Electronic Journal of Applied Statistical Analysis
EJASA, Electron. J. App. Stat. Anal.
http://siba-ese.unisalento.it/index.php/ejasa/index
e-ISSN: 2070-5948
DOI: 10.1285/i20705948v18n2p313

Future scenarios: a financial network analysis of stock market returns in the metaverse environment

By Emma Zavarrone, Alessia Forciniti, Emanuele Mario Parisi, Angelo Miglietta

15 October 2025

Electronic Journal of Applied Statistical Analysis
Vol. 18, Issue 02, 15 October 2025, 313-343
DOI: 10.1285/i20705948v18n2p313

Future scenarios: a financial network analysis of stock market returns in the metaverse environment

Emma Zavarrone[a], Alessia Forciniti*[a], Emanuele Mario Parisi[a], and Angelo Miglietta[a]

[a]*IULM University, Department of Humanities, Via Carlo Bo, 20143, Milan*

15 October 2025

The paper examines the financial market as a potential environment for the transformative power of the metaverse.
The primary hypothesis is to construct future scenarios by investigating the metaverse's influence on the financial returns of companies involved in its development. The focus lies on analyzing the relationship between the Metaverse Index (MVI) returns and the returns of metaverse-oriented companies, with the aim of predicting emerging socio-technological trends.
A dataset comprising daily closing prices of the time series from 2019 to 2023 was collected, including the MVI and 47 metaverse-related assets classified into 13 business areas. A two-step methodological approach was adopted: 1) correlation network analysis and 2) graph embedding strategy performed on correlation networks. The results highlight that the current scenario, characterized by a strong connection between MVI, technologies, cryptocurrencies, and real estate, which defines the meta-economy and digital property, will play a pivotal role in the future. The forecasts emphasize the development of metaverse-native enterprises, the creation of new stock market indexes designed to assess metaverse performance, and the development of customized intellectual property for their business models.

keywords: metaverse, MVI, correlation network analysis, financial markets prediction, future scenario, node2vec

*Corresponding author: `alessia.forciniti@iulm.it`

ISSN: 2070-5948
http://siba-ese.unisalento.it/index.php/ejasa/index

1 Emerging market: the metaverse as a new frontier

The digital landscape is undergoing a paradigm shift, marked by the convergence of immersive technologies, data-driven environments, and new forms of interaction - social, economic, and experiential. At the core of this evolution lies the concept of the *metaverse* as a hybrid space where virtual and physical realities intertwine. Weinberger (2022) defined the metaverse as "an interconnected web of ubiquitous virtual worlds, partially overlapping with and enhancing the physical world".

Although the concept of the metaverse has recently been revived within the tech world, its conceptual roots lie in a broader cultural tradition. As early as 1982, William Gibson introduced an embryonic idea of digital worlds in the short story *The Night We Burned Chrome*, later developed in the seminal novel *Neuromancer* (1984), where "cyberspace" is portrayed as a parallel reality accessed through neural interfaces. The term *metaverse* in the strict sense was coined by Neal Stephenson in his 1992 novel *Snow Crash*, which remains a key reference in the virtual imagination. In 2003, *Second Life* marked a turning point in the social and commercial experimentation of virtual worlds, introducing an internal economy based on the digital currency Linden Dollar, which closely resembles the current concept of the metaverse. More recently, platforms such as *Decentraland* and *The Sandbox*, built on blockchain technologies and cryptocurrencies, have demonstrated the consolidation of a digital economy where virtual property and economic exchanges have become fundamental structural elements. The characterizing virtual worlds of metaverse enable users, represented by avatars, to connect and interact with each other and to experience and consume user-generated contents in an immersive, scalable, synchronous, and persistent environment. The emerging technologies, include Web 3.0 technologies such as Virtual Reality (VR) and Augmented Reality (AR), the new models of decentralization, and the reshaping of work and leisure activities within the metaverse, have the potential to create novel ecosystems with unique economic structures. Emerging technologies are enabling novel levels of interoperability among virtual platforms, reshaping how digital identities are managed, enhancing user experiences, and altering economic interactions. Decentralized blockchain-based solutions are strengthening individual ownership of digital assets and identities, while immersive interfaces like VR and AR are revolutionizing the way social spaces are perceived online. At the same time, critical concerns arise regarding the environmental impact of infrastructure systems, privacy issues, and the cultural homogenization driven by global platforms. In this context, it is clear that the metaverse is not a new concept, but rather an idea that has progressively evolved over time, adapting to different historical and technological phases. Its conceptualization changes and expands in relation to social, cultural, and economic transformations, often serving as a collective projection of possible futures, especially during periods marked by crisis or uncertainty about what lies ahead.

