1} + \epsilon_t^{\theta}, \tag{9}$$

which provides an expression for the relationship between the θ-quantile of an NFT token's returns and the τ-quantile of the returns of its trading volume. As mentioned above, this approach offers a comprehensive view of the relationship between the returns of an NFT token's prices and trading volume across their entire distributions.

Table 3
Brief summaries of the five NFTs analyzed.

Token	Description
AXS	AXS is the token for Axie Infinity, a game where players collect and trade digital creatures called "Axies". The token was launched in 2018 and is headquartered at the Sky Mavis studio in Vietnam. It operates on the Ethereum blockchain and utilizes the Ronin sidechain as its decentralized app (dApp) platform [137]. AXS is not mineable.
MANA	MANA is the currency for Decentraland, a decentralized virtual world where users own and trade land. Launched in 2017, the token is headquartered in California, USA, and operates on the Ethereum blockchain [71]. MANA is used within the Decentraland virtual world and is not mineable.
ENJ	ENJ is a token used for purchasing digital goods in games like Minecraft. Launched in 2018 and based in Singapore, it operates on the Ethereum blockchain and is utilized within the Enjin platform for digital goods [138]. ENJ is not mineable.
THETA	THETA is a token used on the THETA Network, a decentralized infrastructure for video, AI, and entertainment use cases. Launched in 2019 and based in the United States, it operates on its own THETA blockchain but can also run on Ethereum [139]. THETA is not mineable.
SAND	SAND is the utility token for The Sandbox, a virtual gaming world. Launched in 2012 and headquartered in Hong Kong, it operates on the Ethereum blockchain and is utilized within the Sandbox platform [72]. SAND is not mineable.

The final step is to estimate Eq. (9) and obtain estimates of β_0 and β_1. We note that in this analysis we work directly with the sample values of the returns of the prices and trading volume, so unlike Sim and Zhou [134] it is not necessary to estimate any data values. To estimate Eq. (9), the following minimization problem is solved

$$\min_{b_0,b_1} \sum_{t=1}^{n} \rho_\theta \left[NFT_t - b_0 - b_1\left(VOLM_t - VOLM^\tau\right) - \alpha^\theta NFT_{t-1}\right] K\left(\frac{F_n\left(VOLM_t\right) - \tau}{h}\right), \tag{10}$$

where ρ_θ denotes the tilted absolute value function giving the θ-conditional quantile of $TOKEN_t$ as the solution, $F_n(\cdot)$ is the empirical distribution function, $K(\cdot)$ is the Gaussian kernel, and h is the bandwidth. We note that the solutions of b_0 and b_1 to the minimization problem thus correspond with the optimal values of the estimates $\hat{\beta}_0(\theta,\tau)$ and $\hat{\beta}_1(\theta,\tau)$ for each combination of θ and τ.

This method is applicable to NFT tokens in general, therefore, the process is identical for all NFT tokens and can be adapted by simply substituting the specific token of interest. For further details and discussion regarding this method, we refer readers to Sim and Zhou [134].

4. Data

This paper analyzes the historical daily closing prices of five NFTs, namely Axie Infinity (AXS), Decentraland (MANA), Enjin Coin (ENJ), Theta Network (THETA), and The Sandbox (SAND) in US Dollars (USD) for the period of November 2020 to October 2022. The five NFTs were selected based on their market capitalization ranking, trading volume, and continuous availability for trading from November 2020 to October 2022. Moreover, the NFTs were chosen for their dominance, as they accounted for 50%–65% of the total market capitalization of the NFT market during the two years preceding the end of our sample period. For a brief summary of the five tokens, we refer the readers to Table 3. The data was sourced from CoinMarketCap [135], which provides a unified daily closing price for each token by computing the volume-weighted average of all market pair prices across available exchanges. In the following analysis, we utilized the returns of the five NFTs. To achieve stationarity, the data was adjusted using the procedure outlined by Gallant and Tauchen [136], resulting in the log returns of each token, which were computed as

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right),$$

where P_t and P_{t-1} refer to the closing prices on days t and $t-1$, respectively.

4.1. Summary statistics

Summary statistics for the daily returns of the prices and volume of the five NFTs are provided in Tables 4 and 5. Statistics include the number of observations (N), minimum, maximum, mean, median, skewness, kurtosis, standard deviation (SD), variance, range, and interquartile range (IQR). In particular, the skewness and kurtosis are analyzed to measure the level of symmetry in the returns and quantify the heaviness of the tails of the distribution of returns.

The results in Tables 4 and 5 show that AXS/USD exhibits the lowest minimum returns across prices and volume. MANA/USD exhibits the highest maximum returns of prices in Table 4, while SAND/USD exhibits the highest maximum returns of volume in Table 5. The mean returns for prices and volume across all NFT tokens are close to zero, and the median values for the returns of prices are also close to zero. However, the median values for the returns of volume appear lower than those for the returns of prices and are all negative.

With respect to the returns of prices, all kurtosis values exceed the typical value of three and indicate more peaked and heavier-tailed returns compared to the normal distribution. In contrast, most volume returns exhibit lighter tails, except for AXS/USD, which has a kurtosis value slightly above three. The returns of prices are generally positively skewed, except for THETA/USD, which shows

Table 4
Summary statistics of the log returns of daily market prices for AXS/USD, MANA/USD, ENJ/USD, THETA/USD, and SAND/USD, over the full sample period. Test statistics are shown for the tests of normality, stationarity, and serial correlation.

Statistics	NFT Price Returns				
	AXS	MANA	ENJ	THETA	SAND
Observations	706	706	706	706	706
Minimum	−0.500	−0.371	−0.438	−0.495	−0.459
Q1	−0.043	−0.039	−0.041	−0.035	−0.039
Median	−0.002	0.000	0.000	0.003	0.000
Mean	0.006	0.003	0.002	0.001	0.005
Q3	0.043	0.036	0.041	0.038	0.040
Maximum	0.530	0.933	0.442	0.260	0.701
Skewness	0.974	2.116	0.420	−0.565	1.054
Kurtosis	4.962	20.265	5.247	4.679	8.694
SD	0.093	0.088	0.079	0.071	0.090
Variance	0.009	0.008	0.006	0.005	0.008
Range	1.030	1.304	0.880	0.755	1.160
IQR	0.086	0.075	0.082	0.073	0.079
Jarque–Bera	843.05*	12688*	837.83*	687.89*	2371.4*
Kolmogorov–Smirnov	0.420*	0.421*	0.418*	0.425*	0.419*
Augmented Dickey–Fuller	−8.472*	−9.117*	−8.799*	−8.081*	−8.680*
Ljung–Box	0.015*	0.320*	1.465*	6.580*	0.111*

* Indicates statistical significance at the 1% level of significance.

Table 5
Summary statistics of the log returns of daily trading volume for AXS/USD, MANA/USD, ENJ/USD, THETA/USD, and SAND/USD, over the full sample period. Test statistics are shown for the tests of normality, stationarity, and serial correlation.

Statistics	NFT Volume Returns				
	AXS	MANA	ENJ	THETA	SAND
Observations	706	706	706	706	706
Minimum	−3.134	−1.461	−1.702	−1.144	−1.369
Q1	−0.301	−0.293	−0.257	−0.273	−0.293
Median	−0.035	−0.044	−0.041	−0.033	−0.019
Mean	0.002	0.003	0.003	0.001	0.005
Q3	0.233	0.238	0.235	0.230	0.277
Maximum	2.305	2.197	2.509	1.867	3.034
Skewness	0.457	0.630	0.842	0.533	0.698
Kurtosis	3.817	1.349	2.953	1.053	2.636
SD	0.514	0.445	0.448	0.424	0.481
Variance	0.265	0.198	0.200	0.180	0.231
Range	5.439	3.658	4.211	3.011	4.403
IQR	0.534	0.531	0.493	0.505	0.570
Jarque–Bera	457.57*	101.42*	343.25*	66.965*	264.41*
Kolmogorov–Smirnov	0.203*	0.214*	0.213*	0.219*	0.197*
Augmented Dickey–Fuller	−10.706*	−11.406*	−11.441*	−11.855*	−10.889*
Ljung–Box	27.441*	1.8734*	27.201*	30.702*	4.940*

* Indicates statistical significance at the 1% level of significance.

negative skewness. Regarding variability, both price and volume returns have similar standard deviations within their categories, approximately 8%–9% for price returns and 40%–50% for volume returns, with THETA/USD exhibiting the smallest volatility.

Each of the daily returns series was also subject to the Jarque–Bera (JB) [140] and Kolmogorov–Smirnov (KS) [141,142] tests to examine the normality of the returns series. Stationarity was tested using the Augmented Dickey–Fuller (ADF) test [143], and serial correlation was examined using the Ljung–Box (LB) test [144]. The JB, KS, ADF, and LB tests for each of the series of returns of the prices and volume for all five NFTs were found to be significant at the 1% level of significance. The JB and KS tests reject the null hypothesis of normality, confirming our previous findings for the kurtosis. The ADF test rejects the null hypothesis of a unit root, indicating stationarity in the data. Lastly, the LB test rejects the null hypothesis of no serial correlation. For example, the Ljung–Box text result for AXS in Table 4 indicates that the returns of AXS prices are correlated, suggesting that past returns of AXS prices influence future returns of AXS prices.

5. Results and discussion

5.1. Heavy tail behavior

The Hill tail index estimator, as proposed by B.M. [145], was applied to the daily log returns of prices for the five NFTs over the sample period. The premise of heavy tails relates to the power law distribution and its scaling, where the tail index is the

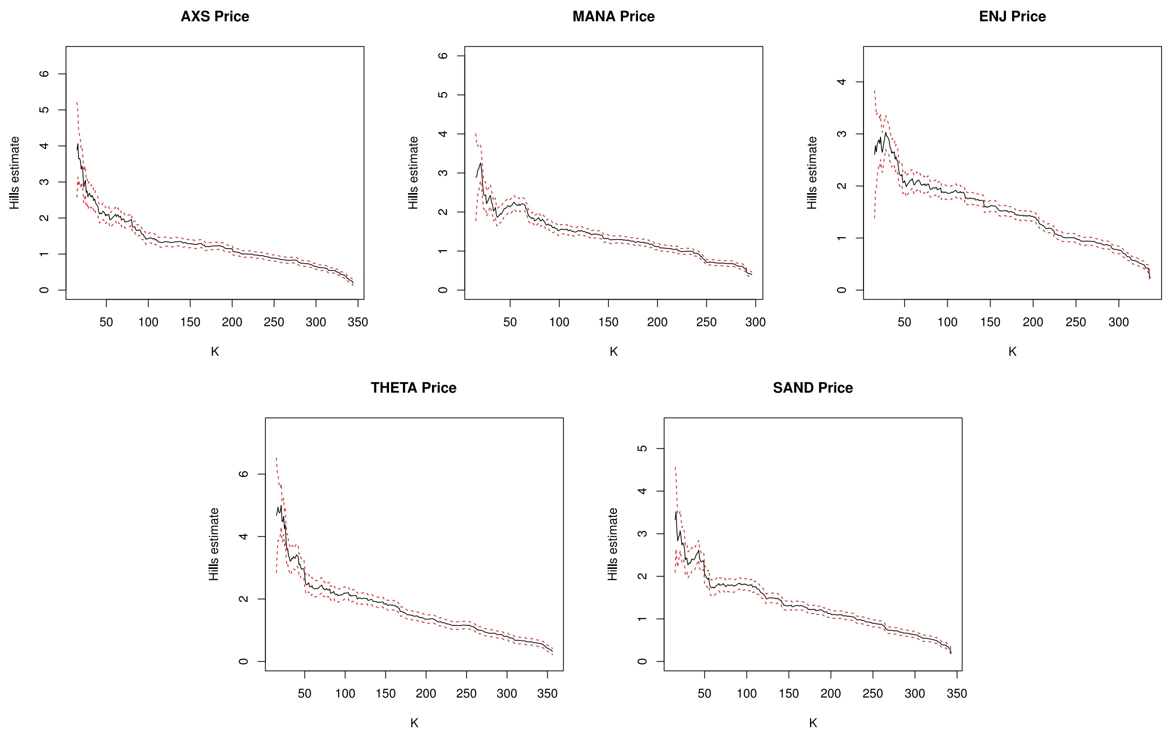

Fig. 5. Plots of the Hill tail index estimates for the log returns of prices of the five NFTs using varying numbers of samples K. The upper and lower bounds of the 95% confidence intervals are indicated by the red dashed lines.

parameter in the power law that determines how heavy the tail is, where the higher the tail index the thinner the tail. The analysis was conducted in R [146], and the results are illustrated in Fig. 5. The plots serve as robust indicators for analyzing the heavy-tailed nature of NFT returns.