Therefore, the metaverse represents a modern evolution in a new era with novel ecosystems, economic structures, and social and ethical considerations. In fact, the Citi Group predicts that by 2030, the metaverse will reach a staggering 5 billion users and a market value between \$8 and \$13 trillion (Citi, 2022).

The persistent and interconnected network of the metaverse and its revolution (Ball,

2022) have attracted the attention of numerous stakeholders across various fields. The wide appeal of the metaverse has led scholars to question its definition and potential value. Although a universally accepted definition remains elusive, the growing interest in both academic literature and the general public highlights significant attention to this emerging concept. For example, Google Trends (GT) recorded 3,471 searches from October 2021 to July 2024, while the Web of Science database (up to July 2024) lists 2,577 scientific publications on the topic during the same period. However, it is important to emphasize the methodological limitations associated with the use of GT, including the lack of information about the actual search intentions of users, the presence of demographic biases (related to Internet access or search engine usage), and the exclusively quantitative nature of the tool, which measures search frequency but does not qualify the content or cognitive depth of the searches. Despite these limitations, analyzing digital trends remains a useful starting point for understanding the evolution of collective interest in emerging phenomena. The timeframe under consideration for both public interest and academic as well as popular scientific output aligns with the exponential rise in public awareness of the metaverse concept, notably triggered by Mark Zuckerberg's official announcement of Facebook Inc.'s rebranding to Meta. The focus on the metaverse reached a pivotal moment in October 2021, when Zuckerberg, the founder and CEO of Meta Platforms Inc., publicly unveiled his company's vision for the future of digital interactions. During this event, he described the metaverse as "the next evolution of the Internet" and "the ultimate platform for digital socialization," emphasizing the goal of fundamentally transforming how people live, work, and connect online. This proclamation played a key role in sparking widespread attention from both media outlets and the academic community, placing the metaverse at the forefront of global discussions. In fact, the announcement marked a paradigmatic shift in the public and industrial perception of the metaverse. Zuckerberg's strategic redefinition acted as a catalyst, intensifying media and academic attention and serving as an accelerator for investments, research, and experimentation in the field. Since October 2021, the metaverse has become one of the central topics in discussions about global digital transformations.