In all instances, estimates of the Hill tail index exhibit a decreasing trend with an increasing number of samples, K, indicating that NFT returns are characterized by heavy tails. This behavior of the tail index is significant as it quantitatively confirms the presence of extreme values with a higher probability than would be expected under a normal distribution. A lower tail index suggests a higher likelihood of extreme return events, highlighting potential risks and opportunities for investors in the NFT market. Such insights are crucial for risk management and for understanding the behavior of assets within the rapidly evolving NFT ecosystem. For a more technical discussion of tail index estimation, we refer readers to B.M. [145].

5.2. Autocorrelation

The autocorrelation of daily log returns for the five NFTs over the sample period is shown in Fig. 6. For each lag, the vertical bar indicates the value of the autocorrelation function — where any bar exceeding the 95% confidence interval represented by the blue dotted line (above or below) indicates significant autocorrelation at that lag. Fig. 6 reveals that for all five NFTs, the autocorrelation values decay rapidly and to within the blue dotted lines as the lag value increases and remain within the 95% confidence interval after only a few lags. This suggests that for most lags, the autocorrelation is statistically insignificant and that past returns have little to no influence on current returns.

5.3. Long range dependence

In the context of financial markets, the Hurst exponent, computed using the DFA method, provides a statistic that indicates deviations from a state of market efficiency. Additionally, it can offer insights into the particular behavior of the market, such as trend reinforcement or anti-persistence, throughout the period analyzed. Fig. 7 presents the plots of the Hurst exponent, calculated using a sliding window of 60 lagged returns of prices covering approximately two calendar months, over the entire sample period for each NFT. As noted by Plakandaras et al. [147] and Selmi et al. [148], there are no specific guidelines on selecting an optimal window size — instead, general recommendations simply suggest that sliding windows should not be too large or too small. However, we note that numerous related studies use relatively small sliding window sizes or sliding windows that reflect smaller time periods, which are consistent with our choice of window length. For example Zhang et al. [128] use windows of 720 hourly returns (covering one calendar month); Zhang et al. [149] use windows of 1000 hourly returns (covering approximately 42 days); Zargar and Kumar

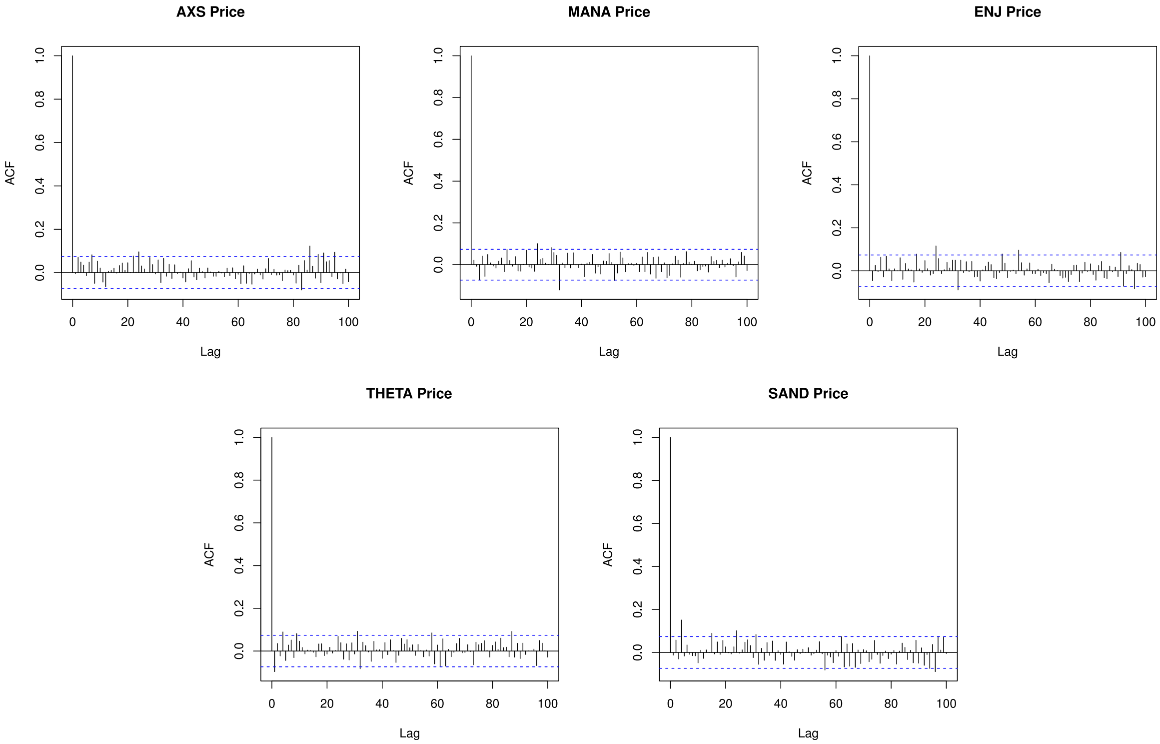

Fig. 6. Plots of the autocorrelation function of the log returns of prices for the five NFTs, for lags one to 100 over the sample period. The upper and lower bounds of the 95% confidence interval are indicated by the blue dashed lines.

[150], David et al. [151], and Bielinskyi et al. [152] all use windows of 100 daily data points (covering approximately three calendar months). Therefore, in line with the existing literature, we believe that our choice of a 60-day sliding window with daily frequency data achieves a balance between a small enough window that is able to capture trends in the Hurst exponent but a large enough window that reduces the influence of noise.

Taking the example of the Hurst exponent for AXS, throughout the entire sample period, the estimated Hurst exponent values for AXS fluctuate significantly between 0.3 and 0.8. This suggests that the log returns of AXS prices are relatively inefficient (exhibiting non-random walk behavior), and demonstrate varying degrees of trend reinforcement (an exponent greater than 0.5) and anti-persistence (an exponent less than 0.5) throughout the sample period. In general, it can be seen that for the remaining four NFTs of MANA, ENJ, THETA, and SAND, a similar conclusion is also reached. This variability in market behavior can present opportunities for traders and investors who are able to identify and capitalize on these patterns. For the broader NFT market, the analysis of the Hurst exponent can provide insights into the overall market efficiency and the presence of trends or reversals. Understanding these dynamics can be crucial for investors, collectors, and creators in the NFT space, as it can influence pricing, development of investment strategies, and market sentiment.

We note that similar findings have been observed in other blockchain-related products, such as cryptocurrencies and decentralized finance (DeFi) tokens. For instance, Khuntia and Pattanayak [153] applied non-linear dependence tests for the martingale difference hypothesis (MDH) to explore the adaptive market hypothesis in daily Bitcoin returns, revealing that market efficiency evolves dynamically over time. Additionally, Chu et al. [154] used the MDH test to analyze the adaptive market hypothesis in the high-frequency (hourly) markets of the two largest cryptocurrencies, Bitcoin and Ethereum, against the Euro and US dollar. Results observed are also consistent with the present study in that the dependence and predictability of returns varies over time, shifting between random behavior, and trend reinforcing or anti-persistent behavior. Interestingly, Zhang et al. [155] discovered that DeFi market returns are mostly efficient, with only brief periods of inefficiency and predictability in their prices each year.

5.4. Volatility clustering

We applied the ARCH test and GARCH $(1,1)$ model to analyze the volatility clustering in the daily log returns of NFT prices, with the results presented in Table 6. The significance of the ARCH test at the 1% level for all five NFTs indicates the presence of time-varying volatility, a prerequisite for implementing the GARCH model. The implementation of the GARCH$(1,1)$ model reveals that the estimates of the persistence parameter, $\alpha + \beta$, are significantly positive for all NFTs, confirming the presence of volatility clustering and are close to one for all tokens, suggesting the high persistence of volatility shocks over time. However, the MANA

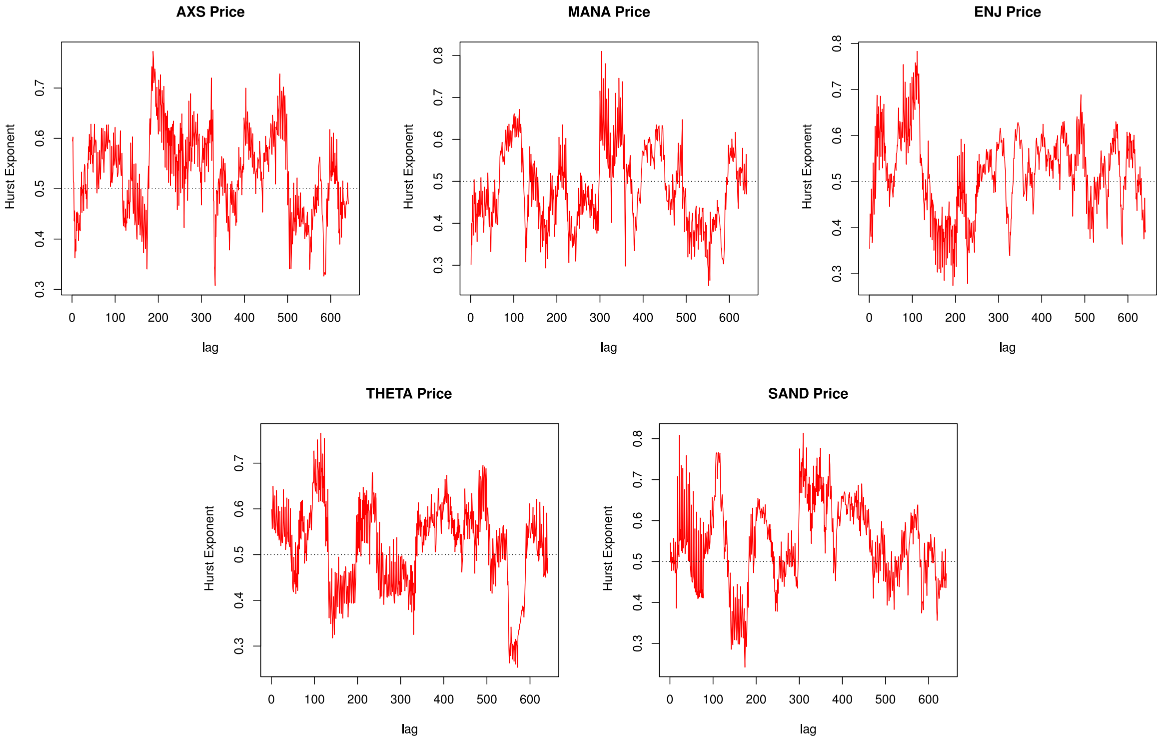

Fig. 7. Plots of the estimated Hurst exponents computed via the DFA method for the five NFTs over the entire sample period, using a sliding window of 60 lagged returns of prices.

Table 6
Estimates of the ARCH test statistics and GARCH(1,1) model parameters of the ARCH term, GARCH term and the persistence parameter.

Token	ARCH test	ARCH (α)	GARCH (β)	$\alpha + \beta$
AXS	841.67*	0.047	0.951	0.998
MANA	12884*	0.514	0.286	0.800
ENJ	835.92*	0.070	0.915	0.985
THETA	687.36*	0.072	0.899	0.971
SAND	2371.4*	0.143	0.811	0.954

* Indicates significance at the 1% level.

Table 7
Estimates of the GJR(1,1) model parameters of the constant, ARCH term, GARCH term, leverage parameter and the stationarity parameter.

Token	Constant	ARCH (α)	GARCH (β)	Leverage (ξ)	$1 - \alpha - \beta - 0.5\xi$
AXS	0.000	0.027	0.954	0.036	0.001
MANA	0.002	0.542	0.281	−0.069	0.212
ENJ	0.000	0.071	0.918	−0.008	0.015
THETA	0.000	0.067	0.910	−0.002	0.024
SAND	0.001	0.174	0.801	−0.084	0.067

token exhibits a persistence value of 0.800, indicating moderate persistence and greater volatility in response to variance changes. Overall, all five NFTs show volatility clustering with varying levels of persistence, with volatility shocks generally persisting over time.

5.5. Asymmetric volatility clustering

We employ the GJR model to investigate the leverage effect in the daily log returns of NFT prices, with the results shown in Table 7. The leverage effect is determined by the parameter ξ in the GJR model. For the majority of NFTs (MANA, ENJ, THETA, SAND), the leverage effect is found to be negative, implying that negative returns decrease volatility. In contrast, AXS exhibits a positive leverage effect, suggesting that negative returns increase volatility more than positive returns. Additionally, for all NFTs,

$1 - \alpha - \beta - 0.5\xi > 0$, indicating that the time series of log returns of the prices of all NFTs are stationary and the volatility in all cases is mean-reverting, which corroborates the findings from the previous section.

Empirical research into leverage effects across cryptocurrency markets reveals both similarities and differences. Panagiotidis et al. [156] observed that most cryptocurrencies exhibit an inverse leverage effect, with stronger reactions to positive past returns than to negative returns, suggesting an unconventional response compared to traditional financial markets. Conversely, Yu [157] emphasized the significant influence of leverage effects on Bitcoin's future volatility, with these effects being particularly pronounced in predictive scenarios, thereby underscoring the unique role of leverage dynamics within this context.

5.6. Return-volume relationship

We apply the QQR method to analyze the relationship between daily returns of NFT prices and trading volume. All QQR analyses were conducted using R [146]. The results are presented in Fig. 8, which displays the estimates of β_1 at various quantiles of the returns of NFT prices (θ) and returns of trading volume (τ), as described in Eq. (10), for the range of $0.05 \leq \theta, \tau \leq 0.95$.

The results reveal both similarities and variations in trends across different quantile combinations. Generally, at the upper quantiles of trading volume returns (τ close to one) and price returns (θ close to one), with the exception of the SAND token, the estimated values of $\hat{\beta}_1$ are predominantly large and negative compared to other quantiles. This negative relationship at the upper quantiles may reflect market sentiment, where high trading volumes coupled with decreasing price returns could indicate a bearish outlook among investors or profit-taking, leading to downward pressure on prices. However, this negative relationship is not observed for the opposite combination of lower quantiles of returns (θ and τ close to zero), indicating that significant negative changes in trading volume and prices do not commonly occur together, and do not appear to influence each other. Near the middle quantiles of trading volume returns (τ approximately 0.5) and price returns (θ approximately 0.5), estimates of $\hat{\beta}_1$ are typically close to zero. This suggests that when NFT prices and volume are not showing significant movements, there is little or no relationship between the returns of prices and volume.

Surprisingly, the SAND token exhibits unique results compared to all other tokens. At the upper quantiles of trading volume returns (τ above 0.8), $\hat{\beta}_1$ is generally positive and larger than at any other quantile, indicating that large positive changes in trading volume are positively correlated with the returns of SAND token prices, regardless of market conditions. Moreover, near the median of trading volume returns (τ around 0.5), $\hat{\beta}_1$ tends to be close to zero, suggesting that when trading volume is relatively stable, the returns of SAND token prices do not significantly correlate with volume changes.

Existing studies have produced mixed findings on the relationship between trading volume and returns in the cryptocurrency market. Chan et al. [158] observed only a weak positive correlation between return and volume at the tails, challenging the common belief that volume significantly influences prices. This suggests a potential misinterpretation among market participants, contributing to market illiquidity and extreme price movements. Conversely, Cagli [159] demonstrated a causal link where trading volume predicts returns for Bitcoin and other altcoins. Aalborg et al. [160] found that while Bitcoin trading volume does not directly predict returns, there is a significant correlation with price volatility, indicating an indirect effect on returns. In earlier research, Kokkinaki et al. [161] noted a positive, significant relationship between Bitcoin trading volume and returns before the 2014 Mt. Gox exchange hack, attributed to a return premium from increased investor attention. Hau et al. [162] used quantile regression to show a positive relationship between transaction activity and returns, intensifying at higher return quantiles. However, using multifractal analysis, El Alaoui et al. [163] found Bitcoin prices changes and changes in trading volume to mutually interact in a nonlinear way. This was attributed to significant long-range cross correlations, where the widths of multifractal spectra for price-volume cross-correlation were significantly different from zero, thus signaling a clear departure from a random walk process. A negligible linear correlation between Bitcoin price changes and volume was found, which presumes nonlinear cross-correlation between the series, but strong price-volume cross-correlations were confirmed via the detrended cross-correlation analysis. Together, these results suggest a nonlinear relationship between price and volume, and multifractality.

With respect to alternative digital asset classes, Chu et al. [164] applied the QQR method and extreme value theory to explore how trading volumes and daily returns of DeFi tokens interact at various quantiles and extreme tails. Results showed that significant increases in trading volume typically lead to positive returns, although this relationship can be negative in some instances. The volume-return dependence is notably asymmetric, being insignificant under extreme negative conditions but pronounced under extreme positive conditions.

6. Robustness tests

6.1. Bloomberg metaverse index and yield guild games token

To further ensure the robustness of our findings from Section 5, we extend our analysis to other financial metaverse products that comprise technology companies and gaming tokens. Specifically, we apply the methodology described in Section 3 to the Bloomberg Metaverse Index (BBMI) and the Yield Guild Games (YGG) token price.

The BBMI, developed by Bloomberg Intelligence, tracks the performance of companies with substantial revenue from virtual reality platforms and experiences. Fig. 9 and Table 8 outline the breakdown of sectors and most influential companies that make up the BBMI. The index has a strong focus on the Internet Media and Services sector, with major contributions from Alphabet Inc, Tencent Holdings Ltd, and Meta Platforms Inc, which together make up 17.02% of the index. Other significant sectors include Semiconductors, led by NVIDIA Corporation with a 8.59% weight; E-commerce Discretionary, dominated by Amazon.com Inc with

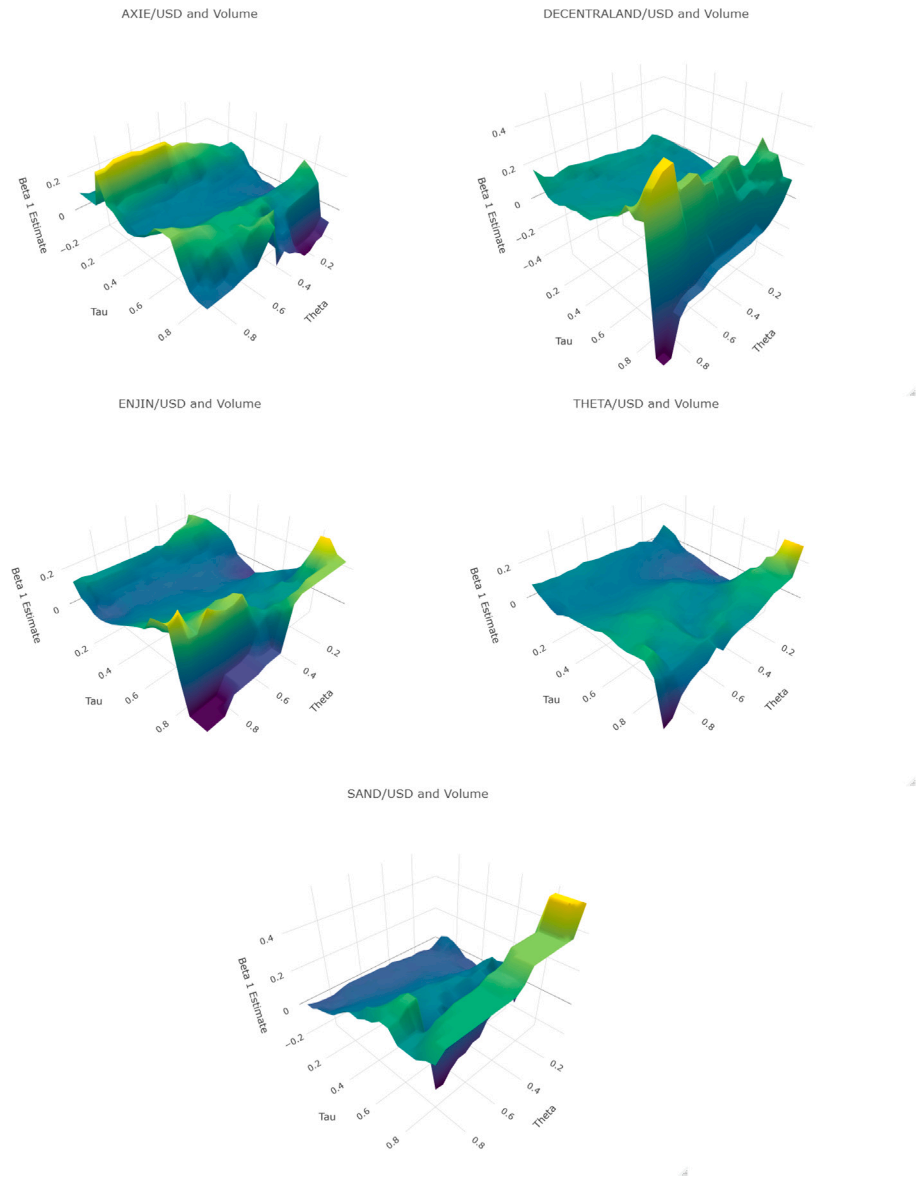

Fig. 8. Quantile-on-quantile regression plots for the returns of the prices of the five NFTs. Surface plots indicate estimates $\hat{\beta}_1(\theta,\tau)$ at $0.05 \leq \theta,\tau \leq 0.95$, corresponding to trading volume returns.

a weight of 7.95%; Technology Hardware and Software, with Apple Inc and Adobe Inc having notable weights of 6.93% and 4%, respectively. The Entertainment sector is also well-represented, with Walt Disney Co and Sony Group Corp holding substantial positions.