Although it has been three years since peak interest, the metaverse is still in its early stages, where the uncertain trajectory is heavily influenced by the interplay of socio-technological trends: a) ownership and literacy of Web 3.0 technologies (Tan et al., 2022); b) decentralization systems for higher control on digital identities and assets; c) reshaping of work and leisure; e) homogenization of global culture. There are numerous established real-world scenarios that define the metaverse environments, including opportunities and risks related to customer engagement, operational efficiency, virtual economies, stock market, academic issues like user experience, and security and privacy. The metaverse-related topics examined in this study are connected to the financial market and business sectors, representing one of the possible scenarios illustrating the transformative potential of this shift. The business domain is among the most developed areas, where the metaverse manifests through virtual events and showrooms, 3D products, immersive shopping experiences, and interactive brand storytelling. Remote collaboration, virtual training, prototyping, and testing form the foundation of operational efficiency, enabling immersive training simulations, cost reductions, and accelerated development cycles. Users gain influence by participating in the metaverse economy, where new revenue streams emerge based on virtual assets and virtual ownership, enhanced by decentralized finance (DeFi) powered by cryptocurrencies within the so-called meta-economy. Ownership is represented by Non-Fungible Tokens (NFTs), which function as unique digital deeds for specific items. Real estate investments—specifically the purchase of virtual land—are inherently the only investment fully accepted within the metaverse (Yemenici, 2022). The growing metaverse cryptocurrency ecosystem includes various coins, such as SAND, used within Sandbox, and MANA, the native currency of Decentraland. Decentraland is a virtual reality platform built on the Ethereum blockchain, allowing users to buy and sell virtual land, create and explore virtual worlds, and interact with others. It can be thought of as a virtual universe where users can explore, socialize, and even generate income. Virtual currencies like SAND and MANA can be purchased with real money at a specified exchange rate and sold back for real money at a different rate. The investment landscape related to the metaverse is marked by significant speculation and the absence of standardized reference metrics, complicating investors' decision-making processes. Given the metaverse's multi-dimensional nature—spanning digital and physical infrastructures, both centralized and decentralized, without a standard reference index—it is crucial to develop adequate analytical tools to monitor its economic evolution. Furthermore, the rising interest in the metaverse is fueled by technological advances and investments from major companies such as Meta, Nvidia, and Microsoft.

Nonetheless, the financial impact of this phenomenon remains partially unexplored, particularly regarding the relationship between the development of the metaverse and traditional financial markets. Analyzing the main financial assets connected to the metaverse may provide valuable insights into current and future scenarios, using the *Metaverse Index (MVI)* as a benchmark. Composed of a panel of 15 decentralized tokens, the MVI serves as a key cross-sector reference index for tracking the growth of the metaverse.

This study aims to contribute to the existing literature by proposing a methodological approach to stock return forecasting, with a focus on the metaverse as a catalyst for new economic paradigms, investment strategies, and ownership models. Our research investigates the network-based correlations between the MVI and the daily stock performance of metaverse-focused firms.

More properly, this paper builds upon Bushnell (2022)'s work on the interconnections between cryptocurrencies and other financial assets, aiming to identify recurring patterns between the MVI and equity prices. Through the development of multi-step model, we determine whether the excitement surrounding the metaverse hype is primarily driven by speculative dynamics or reflects a tangible relationship with the value of other financial assets.

To guide this investigation, the following research question (RQ) is explored:

- *RQ:* To what extent do correlations between the MVI and the equity returns of metaverse-related companies reflect broader market trends and signal emerging socio-technological developments?

2 Literature Review

In the existing literature, the financial aspects of the metaverse remain under-explored, with most studies providing insights through conventional quantitative approaches.

Among recent works, Xu et al. (2024) studied the business ecosystem literature of the metaverse within the Chinese stock market. Based on a sample of 642 Chinese listed firms in 2021, their results showed a positive stock market reaction subject to three moderating effects: Information Technology (IT) readiness, ecosystem readiness, and digital infrastructure readiness.

"Ozkal et al. (2024) forecasted metaverse token prices by analyzing a time series from 2017 to 2022, focusing on opening price, highest value, lowest value, closing price, and volume value. Using artificial neural networks and an adaptive neural fuzzy inference system, they concluded that the metaverse has the potential to enhance learning capabilities and motivation, as well as make significant contributions to industrial production.

Ergun and Karabiyik (2023) proposed a study on the price determinants of NFTs using Adaptive Network-Based Fuzzy Inference System techniques. Categories such as collectibles, gaming, art, and utilities were identified, with Bitcoin and Ethereum prices being the best input variables for forecasting NFT prices in the metaverse.

Mukherjee and Hussaini (2023) investigated the relationship between NFT returns, related categories, and fear indices during times of crisis. They aimed to analyze whether fear indices influenced NFT holders' performance. Their findings revealed no short-term association between NFT returns and most fear indices, except for the Twitter-based Economic Uncertainty Index. Interestingly, NFT Metaverse returns were found to have a positive association with at least one fear index during short periods of crisis.