YGG is a Decentralized Autonomous Organization (DAO) focused on investing in NFTs used in blockchain-based games and virtual worlds. Its goal is to create the largest virtual economy by maximizing the utility of its community-owned assets and distributing earnings to token holders. These assets are integral to Web3 games, which are central to the metaverse concept, including digital land and assets on blockchain platforms. YGG was co-founded in 2020 by Gabby Dizon and Beryl Li, inspired by the rising popularity of blockchain gaming in Southeast Asia. The organization began by lending in-game NFT characters to players who could not afford them, particularly in developing regions, thereby empowering them to participate in the play-to-earn gaming community.

Our selection of the two assets for the robustness analysis is based on both assets providing a reflection of the value and potential of the metaverse as a whole: the BBMI through its capturing of the most dominant companies involved and invested in the metaverse, and the YGG token reflecting the performance and partnerships of major Web3 companies in which YGG is invested in. As in the main

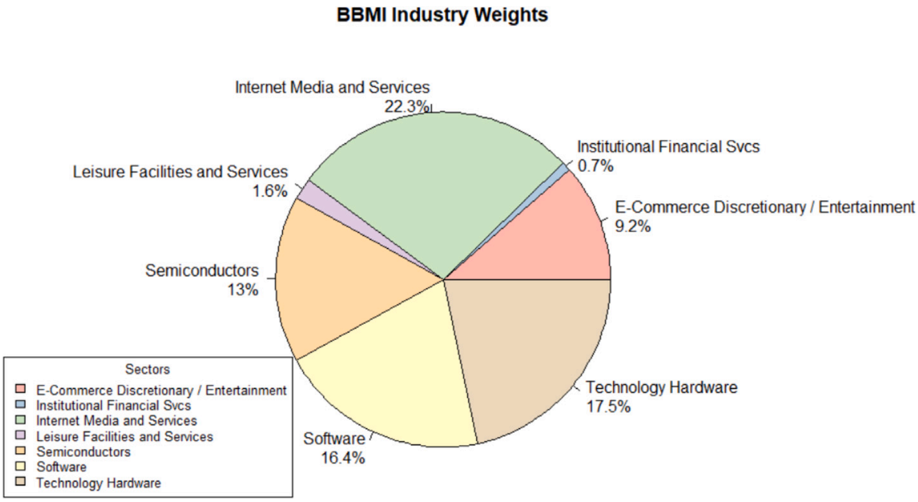

Fig. 9. Visual representation and breakdown of the industry weights within the BBMI.

Table 8
Breakdown of the most significant companies in the BBMI, and their corresponding weights and industries.

Security	Ticker Symbol	Weight	Industry
NIVIDIA Crop	NVDA	8.59%	Semiconductors
Amazon.com Inc	AMZN	7.95%	E-commerce Discretionary
Alphabet Inc	GOOGL	7.29%	Internet Media and Services
Apple Inc	AAPL	6.93%	Technology Hardware
Tencent Holdings Ltd	700	4.91%	Internet Media and Services
Meta Platforms Inc	META	4.82%	Internet Media and Services
Adobe Inc	ADBE	4.00%	Software
Walt Disney Co/The	DIS	3.98%	Entertainment Content
Sony Group Crop	6758	3.94%	Technology Hardware

Table 9
Summary statistics of the log returns of daily market prices and volume for BBMI from November 2020 to October 2022, and YGG from August 2021 to October 2022. Test statistics are shown for the tests of normality, stationarity, and serial correlation.

Statistics	BBMI (Prices)	BBMI (Volume)	YGG (Prices)	YGG (Volume)
Observations	503	503	436	436
Minimum	−0.053	−3.264	−0.461	−1.475
Q1	−0.009	−0.187	−0.052	−0.296
Median	0.001	−0.016	−0.013	−0.035
Mean	−0.001	−0.001	−0.004	0.000
Q3	0.007	0.185	0.038	0.237
Maximum	0.064	2.857	0.42251	2.712
Skewness	−0.205	−0.041	0.647	0.954
Kurtosis	1.241	10.539	7.763	6.424
SD	0.015	0.478	0.089	0.479
Variance	0.000	0.228	0.008	0.229
Range	0.117	6.121	0.883	4.187
IQR	0.016	0.372	0.089	0.533
Jarque–Bera	36.716*	2352*	441.59*	278.57*
Kolmogorov–Smirnov	0.482*	0.249*	0.415*	0.209*
Augmented Dickey–Fuller	−8.819*	−13.108*	−6.961*	−10.316*
Ljung–Box	10.388*	61.69*	0.455*	24.362*

* Indicates statistical significance at the 1% level of significance.

analysis, to achieve stationarity for the returns, the data was adjusted according to the procedure outlined in Section 4, resulting in the log returns of the prices and volume of BBMI and YGG for conducting the robustness checks.

6.1.1. Summary statistics

Table 9 provides the summary statistics for the returns of BBMI and YGG prices and trading volume. Note that there is a slight difference in the sample periods due to the two assets starting trading at different times. The statistics computed are the same as

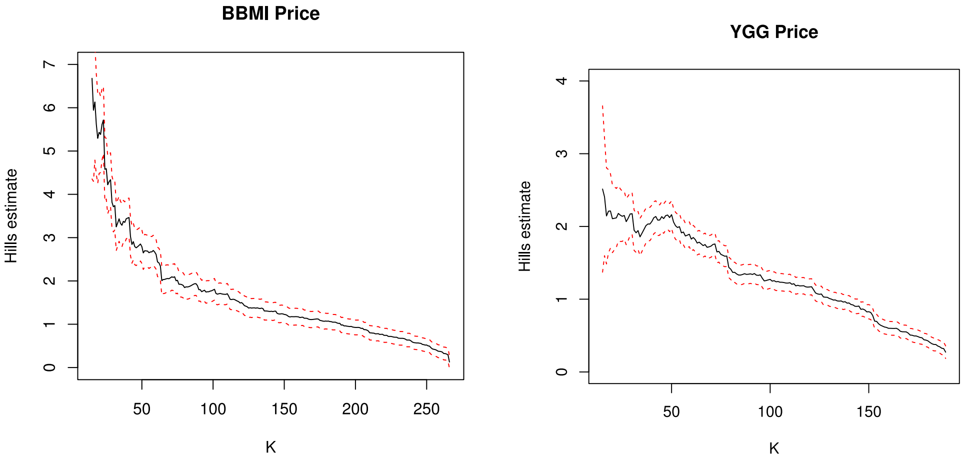

Fig. 10. Plots of the Hill tail index estimates for the log returns of prices of BBMI and YGG using varying numbers of samples K. The upper and lower bounds of the 95% confidence intervals are indicated by the red dashed lines.

those for the five NFTs as presented in Tables 4 and 5. The returns of the prices and volume of both BBMI and YGG exhibit mean values close to zero, similar to NFT price and volume returns. However, the medians of both price and volume returns for YGG are negative, also mirroring the same results as for the majority of the NFTs. The YGG price returns exhibit a greater range than BBMI and some NFTs. In terms of the kurtosis, the returns of volume for BBMI and YGG, and prices for YGG, are more peaked and heavier tailed than a normal distribution. The returns of BBMI trading volume appear to be the most peaked and extremely heavy-tailed, though less so compared with MANA. Similar to NFTs, the standard deviation of the returns of prices for both indices is lower than that of volume. The results of the JB, KS, ADF, and LB tests for the indices are fairly similar to those for the NFTs in terms of the rejections of the null hypotheses.

6.1.2. Heavy tail behavior

The plot of the Hill tail index estimates for BBMI exhibits a decrease as the number of samples, K, increases, thereby indicating heavy tails as was observed with all five NFTs, and showing the greatest similarity in shape with the AXS token. For YGG, the trend in the tail index appears most similar to ENJ, as there is also a general decrease in the estimates of the Hill tail index as the number of samples, K, increases (see Fig. 10).

6.1.3. Autocorrelation

From Fig. 11, both BBMI and YGG generally exhibit no significant autocorrelation at most lags, however, there are a few lags at which the autocorrelation is significant for BBMI and extends just beyond the bounds of the 95% confidence interval, for example at lags 1 and 2, indicating that there is some correlation that exists, and an element of influence from past returns on current returns. As indicated by Fig. 11, this suggests that pairs of returns that are separated by one time period are positively correlated - i.e. if $R_{t-1} > 0$ then it is likely that $R_t > 0$; pairs of returns that are separated by two time periods are negatively correlated - i.e. if $R_{t-2} > 0$ then it is likely that $R_t < 0$.

6.1.4. Long range dependence

The estimates of the Hurst exponent, computed via the DFA method, for both BBMI and YGG show that, although in a few instances the exponent moves between values of 0.4 and 0.7 reflecting price movements resembling a random walk, in most cases, the exponent fluctuates significantly. This is suggesting that BBMI and YGG both exhibit long term positive autocorrelation corresponding to higher Hurst exponent values and complete anti-correlation corresponding to lower values at different periods, as was observed for many NFTs (see Fig. 12).

6.1.5. Volatility clustering

Similar to the five NFTs, BBMI exhibits a persistence parameter $\alpha+\beta$ that is close to one, indicating that there is strong stationarity in the returns. In addition, $\alpha + \beta < 1$ shows that the GARCH model has been persistent and stable for the entire model [124]. The results for BBMI most closely match the results for AXS, such as how its value is very close to one indicating strong stationarity and a greater persistence to volatility shocks. For YGG, the parameters for the ARCH test and ARCH(α) are greater than those for BBMI, whereas the opposite is observed for the two GARCH parameters. Nonetheless, similar to BBMI, YGG is also persistent and stable for the entire model, and upon comparison with the five NFTs, it is found to be similar to THETA and SAND (see Table 10).

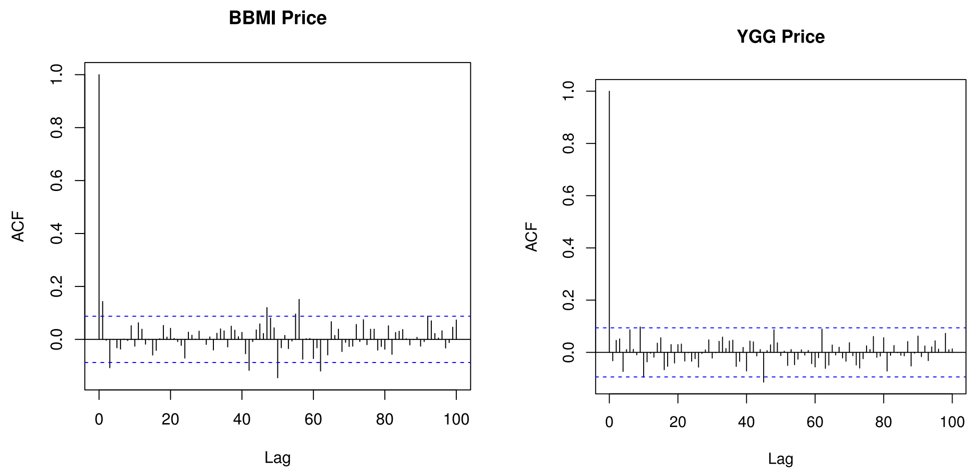

Fig. 11. Plots of the autocorrelation function of the log returns of prices for BBMI and YGG, for lags one to 100 over the sample period. The upper and lower bounds of the 95% confidence interval are indicated by the blue dashed lines.

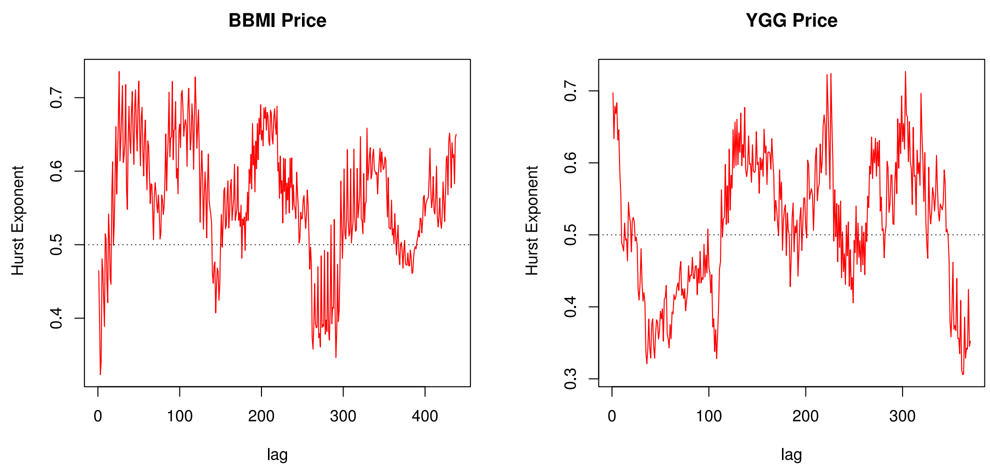

Fig. 12. Plots of the estimated Hurst exponents computed via the DFA method for BBMI and YGG over the respective sample periods, using a sliding window of 60 lagged returns of prices.

Table 10
Estimates of the ARCH test statistics and GARCH(1,1) model parameters of the ARCH term, GARCH term and the persistence parameter for BBMI and YGG.

	ARCH test	ARCH (α)	GARCH (β)	$\alpha + \beta$
BBMI	38.009*	0.086	0.907	0.993
YGG	463.590*	0.165	0.797	0.962

* Indicates significance at the 1% level.

6.1.6. Asymmetric volatility clustering

The results for $1 - \alpha - \beta - 0.5\xi$ for both BBMI and YGG are greater than zero, indicating stationarity in their returns and mean-reverting volatility, similar to the results for the five NFTs. Considering the leverage values for BBMI and YGG, interestingly both exhibit a significantly positive leverage effect that is much greater in magnitude than that of AXS — the only NFT that shows positive leverage (see Table 11).

6.1.7. Return-volume relationship

The surface plot for BBMI shows that estimates of β_1 are generally positive or zero regardless of the considered quantile of volume returns, implying that when trading volume of BBMI is stable or showing significant changes, there is minimum movement of the price of BBMI with the volume. However at the upper quantiles of trading volume returns τ and returns of prices θ (both above 0.7), estimates of β_1 are generally found to be negative. The overall shape of the QQR plot appears to be similar to that of SAND (as

Table 11
Estimates of the GJR(1,1) model parameters of the constant, ARCH term, GARCH term, leverage parameter and the stationarity parameter.

	Constant	ARCH (α)	GARCH (β)	Leverage (ξ)	$1-\alpha-\beta-0.5\xi$
BBMI	0.000	0.022	0.899	0.121	0.019
YGG	0.000	0.0791	0.825	0.161	0.0154

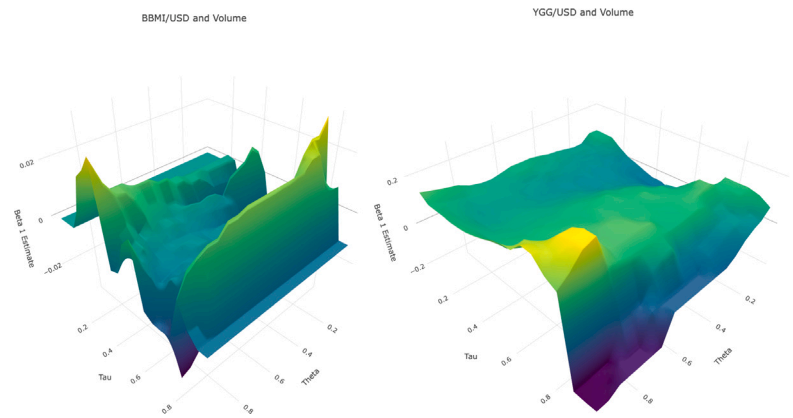

Fig. 13. Quantile-on-quantile regression plots for the returns of the prices of BBMI and YGG. Surface plots indicate estimates $\hat{\beta}_1(\theta,\tau)$ at $0.05 \leq \theta, \tau \leq 0.95$, corresponding to trading volume returns.

in Fig. 8). With regards to the YGG surface plot, estimates of β_1 are generally positive and exhibit a relatively stable contour, with only a sharp decline to negative values at the combination of the upper quantiles of trading volume returns τ and price returns θ. The overall shape of the QQR plot resembles that of THETA to a reasonable extent (as in Fig. 8) (see Fig. 13).

7. Conclusion

In this paper, we provide an in-depth analysis of the stylized facts of five of the most prominent NFTs: Axie Infinity, Decentraland, Enjin Coin, Theta Network, and The Sandbox. We examine the (i) descriptive statistics; (ii) heavy tail behavior (Hill tail index); (iii) long-range dependence (detrended fluctuation analysis); (iv) volatility clustering (GARCH); (v) asymmetric volatility clustering (GJR); (vi) return-volume relationship (quantile-on-quantile regression). This analysis is complemented by a comprehensive review of the history and benefits of the metaverse and NFTs, a discussion of Web2 and Web3 concepts, and comparisons between the past and present forms of the metaverse.

Using data on the price returns and trading volumes for the five tokens over the period of November 2020 to October 2022, our results showed that all NFT returns were peaked, heavy-tailed, and stationary, exhibiting serial correlation as evidenced by relevant statistical tests. The returns also exhibited volatility clustering with instances of trend reinforcement or anti-persistence, indicating relative inefficiency according to DFA and GARCH analyses. With the exception of the Axie Infinity NFT, all other NFTs exhibited negative leverage. However, all five NFTs demonstrated mean-reverting volatility. The quantile-on-quantile analysis revealed both similarities and differences in trends across different quantile combinations. In general, at the upper quantiles of trading volume returns and price returns, high trading volumes coupled with decreasing price returns (except for the SAND token) suggest a bearish outlook or profit-taking, leading to downward pressure on prices. However, this negative relationship is not observed at the lower quantiles of returns, indicating that significant negative changes in trading volume and prices do not commonly occur together and do not appear to influence each other.

The robustness of our results for NFTs was further tested by analyzing the same stylized facts for two other metaverse-related assets, the Bloomberg Metaverse Index and Yield Guild Games Web3 gaming token. The robustness analysis supported the findings for NFTs, with both metaverse-related assets exhibiting similar trends for the summary statistics, heavy tail behavior, autocorrelation, efficiency and volatility, and return-volume relationship. Specifically, the returns of both the Bloomberg Metaverse Index and Yield Guild Games Web3 gaming token were also peaked and heavy tailed, exhibited positive autocorrelation and anti-correlation, and mean-reverting volatility, as was the case for many NFTs. In addition, the quantile-on-quantile analysis showed that the Bloomberg Metaverse Index and Yield Guild Games tokens exhibit a return-volume relationship similar to The Sandbox, Theta Network, and Enjin Coin. This suggests that despite metaverse-related financial assets taking various forms such as NFTs, tracking indices, or gaming tokens, their behaviors in terms of stylized facts remain consistent with each other.

Overall, our analysis of metaverse tokens provides valuable insights into their structures and characteristics for academics, industry professionals, and enthusiasts. Academics can build on these findings to refine theoretical models across several key areas. First, insights from the analysis of metaverse tokens, such as their heavy-tailed distributions and volatility clustering, can be used

Table 12
Table of abbreviations and acronyms used in the manuscript.

Definition	Abbreviation
Artificial Intelligence	AI
Autoregressive conditional heteroskedasticity	ARCH
Augmented Reality	AR
Axie Infinity	AXS
Bloomberg Metaverse Index	BBMI
Decentraland	MANA
Decentralized Autonomous Organization	DAO
Decentralized Finance	DeFi
Detrended Fluctuation Analysis	DFA
Deep Learning Super Sampling	DLSS
Distributed Ledger Technology	DLT
Enjin Coin	ENJ
Ethereum Request for Comment 20	ERC-20
Ethereum Request for Comments 721	ERC-721
First Quartile	Q1
Generalized Autoregressive Conditional Heteroskedasticity	GARCH
Glosten, Jagannathan, and Runkle	GJR
Graphics Processing Unit	GPU
Gross National Product	GNP
Initial Coin Offering	ICO
Jarque–Bera	JB
Kolmogorov–Smirnov	KS
Ljung–Box	LB
Machine Learning	ML
Martingale Difference Hypothesis	MDH
Massively Multiplayer Online Role-Playing Game	MMORPG
Non-Fungible Token	NFT
Proof of Work	PoW
Quantile-on-Quantile Regression	QQR
Real-Money Trade	RMT
Rescaled Range	R/S
Second Generation World Wide Web	Web2
The Sandbox	SAND
Theta Network	THETA
Third Generation World Wide Web	Web3
Third Quartile	Q3
Virtual Reality	VR
World of Warcraft	WoW
Yield Guild Games	YGG

to develop advanced pricing models that account for the unique characteristics of NFTs and metaverse tokens, improving market behavior predictions. Second, understanding stylized facts like leverage effects and long-range dependence can enhance existing risk management frameworks, allowing for better assessment and mitigation of risks associated with extreme market movements and long-term dependencies in NFT markets. Third, the relationship between returns and trading volume, along with observed autocorrelation in metaverse tokens, can be leveraged to test and refine behavioral finance theories, deepening our understanding of how investor behavior and market sentiment influence price dynamics. While industry professionals can use them to develop sophisticated pricing models and risk assessment tools for metaverse-based financial products. Enthusiasts and investors can make more informed decisions by understanding the underlying behavior of these assets, ultimately enhancing their investment strategies and risk management practices.

Future related work can focus on several key aspects to deepen our understanding and broaden the application of findings related to metaverse tokens. One avenue is developing and testing advanced econometric and machine learning models to predict the pricing and volatility of metaverse tokens, incorporating the unique characteristics identified in this study. Another avenue is to explore investor behavior and sentiment in the metaverse using sentiment analysis and behavioral finance approaches. This includes examining psychological factors such as overconfidence, fear of missing out (FOMO), herd behavior, and loss aversion to understand their impact on market trends, price fluctuations, and overall sentiment in the metaverse and NFT markets. Additionally, analyzing the effects of existing and potential regulatory frameworks on the stability, growth, and acceptance of metaverse tokens within the broader financial system can provide valuable insights. By pursuing these paths, future research can offer a deeper and more comprehensive understanding of metaverse tokens and their role in the evolving digital economy.