Horky (2023) explored the relationship between financial trends of leading metaverse tokens, public attention measured by GT, and global stock indices. This study aimed to guide financial investors in the digital asset landscape. The results exhibited a bubble-like behavior, particularly during periods of peak GT attention linked to the technology sector.

Pamucar and Biswas (2023) compared the market performance of metaverse crypto assets and alternative variables such as return, momentum of the daily closing price, market capitalization, trading volume, and risk. The Logarithmic Percentage Change driven Compromise Solution based Appraisal showed that the momentum of closing prices and price movement volatility held higher importance as derived from objective weights.

Aharon et al. (2022) measured the market reaction to firms' Securities and Exchange Commission disclosures. An analysis of activities and announcements revealed an initial surge in stock prices for companies publicly announcing their involvement in the metaverse. This upward trend tended to dissipate quickly, regardless of the company's characteristics or the nature of their announcement.

Chen (2022) examined the impact of the metaverse on different industries in the U.S. stock market. Using the well-known Fama-French model to analyze data from the New York Stock Exchange, the American Stock Exchange, and the Nasdaq, the study determined that the metaverse has particularly affected the stock prices of technology companies, as well as tech monopolies and real estate.

On June 7^{th} 2021, when the Global Stock Markets were reaching their historical heights, was launched the MVI with the promise to replicate the metaverse financial interests.

Given the short life span of the index, its literature is rather recent. Mentions can be referred to Vidal-Tomás (2021) that investigated the potential of combining blockchain technologies with the "play-to-earn" model within the metaverse gaming landscape. His study, based on the performance of 174 tokens, showed the absence of high correlations between NFT features (such as the number of transactions, sales, and Google search volume) and the MVI due to market volatility.

Momtaz (2022) offered an empirical discussion based on the market capitalization of established Web 2.0 companies and startups (proxied by Coinmarketcap).

Schnoering and Inzirillo (2022) investigated the dynamics and performance of NFTs in relation to the MVI, and proposed the construction of price indices for the NFT markets.

Thus, the relationship between MVI returns and other metaverse-related financial assets has been scarcely explored in the literature. This paper proposes a model to capture the connection between the financial returns of metaverse-focused companies—including intellectual property—and the MVI. Furthermore, our methodological framework aims to leverage these relationships to forecast future trends and track the ongoing transformation driven by the metaverse across multiple sectors.

3 Methods

This section describes the methodological approach to analyze the structure of relationships among metaverse-related financial assets and to predict future scenarios in the market structure.

The process is divided into four main steps, as illustrated in Figure 1, which summarizes the sequential methodological pipeline adopted in this paper.

1. **Raw price data pre-processing:** The daily closing price of each asset in the dataset was transformed into logarithmic returns to normalize the time series and make them comparable across assets and over time.

2. **Construction of correlation matrices:** For each time series from 2019 to 2023, a linear correlation matrix was computed based on the assets' logarithmic returns. Each annual matrix, with dimensions $n \times n$ (where n is the number of assets), serves as the basis for subsequent financial network modeling.

3. **Construction of correlation networks:** Using the annual return correlation matrices, financial graphs were constructed in which each node represents an asset and each edge denotes a weighted correlation-based connection. These network structures enable the visualization and analysis of interdependencies among metaverse-oriented financial assets.

4. **Graph embedding:** The correlation networks were projected into latent vector spaces using a graph embedding algorithm. The resulting vectors represent each node/asset and are employed to predict future links, uncover latent structures, and generate forecast scenarios.