Abbreviations

See Table 12.

CRediT authorship contribution statement

Stephen Chan: Writing – review & editing, Writing – original draft, Supervision, Methodology, Funding acquisition, Conceptualization. **Durga Chandrashekhar:** Writing – review & editing, Writing – original draft, Methodology. **Ward Almazloum:** Writing – review & editing, Writing – original draft, Methodology. **Yuanyuan Zhang:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Funding acquisition, Conceptualization. **Nicholas Lord:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Joerg Osterrieder:** Writing – review & editing, Writing – original draft, Methodology, Funding acquisition, Conceptualization. **Jeffrey Chu:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Acknowledgments

The authors would like to thank the Editor and the two anonymous referees for careful reading and comments which greatly improved the paper.

Funding sources

This work was supported by COST (European Cooperation in Science and Technology) (COST Action CA19130, COST Action CA21163); the Marie Skłodowska-Curie Actions (No. 101119635); the Swiss National Science Foundation (IZCNZ0-174853, IZSEZ0-211195, IZCOZ0-213370); the American University of Sharjah (Faculty Research Grant FRG23-C); the Fundamental Research Funds for the Central Universities, and the Research Funds of Renmin University of China (No. 22XNF042), the Beijing Natural Science Foundation (No. IS23126); the University of Manchester Internationalisation: Global Scholars Fund 2023–2024; European Union Horizon 2020 (No. 825215); Horizon Europe (No. 101119635); International Advanced Fellowship Programme UBB (No. 21PFE/30.12.2021); SNFS Leading House Asia, No. ARPG_112023_8.

The supporting institutions had no role in study design; in the collection, analysis and interpretation of data; in the writing of the report; and in the decision to submit the article for publication.

Appendix

Derivation for the GJR model

The expression $1 - \alpha - \beta - 0.5\xi > 0$ indicates stationarity and mean reversion in an extended GARCH model. In a standard GARCH(1,1) model, the conditional variance equation is:

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

with the stationarity condition being $\alpha + \beta < 1$. This ensures that the variance process is mean-reverting and does not explode. In the extended model:

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \xi Z_{t-1}$$

where ξ is an additional coefficient and Z_{t-1} is another factor affecting variance. The stationarity condition becomes $\alpha+\beta+0.5\xi < 1$, ensuring that the overall effect on variance remains controlled. Thus, the expression $1 - \alpha - \beta - 0.5\xi > 0$ guarantees the variance is stationary and mean-reverting, preventing it from exploding and ensuring it returns to its long-term mean.

References

[1] S. Mystakidis, Metaverse, Encyclopedia 2 (1) (2022) 486–497.
[2] J. Constine, Facebook's $2 billion acquisition of Oculus closes, now official. TechCrunch, 2014, Available at: https://techcrunch.com/2014/07/21/facebooks-acquisition-of-oculus-closes-now-official/.
[3] S. Ghaffary, S. Morrison, Can Facebook monopolize the metaverse? 2022, Vox. Available at: www.vox.com/recode/22933851/meta-facebook-metaverse-antitrust-regulation.
[4] G. Dean, Mcdonald's has filed a trademark for a restaurant in the metaverse that will actually deliver food to your home, 2022, Business Insider. Available at: https://www.businessinsider.in/tech/news/mcdonalds-has-filed-a-trademark-for-a-restaurant-in-the-metaverse-that-will-actually-deliver-food-to-your-home/articleshow/89479350.cms.
[5] M. Ball, The metaverse: What it is, where to find it and who will build it. MatthewBall.Vc, 2020, Available at: https://www.matthewball.vc/all/themetaverse.
[6] P. Fernandez, Facebook, meta, the metaverse, and libraries, Library Hi Tech News 39 (4) (2022) 1–5.
[7] A. Bosworth, Building the metaverse responsibly, 2021, Meta Available at: https://about.fb.com/news/2021/09/building-the-metaverse-responsibly/.
[8] S. Mittal, J. Cheah, Can the metaverse break the constraints of the physical world?, 2022, DBS Technology of the Future. Available at: https://www.dbs.com/metaverse/can-the-metaverse-break-the-constraints-of-physical-world.html.
[9] Y.K. Dwivedi, L. Hughes, A.M. Baabdullah, S. Ribeiro-Navarrete, M. Giannakis, M.M. Al-Debei, D. Dennehy, B. Metri, D. Buhalis, C.M. Cheung, K. Conboy, Metaverse beyond the hype: Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy, Int. J. Inf. Manage. 66 (2022) 102542.
[10] Gartner, Gartner predicts 25% of people will spend at least one hour per day in the metaverse by 2026, 2022, Gartner. Available at: https://www.gartner.com/en/newsroom/press-releases/2022-02-07-gartner-predicts-25-percent-of-people-will-spend-at-least-one-hour-per-day-in-the-metaverse-by-2026.
[11] Medium, What is the goal of metaverse?, 2023, Available at: https://medium.com/@donnalenk0420/what-is-the-goal-of-metaverse-e2d20ba09622.
[12] Genesis IT Lab, What is the end goal of metaverse?, 2023, Available at: https://www.genesislab.com/blog/what-is-the-end-goal-of-metaverse/1518.
[13] D. Vidal-Tomás, The illusion of the metaverse and meta-economy, Int. Rev. Financ. Anal. 86 (2023) 102560.
[14] T. Huynh-The, T.R. Gadekallu, W. Wang, G. Yenduri, P. Ranaweera, Q.V. Pham, D.B. da Costa, M. Liyanage, Blockchain for the metaverse: A review, Future Gener. Comput. Syst. 143 (2023) 401–419.
[15] N. Tyagi, S. Gautam, A. Goel, P. Mann, A framework for blockchain technology including features, in: Emerging Technologies in Data Mining and Information Security: Proceedings of IEMIS 2020, Vol. 1, 2021, pp. 633–645.
[16] Z. Zheng, S. Xie, H. Dai, X. Chen, H. Wang, An overview of blockchain technology: Architecture, consensus, and future trends, in: IEEE International Congress on Big Data, BigData Congress, 2017, pp. 557–564, Available at: https://ieeexplore.ieee.org/document/8029379.
[17] A. Narayanan, J. Bonneau, E. Felten, A. Miller, S. Goldfeder, Bitcoin and Cryptocurrency Technologies, Princeton University Press, 2016.
[18] D. Yermack, Is bitcoin a real currency? An economic appraisal, Handb. Dig. Curr. 3 (2015) 1–43.
[19] M. Yilmaz, T. Hacaloğlu, P. Clarke, Examining the use of non-fungible tokens (NFTs) as a trading mechanism for the metaverse, in: European Conference on Software Process Improvement, Springer, Cham, 2022, pp. 18–28.
[20] Merriam-Webster, NFT definition & meaning, 2024, Merriam-Webster. Available at: https://www.merriam-webster.com/dictionary/NFT.
[21] U.W. Chohan, Non-fungible tokens: Blockchains, scarcity, and value, in: Non-Fungible Tokens, Routledge, 2021, pp. 1–11.
[22] Token Minds, NFT Token: 7 exciting methods of determining the value of a non-fungible token, 2023, Available at: https://tokenminds.co/blog/nft-marketing/nft-token.
[23] Q. Wang, R. Li, Q. Wang, S. Chen, Non-fungible token (NFT): Overview, evaluation, opportunities and challenges, 2021, pp. 1–22, arXiv.
[24] Medium, How to design & then develop an NFT marketplace — Understanding the Architecture behind it!, 2022, Available at: https://medium.com/coinmonks/how-to-design-then-develop-an-nft-marketplace-understanding-the-architecture-behind-it-bdeb8af9fbc2.
[25] The Block, Practical use cases of NFTs, 2023, Available at: https://www.theblock.co/learn/251481/practical-use-cases-of-non-fungible-tokens.
[26] CoinTelegraph, How to create an NFT: A guide to creating a nonfungible token, 2024, Available at: https://cointelegraph.com/learn/how-to-create-an-nft.
[27] Builtin, Metaverse NFTs: A guide, 2023, Available at: https://builtin.com/blockchain/metaverse-nft.
[28] B. Guidi, A. Michienzi, From NFT 1.0 to NFT 2.0: A review of the evolution of non-fungible tokens, Future Internet 15 (6) (2023) 189.
[29] PrimaFelicitas, NFT 2.0 – The era of programmable assets, 2023, PrimaFelicitas. Available at: https://www.primafelicitas.com/nft/nft-2-0-the-era-of-programmable-assets/.
[30] Decentraland, Community highlights: A new way to rent LAND in Decentraland, 2022, Available at: https://decentraland.org/blog/community-projects/community-highlights-a-new-way-to-rent-land-in-decentraland.
[31] GAM3S.GG, Axie infinity introduces 'stage 2' evolution for NFTs, 2023, Available at: https://gam3s.gg/news/axie-infinity-introduces-stage-2-evolution-for-nfts/.
[32] Ozone Technologies Ltd, Ozone metaverse platform, 2023, Available at: https://ozonemetaverse.io/.
[33] F. Regner, N. Urbach, A. Schweizer, NFTs in practice–non-fungible tokens as core component of a blockchain-based event ticketing application, in: Fortieth International Conference on Information Systems, Munich 2019, 2019.
[34] C. Walton, Navigating NFT scarcity: How rarity affects fair market value, 2023, Available at: https://etonvs.com/crypto/nft-scarcity-how-rarity-affects-fair-market-value.
[35] Entrepreneur staff, What is the metaverse and why is it important to entrepreneurs? 2023, Entrepreneur. Available at: https://www.entrepreneur.com/science-technology/what-is-the-metaverse-and-why-is-it-important-to/442015.
[36] R. Di Pietro, S. Cresci, Metaverse: Security and privacy issues, in: 2021 Third IEEE International Conference on Trust, Privacy and Security in Intelligent Systems and Applications, TPS-ISA, IEEE, 2021, pp. 281–288.
[37] P. Casey, I. Baggili, A. Yarramreddy, Immersive virtual reality attacks and the human joystick, IEEE Trans. Dependable Secure Comput. 18 (2021) 550–562.
[38] J. Wu, K. Lin, D. Lin, Z. Zheng, H. Huang, Z. Zheng, Financial crimes in web3-empowered metaverse: Taxonomy, countermeasures, and opportunities, IEEE Open J. Comput. Soc. 4 (2023) 37–49.
[39] Elliptic, 2024. Available at: https://www.elliptic.co/blog/analysis/navigating-the-shifting-landscape-of-nft-crime-current-typologies-and-future-trends.
[40] M.J. Rajaei, Q.H. Mahmoud, A survey on pump and dump detection in the cryptocurrency market using machine learning, Future Internet 15 (8) (2023).
[41] M. Balcilar, H. Ozdemir, On the risk spillover from bitcoin to altcoins: The fear of missing out and pump-and-dump scheme effects, J. Risk Financial Manag. 16 (1) (2023).
[42] I.E. Okonkwo, NFT, copyright and intellectual property commercialization, Int. J. Law Inf. Technol. 29 (4) (2021) 296–304.
[43] H. Firlana, P.D.K. Wibowo, The future of intellectual property protection: Issues against the metaverse and non-fungible tokens (NFTs), Indonesian Law J. 16 (2) (2023) 185–203.
[44] M. Yoder, An OpenSea of infringement: The intellectual property implications of NFTs, Univ. Cincinnati Intell. Prop. Comput. Law J. 6 (2) (2022).
[45] A. Procopiou, A. Piki, #HerMetaverseToo-gender-based hate and abuse in the metaverse: The case of female athletes, in: 2023 10th International Conference on Behavioural and Social Computing, BESC, IEEE, 2023, pp. 1–8.

[46] M. Al Shamsi, D. Smith, K. Gleason, Space transition and the vulnerabilities of the NFT market to financial crime, J. Financial Crime 30 (6) (2023) 1664–1673.
[47] M. Kalyvaki, Navigating the metaverse business and legal challenges: Intellectual property, privacy, and jurisdiction, J. Metaverse 3 (1) (2023) 87–92.
[48] R. Ravelli, NFT's (non-fungible tokens) - Risks, regulation and the law, 2024, Rahman Ravelli. Available at: https://www.rahmanravelli.co.uk/expertise/nfts-non-fungible-tokens-risks-regulation-and-the-law/.
[49] A. Vigderman, NFT awareness and adoption report. Security.org, 2024, Available at: https://www.security.org/digital-security/nft-market-analysis/.
[50] R. Cont, Empirical properties of asset returns: stylized facts and statistical issues, Quant. Finance 1 (2) (2001) 223.
[51] W. Breymann, A. Dias, P. Embrechts, Dependence structures for multivariate high-frequency data in finance, Quant. Finance 3 (1) (2003) 1.
[52] J. Huber, D. Kleinlercher, M. Kirchler, The impact of a financial transaction tax on stylized facts of price returns—Evidence from the lab, J. Econom. Dynam. Control 36 (8) (2012) 1248–1266.
[53] J. Batten, B. Lucey, F. McGroarty, M. Peat, A. Urquhart, Stylized facts of intraday precious metals, PLoS One 12 (4) (2017) e0174232.
[54] J.R. Lothian, Some new stylized facts of floating exchange rates, J. Int. Money Finance 17 (1) (1998) 29–39.
[55] W. Zhang, P. Wang, X. Li, D. Shen, Some stylized facts of the cryptocurrency market, Appl. Econ. 50 (55) (2018) 5950–5965.
[56] A. Phillip, J.S. Chan, S. Peiris, A new look at cryptocurrencies, Econom. Lett. 163 (2018) 6–9.
[57] N. Borri, Y. Liu, A. Tsyvinski, The economics of non-fungible tokens, 2022, pp. 1–51, SSRN.
[58] R. Belk, M. Humayun, M. Brouard, Money, possessions, and ownership in the Metaverse: NFTs, cryptocurrencies, Web3 and Wild Markets, J. Bus. Res. 153 (2022) 198–205.
[59] L. Kugler, Non-fungible tokens and the future of art, Commun. ACM 64 (9) (2021) 19–20.
[60] L.J. Trautman, Virtual art and non-fungible tokens, Hofstra L. Rev. 50 (361) (2021).
[61] J.A. Fairfield, Tokenized: The law of non-fungible tokens and unique digital property, Ind. LJ 97 (2022) 1261.
[62] CNN, It's not quite the metaverse, but Meta is launching its virtual world, 2021, Available at: https://edition.cnn.com/2021/12/09/tech/meta-launches-horizon-worlds/index.html.
[63] S. Rodriguez, Facebook changes company name to Meta, 2021, CNBC. Available at: https://www.cnbc.com/2021/10/28/facebook-changes-company-name-to-meta.html.
[64] T. Huynh-The, Q.V. Pham, X.Q. Pham, T.T. Nguyen, Z. Han, D.S. Kim, Artificial intelligence for the metaverse: A survey, Eng. Appl. Artif. Intell. 117 (2023) 105581.
[65] A. Sarkar, S. Cooper, Towards game design via creative machine learning (GDCML), in: 2020 IEEE Conference on Games, CoG, IEEE, 2020, pp. 744–751.
[66] H.W.L. Mak, R. Han, H.H. Yin, Application of variational autoEncoder (VAE) model and image processing approaches in game design, Sensors 23 (3457) (2023).
[67] Y. Otoum, N. Gottimukkala, N. Kumar, A. Nayak, Machine learning in metaverse security: Current solutions and future challenges, ACM Comput. Surv. 56 (2024) 1–36.
[68] N. Ghantous, C. Fakhri, Empowering metaverse through machine learning and blockchain technology: A study on machine learning, blockchain, and their combination to enhance metaverse, 2022, ScienceOpen Preprints.
[69] Y. Wu, A. Yi, C. Ma, L. Chen, Artificial intelligence for video game visualization, advancements, benefits and challenges, Math. Biosci. Eng. 20 (2023) 15345–15373.
[70] W. Xi, Research on application of artificial intelligence in VR games, in: Fuzzy Systems and Data Mining VI, IOS Press, 2020, pp. 247–254.
[71] Decentraland, Welcome to Decentraland, 2024, Available at: https://decentraland.org/.
[72] The Sandbox, 2024 Available at: https://www.sandbox.game/en/.
[73] NVIDIA Omniverse, 2024. Available at: https://www.nvidia.com/en-us/omniverse/.
[74] Metaverse Startups, Crunchbase. Available at: https://www.crunchbase.com/hub/metaverse-startups.
[75] A. Webster, Travis Scott's first Fortnite concert was surreal and spectacular, 2020, The Verge. Available at: https://www.theverge.com/2020/4/23/21233637/travis-scott-fortnite-concert-astronomical-live-report.
[76] B. Mason, Warner music group to go metaverse with sandbox music theme park, 2022, FX Empire. Available at: https://www.fxempire.com/news/article/warner-music-group-to-go-metaverse-with-sandbox-music-theme-park-880229.
[77] B. Mason, A U.S-South Korean partnership takes kpop metaverse, 2022, FX Empire. Available at: https://www.fxempire.com/news/article/a-u-s-south-korean-partnership-takes-kpop-metaverse-864344.
[78] L. White, HSBC buys virtual plot of land in digital push, 2022, Reuters. Available at: https://www.reuters.com/business/finance/hsbc-buys-virtual-plot-land-digital-push-2022-03-17/.
[79] L. Shimron, The Australian open swings into the metaverse, will it be an ace, 2022, Forbes. Available at: https://www.forbes.com/sites/leeorshimron/2022/01/12/the-australian-open-swings-into-the-metaverse-will-it-be-an-ace/?sh=4d54ead2cfe9.
[80] NFT Tech, Case study: Australian open metaverse, 2022, NFT Tech Available at: https://www.nfttech.com/newsroom/case-study-australian-open-metaverse.
[81] M. Leonhardt, Accenture designed its own metaverse for employees, complete with exact replicas of offices, 2022, Fortune. Available: https://fortune.com/2022/04/11/accenture-builds-corporate-metaverse/.
[82] B. Kindig, The key to unlocking the metaverse is Nvidia's omniverse, 2021, Forbes. Available at: https://www.forbes.com/sites/bethkindig/2021/09/02/the-key-to-unlocking-the-metaverse-is-nvidias-omniverse/.
[83] Meta, Introducing 'Facebook Horizon', a new social VR world, coming to oculus quest and the rift platform in 2020, 2019, Meta News. Available at: https://www.meta.com/en-gb/blog/quest/introducing-facebook-horizon-a-new-social-vr-world-coming-to-oculus-quest-and-the-rift-platform-in-2020/.
[84] M. Gwaldis, How the metaverse can transform your business for the better, 2023, SHI Resource Hub. Available at: https://blog.shi.com/digital-workplace/how-the-metaverse-can-transform-your-business-for-the-better/.
[85] Accenture, Meet me in the metaverse | accenture, 2022, Available at: https://www.accenture.com/content/dam/accenture/final/a-com-migration/thought-leadership-assets/accenture-meet-me-in-the-metaverse-full-report.pdf.
[86] C. Moy, A. Gadgil, Opportunities in the metaverse: How businesses can explore the metaverse and navigate the hype vs. reality, 2022, Available at: https://www.jpmorgan.com/content/dam/jpm/treasury-services/documents/opportunities-in-the-metaverse.pdf Erişim Tarihi, 23 (02) p.2022.
[87] J. Dalton, J. Gillham, Seeing Is Believing. PWC, Techreport, 2019, Available at: https://www.pwc.com/gx/en/industries/technology/publications/economic-impact-of-vr-ar.html.
[88] M. Kanterman, N. Naidu, Metaverse may be $800 billion market, next tech platform, 2021, Bloomberg Professional Services. Available at: https://www.bloomberg.com/professional/insights/trading/metaverse-may-be-800-billion-market-next-tech-platform/.
[89] C. Bellavitis, C. Fisch, P.P. Momtaz, The rise of decentralized autonomous organizations (DAOs): a first empirical glimpse, Ventur. Cap. 25 (2) (2023) 187–203.
[90] El Economista, El Gobierno destinará hasta 3 8millones en ayudas al metaverso. ElEconomicsta.es, 2022, Available at: https://www.eleconomista.es/tecnologia/noticias/11859699/07/22/El-Gobierno-destinara-hasta-38-millones-en-ayudas-al-metaverso.html.
[91] P.P. Momtaz, CEO emotions and firm valuation in initial coin offerings: an artificial emotional intelligence approach, Strat. Manag. J. 42 (3) (2021) 558–578.