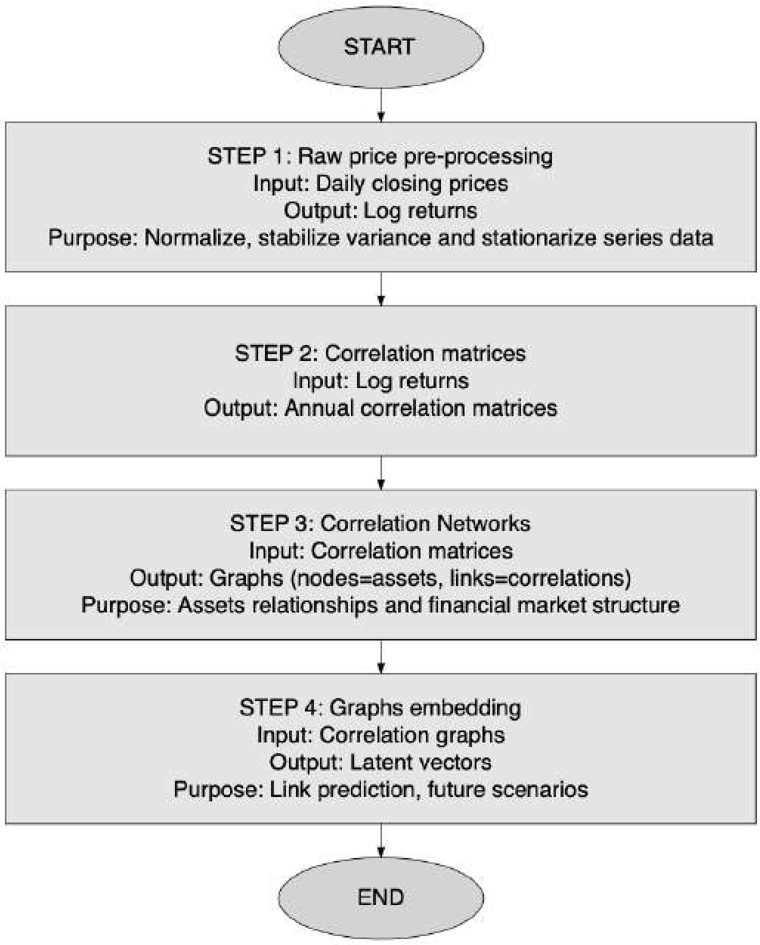


Figure 1: Flow chart of model

Each of these four phases is discussed in detail in the following subsections.

3.1 STEP1: Raw price pre-processing

To enable meaningful comparisons and analysis of the relationships among the daily closing prices of different assets, the raw price data were normalized through a logarithmic returns transformation. This approach accounts for differences in scale and volatility across assets—particularly relevant when comparing companies of varying market capitalizations. For instance, a large-cap company may exhibit relatively stable price movements, while a smaller competitor might experience rapid fluctuations. By using log returns, the analysis focuses on proportional changes over time, rather than absolute price levels, ensuring comparability across the dataset.

Suppose that:

- n: is the number of financial assets
- $P_{i,t}$: represents the price of the i^{th} crypto asset at time t, where t denotes the length of the analysis period expressed in days, t aggregated into months k, computes T as a sum of months.

Let T be defined as the summation of t_k over k, expressed as:

$$T = \sum_{k=1}^{K} t_k,$$

where $k = 1, 2, \ldots, K$, and $K = 1825$, which is calculated as the product of the number of days in a year (365) and the number of years observed (five years). We assume the following relationship:

$$\text{If } 1 \leq k \leq 365, \text{ then } T_1.$$
$$\text{If } 366 \leq k \leq 731, \text{ then } T_2.$$
$$\text{If } 732 \leq k \leq 1097, \text{ then } T_3.$$
$$\text{If } 1098 \leq k \leq 1462, \text{ then } T_4.$$
$$\text{If } 1463 \leq k \leq 1828, \text{ then } T_5.$$

The return of an asset is determined by these relative price fluctuations:

$$r_{i,t} = \frac{P_{i,t}}{P_{i,t-1}} - 1 \quad \text{where} \quad i = 1, \ldots, n \quad \text{and} \quad t = 1, 2, \ldots, T \tag{1}$$

Namely, the return is represented by the difference in price P of an asset i at time t compared to its previous value at time $t - 1$.

A log return is commonly employed to quantify the proportional change in an asset's price, and is denoted as $R_{i,t}$. It is computed as the natural logarithm of the price ratio over time, based on the time series of all asset returns, $r_{i,t}$.