[92] N. Pellas, S. Mystakidis, I. Kazanidis, Immersive virtual reality in K-12 and higher education: A systematic review of the last decade scientific literature, Virtual Reality 25 (3) (2021) 835–861.
[93] H. Duan, J. Li, S. Fan, Z. Lin, X. Wu, W. Cai, Metaverse for social good: A university campus prototype, in: Proceedings of the 29th ACM International Conference on Multimedia, 2021, pp. 153–161.
[94] S. Kaddoura, F. Al Husseiny, The rising trend of Metaverse in education: Challenges, opportunities, and ethical considerations, PeerJ Comput. Sci. 9 (2023) e1252.
[95] K.R. Rahman, S.K. Shitol, M.S. Islam, K.T. Iftekhar, P. Saha, Use of metaverse technology in education domain, J. Metaverse 3 (2023) 79–86.
[96] N. Clegg, How the metaverse can transform education, 2023, Meta Available at: https://about.fb.com/news/2023/04/how-the-metaverse-can-transform-education.
[97] The Investopedia Team, Web 3.0 explained, plus the history of Web 1.0 and 2.0. Investopedia, 2022, Available at: https://www.investopedia.com/web-20-web-30-5208698.
[98] D. Xu, Y. Li, X. Chen, J. Li, P. Hui, S. Chen, J. Crowcroft, A survey of opportunistic offloading, IEEE Commun. Surv. Tutor. 20 (3) (2018) 2198–2236.
[99] R. Li, T. Song, B. Mei, H. Li, X. Cheng, L. Sun, Blockchain for large-scale internet of things data storage and protection, IEEE Trans. Serv. Comput. 12 (5) (2018) 762–771.
[100] G. Zyskind, O. Nathan, Decentralizing privacy: Using blockchain to protect personal data, in: 2015 IEEE Security and Privacy Workshops, IEEE, 2015, pp. 180–184.
[101] W. Cai, Z. Wang, J.B. Ernst, Z. Hong, C. Feng, V.C. Leung, Decentralized applications: The blockchain-empowered software system, IEEE Access 6 (2018) 53019–53033.
[102] R. Qin, J. Li, J. Zhu, Y. Yuan, X. Wang, F.Y. Wang, NFT: Blockchain-based non-fungible token and applications, Chin. J. Intell. Sci. Technol. 3 (2) (2021) 110–118.
[103] G. Angeris, H.T. Kao, R. Chiang, C. Noyes, T. Chitra, An analysis of Uniswap markets, Crypto Econ. Syst. 1 (1) (2021).
[104] W.C. Wei, Liquidity and market efficiency in cryptocurrencies, Econom. Lett. 168 (2018) 21–24.
[105] R.J. Bloomfield, World of bizcraft, 2009, Johnson School Research Paper Series, No. 8-2020. Available at SSRN: https://ssrn.com/abstract=1486210.
[106] C. Vallance, Facebook's metamorphosis – will it work? 2021, BBC. Available at: https://www.bbc.com/news/technology-59090863.
[107] J. Kim, Advertising in the metaverse: Research agenda, J. Interact. Advert. 21 (3) (2021) 141–144.
[108] C. Jones, The metaverse is the future—but are current platforms failing users?, 2022, Cointelegraph. Available at: https://cointelegraph.com/news/the-metaverse-is-the-future-but-are-current-platforms-failing-users.
[109] R. Parloff, From megs to riches, Fortune 152 (11) (2005) 184–+.
[110] E. Howcroft, NFTs worth $100 million stolen in past year, Elliptic says, 2022, Reuters. Available at: https://www.reuters.com/technology/nfts-worth-100-million-stolen-past-year-elliptic-says-2022-08-24/.
[111] S. Reback, Axie infinity plot sells for $2.5M, 2021, YahooFinance. Available at: https://finance.yahoo.com/news/axie-infinity-plot-sells-2-100353547.html.
[112] P. Ludlow, M. Wallace, The Second Life Herald: The Virtual Tabloid that Witnessed the Dawn of the Metaverse, MIT Press.
[113] P. Valdes-Dapena, Real cars drive into second life, 2006, CNNMoney.com. Available at: https://edition.cnn.com/2006/AUTOS/11/17/2nd_life_cars/.
[114] C. Stokel-Walker, Second life's strange second life, 2013, The Verge. Available at: https://www.theverge.com/2013/9/24/4698382/second-lifes-strange-second-life.
[115] Wired, Reuters opens virtual news bureau in 'SecondLife', 2006, Available at: https://www.wired.com/2006/10/reuters-opens-s/.
[116] R. Wood, This oculus VR headset could feature life like resolution – here's why that matters, 2021, TechRadar. Available at: https://www.techradar.com/news/this-oculus-vr-headset-could-feature-lifelike-resolution-heres-why-that-matters.
[117] Baker T., How much is a VR headset? GamesRadar, 2022, Available at: https://www.gamesradar.com/how-much-is-a-vr-headset/.
[118] CEU Analysis, Research Team, Metaverse – Virtual World, Real Challenges, Technical Report, Council of the European Union, 2022, Available at https://www.consilium.europa.eu/media/54987/metaverse-paper-9-march-2022.pdf.
[119] Prosegur Research, Lights and Shadows of the Metaverse, Technical Report, Prosegur, 2022, Available at: https://www.prosegurresearch.com/dam/jcr:41f9de5c-71c2-4204-9e45-cecdaa58f700/Informe%20Metaverso%20-%20Ingl%3Fs.pdf.
[120] A. Patrizio, Virtual baggage, real bucks, 2001, Wired News. Available at: https://www.wired.com/2001/10/virtual-baggage-real-bucks/.
[121] C. Nunley, People in the Philippines are earning cryptocurrency during the pandemic by playing a video game, 2021, CNBC. Available at: https://www.cnbc.com/2021/05/14/people-in-philippines-earn-cryptocurrency-playing-nft-video-game-axie-infinity.html.
[122] T. Bollerslev, Generalized autoregressive conditional heteroskedasticity, J. Econometrics 31 (3) (1986) 307–327.
[123] R.F. Engle, Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation, Econometrica (1982) 987–1007.
[124] I. Yunita, Volatility modeling using ARCH/GARCH method: Aplication on Asia pasific index, in: 3rd International Seminar and Conference on Learning Organization, Atlantis Press, 2016, pp. 182–189.
[125] F. Malik, B.T. Ewing, J.E. Payne, Measuring volatility persistence in the presence of sudden changes in the variance of Canadian stock returns, Rev. canadienne econ. (Can. J. Econ.) 38 (3) (2005) 1037–1056.
[126] L.R. Glosten, R. Jagannathan, D.E. Runkle, On the relation between the expected value and the volatility of the nominal excess return on stocks, J. Finance 48 (5) (1993) 1779–1801.
[127] C.D. Wang, P.A. Mykland, The estimation of leverage effect with high-frequency data, J. Amer. Statist. Assoc. 109 (505) (2014) 197–215.
[128] Y. Zhang, S. Chan, J. Chu, S. Nadarajah, Stylised facts for high frequency cryptocurrency data, Physica A 513 (2019) 598–612.
[129] C.-K. Peng, S. Havlin, H.E. Stanley, A.L. Goldberger, Quantification of scaling exponents and crossover phenomena in nonstationary heartbeat time series, Chaos 5 (1995) 82–87.
[130] C.C. Ying, Stock market prices and volumes of sales, Econometrica (1966) 676–685.
[131] T.N. Puri, G.C. Philippatos, Asymmetric volume-return relation and concentrated trading in LIFFE futures, Eur. Financial Manag. 14 (3) (2008) 528–563.
[132] C. Chiarella, B. Kang, C.S. Nikitopoulos, T.D. Tô, The return–volatility relation in commodity futures markets, J. Futures Mark. 36 (2) (2016) 127–152.
[133] I.C. Tsai, Ripple effect in house prices and trading volume in the UK housing market: New viewpoint and evidence, Econ. Model. 40 (2014) 68–75.
[134] N. Sim, H. Zhou, Oil prices, US stock return, and the dependence between their quantiles, J. Bank. Financ. 55 (2015) 1–8.
[135] CoinMarketCap, Cryptocurrency prices, charts and market capitalizations, 2023, Available at: https://coinmarketcap.com/.
[136] A.R. Gallant, G. Tauchen, A nonparametric approach to nonlinear time series analysis: estimation and simulation, in: New Directions in Time Series Analysis: Part II, Springer New York, New York, NY, 1992, pp. 71–92.
[137] Axie Infinity, Axie infinity, 2024, Available at: https://whitepaper.axieinfinity.com/.
[138] Enjin, The unified blockchain, wallet, marketplace, and API, 2024, Available at: https://enjin.io/.
[139] Theta Network, Theta token, 2024, Available at: https://thetatoken.org/.
[140] C.M. Jarque, A.K. Bera, A test for normality of observations and regression residuals, Rev. Int. Statist. (Int. Stat. Rev.) 16 (1987) 3–172.
[141] A. Kolmogorov, Sulla determinazione empirica di una legge didistribuzione, Giorn Dell'inst Ital Degli Att 4 (1933) 89–91.
[142] N. Smirnov, Table for estimating the goodness of fit of empirical distributions, Ann. Math. Stat. 19 (2) (1948) 279–281.
[143] D.A. Dickey, W.A. Fuller, Distribution of the estimators for autoregressive time series with a unit root, J. Am. Stat. Assoc. 74 (366a) (1979) 427–443.
[144] G.M. Ljung, G.E. Box, On a measure of lack of fit in time series models, Biometrika 65 (2) (1978) 297–303.
[145] Hill B.M., A simple general approach to inference about the tail of a distribution, Ann. Stat. 116 (1975) 3–1174.

[146] R Development Core Team, A Language and Environment for Statistical Computing, R Foundation for Statistical Computing, Vienna, Austria, 2024.
[147] V. Plakandaras, P. Gogas, R. Gupta, T. Papadimitriou, US inflation dynamics on long-range data, Appl. Econ. 47 (2015) 3874–3890.
[148] R. Selmi, A.K. Tiwari, S. Hammoudeh, Efficiency or speculation? A dynamic analysis of the Bitcoin market, Econ. Bull. 38 (2018) 2037–2046.
[149] Y. Zhang, S. Chan, J. Chu, H. Sulieman, On the market efficiency and liquidity of high-frequency cryptocurrencies in a bull and bear market, J. Risk Financial Manag. 13 (8) (2020).
[150] F.N. Zargar, D. Kumar, Long range dependence in the bitcoin market: A study based on high-frequency data, Phys. A 515 (2019) 625–640.
[151] S.A. David, C.M.C. Inacio Jr., R. Nunes, J.A.T. Machado, Fractional and fractal processes applied to cryptocurrencies price series, J. Adv. Res. 32 (2021) 85–98.
[152] A. Bielinskyi, O. Serdyuk, S. Semerikov, V. Soloviev, Econophysics of cryptocurrency crashes: an overview, SHS Web Conf. 107 (03001) (2021).
[153] S. Khuntia, J.K. Pattanayak, Adaptive market hypothesis and evolving predictability of bitcoin, Econom. Lett. 167 (2018) 26–28.
[154] J. Chu, Y. Zhang, S. Chan, The adaptive market hypothesis in the high frequency cryptocurrency market, Int. Rev. Financ. Anal. 64 (2019) 221–331.
[155] Y. Zhang, S. Chan, J. Chu, S.H. Shih, The adaptive market hypothesis of decentralized finance (DeFi), Appl. Econ. 55 (42) (2023) 4975–4989.
[156] T. Panagiotidis, G. Papapanagiotou, T. Stengos, On the volatility of cryptocurrencies, Res. Int. Bus. Finance 62 (2022) 101724.
[157] M. Yu, Forecasting Bitcoin volatility: The role of leverage effect and uncertainty, Physica A 533 (2019) 120707.
[158] S. Chan, J. Chu, Y. Zhang, S. Nadarajah, An extreme value analysis of the tail relationships between returns and volumes for high frequency cryptocurrencies, Res. Int. Bus. Finance 59 (2022) 101541.
[159] E.C. Cagli, The causal relationship between returns and trading volume in cryptocurrency markets: Recursive evolving approach, in: Blockchain Economics and Financial Market Innovation: Financial Innovations in the Digital Age, 2019, pp. 167–190.
[160] H.A. Aalborg, P. Molnár, J.E. de Vries, What can explain the price, volatility and trading volume of Bitcoin? Finance Res. Lett. 29 (2019) 255–265.
[161] A. Kokkinaki, S. Sapuric, I. Georgiou, The relationship between bitcoin trading volume, volatility, and returns: A study of four seasons, in: Information Systems: 15th European, Mediterranean, and Middle Eastern Conference, EMCIS 2018, Limassol, Cyprus, October (2018) 4-5, Proceedings 15, Springer International Publishing, 2019, pp. 3–15.
[162] L. Hau, H. Zhu, M. Shahbaz, W. Sun, Does transaction activity predict Bitcoin returns? Evidence from quantile-on-quantile analysis, North Am. J. Econ. Finance 55 (2021) 101297.
[163] M. El Alaoui, E. Bouri, D. Roubaud, Bitcoin price–volume: A multifractal cross-correlation approach, Finance Res. Lett. 31 (2019).
[164] J. Chu, S. Chan, Y. Zhang, An analysis of the return–volume relationship in decentralised finance (DeFi), Int. Rev. Econ. Finance 85 (2023) 236–254.