The corresponding formula is:

$$R_{i,t} = \ln(1 + r_{i,t}) \tag{2}$$

Logarithmic returns are widely used in financial analysis because they offer a normalized measure of percentage change, accounting for the compounding effect over time. This transformation allows for a more meaningful comparison between assets with different price levels and volatilities, especially when analyzing firms with varying market capitalizations.

3.2 STEP2: Correlation matrices

For each time series from 2019 to 2023, a *linear correlation matrix* based on the log returns $R_{i,t}$ of the financial assets was constructed. The annual correlation matrix $C_T \in \mathbb{R}^{n\times n}$, where n is the number of assets and T denotes the year, is used as the foundation for the subsequent network modeling process.

The generic element $C_T(i,j)$ of the matrix is defined as the Pearson correlation coefficient between the log returns of assets i and j:

$$C_T(i,j) = \frac{\mathrm{Cov}(R_i, R_j)}{\sigma_{R_i} \cdot \sigma_{R_j}} \tag{3}$$

where:

- $\mathrm{Cov}(R_i, R_j)$ is the covariance between the log returns of assets i and j,
- σ_{R_i} and σ_{R_j} denote the standard deviations of their respective returns.

The use of the *Pearson correlation coefficient* is justified by its ability to capture linear dependencies among financial variables and its widespread application in the literature on financial network analysis (Mantegna and Stanley, 2000; Giudici and Spelta, 2016).

Each matrix C_T is symmetric ($C_T(i,j) = C_T(j,i)$) and contains values in the interval $[-1, 1]$. For each year, the matrix was computed using aggregated daily log returns in order to capture structural changes in inter-asset relationships over time. These annual correlation matrices were then employed as input for the construction of correlation networks described in the next subsection.

3.3 STEP3: Correlation networks

The dynamics that characterize the relationships among the asset pricing (Panchenko et al., 2013; Khashanah and Alsulaiman, 2016) can be investigated through the correlation-based networks.

From each matrix $\mathbf{C}_T$, that identifies an adjacency matrix (Wasserman and Faust, 1994) - square and symmetric matrix with identical rows and columns - a correlation network $\mathbf{G}_T = (V_T, E_T, w)$ was derived, where:

- V_T is the set of nodes (assets),
- E_T is the set of links or edges between assets with non-zero correlation,
- $w(i,j) = |C_T(i,j)|$ is the weight assigned to each link, based on the value of the linear correlation.

To better understand and characterize the overall network structure, as well as the properties of individual nodes and edges, standard network analysis metrics were employed. For each annual network $\mathbf{G}_T$, the following metrics were computed:

- *Density*: the ratio between the number of actual edges present and the maximum possible number of edges in the network, indicating how interconnected the nodes are.
$$D = \frac{2 \cdot |E_T|}{|V_T| \cdot (|V_T| - 1)}$$
where $|E_T|$ is the number of observed edges and $|V_T|$ is the number of nodes.

- *Average path length*: the mean geodesic distance between all pairs of connected nodes, reflecting the typical separation or communication efficiency within the network.
$$L = \frac{1}{|P|} \sum_{(i,j) \in P} d(i,j)$$
where P is the set of all connected node pairs, and $d(i,j)$ is the shortest path length between nodes i and j.

- *Standard deviation of distances*: a measure of the variability in the shortest path lengths, which provides insights into the network's cohesion and the uniformity of connectivity.
$$\sigma_d = \sqrt{\frac{1}{|P|} \sum_{(i,j) \in P} (d(i,j) - L)^2}$$
where L is the average path length defined above.

These metrics are presented in Table 2 in the Results section and are used to evaluate the evolution of the network structure over time.

3.4 STEP 4: Graphs embedding for link prediction

To analyze the evolving dynamics of the correlation networks, this study employed a semi-supervised algorithm for graph embedding called *node2vec* (Grover and Leskovec, 2016) - or, more generally, a class of random-walk-based graph embedding - to learn latent vector representations of each node while preserving neighborhood structures.

This approach enables effective modeling of financial interconnections and supports the forecasting of future network configurations. The theoretical foundation see a custom graph-based objective function inspired by advances in natural language processing. In fact, the node2vec extends the idea of *word2vec* (Mikolov et al., 2013), where words are represented in a latent Euclidean space based on their contextual similarity in text (Hiraoka et al., 2024). In this analogy, nodes in a graph take the place of words, and random walks generate sequences of nodes, which encode structural and topological context. Similar to word2vec, nodes sharing similar contexts in the graph are embedded close to each other in the latent space. Node2vec introduce the use of two hyperparameters that control the bias of the walks, offering more flexibility in capturing local and global graph structures. The algorithm has proven effective in various graph-based predictive tasks, such as multi-label classification and link prediction, outperforming previous methods even in the presence of noisy or incomplete data (Perozzi et al., 2014; Tang et al., 2015).

Formally, the node2vec projects each node $v \in V_T$ into a Euclidean space $\mathbb{R}^m$, producing a vector $\vec{v}$ that captures the node's topological context. The objective function optimizes the probability that nodes with similar neighborhoods in the graph have similar embeddings. Thus, it embeds each node $v \in V$ of a weighted, undirected graph $G = (V, E, w)$ into an m-dimensional Euclidean space, $\mathbb{R}^m$. The weight function $w : E \to \mathbb{R}_{\geq 0}$ is symmetric, ensuring $w(v_i, v_j) = w(v_j, v_i)$ for all $v_i, v_j \in V$.

The algorithm minimizes a loss function $\mathcal{L}_o$ that quantifies the discrepancy between the predicted and actual node neighborhoods. Given a node $v \in V$, let $\bar{v} \in \mathbb{R}^n$ be its one-hot encoding. The predicted neighborhood distribution C_v is obtained via (Hiraoka et al., 2024):

$$u_v := \bar{v} \cdot W_1 W_2 \in \mathbb{R}^n \tag{4}$$

$$C_v = \left(\frac{e^{u(1)}}{\sum_{j=1}^{n} e^{u(j)}}, \ldots, \frac{e^{u(n)}}{\sum_{j=1}^{n} e^{u(j)}} \right) \tag{5}$$

The training neighborhood vector $F_v \in \mathbb{R}^n$ is generated through biased random walks. Each node initiates r walks of length l, guided by hyperparameters p and q, which control the likelihood of revisiting nodes or exploring new ones; where p determines how frequently a walk will revisit the previous vertex in the walk; and q: indicates how often a walk will move to a new vertex that is not a neighbor of the previous vertex.

The transition probability at each step is:

$$\frac{\xi(v_{prev}, v_{curr}, v_{next}) \cdot w(v_{curr}, v_{next})}{\sum_{\hat{v} \in V} \xi(v_{prev}, v_{curr}, \hat{v}) \cdot w(v_{curr}, \hat{v})} \tag{6}$$

where the bias function ξ is defined as:

$$\xi(v_{prev}, v_{curr}, v_{next}) = \begin{cases} 0 & \text{if } w(v_{curr}, v_{next}) = 0 \\ \frac{1}{p} & \text{if } v_{next} = v_{prev} \\ 1 & \text{if } v_{next} \neq v_{prev} \text{ and } w(v_{prev}, v_{next}) > 0 \\ \frac{1}{q} & \text{otherwise} \end{cases} \tag{7}$$

Let $f_v(v_j)$ be the frequency with which node v_j is visited across all walks starting from v. The empirical neighborhood distribution F_v is then:

$$F_v = \left(\frac{f_v(v_j)}{l \cdot r} \right)_{1 \leq j \leq n} \tag{8}$$

This embedding process allows the topological structure of the network to be captured in a continuous space, suitable for downstream tasks such as link prediction and clustering.

3.4.1 Embedding Architecture

The embedding architecture is designed from a correlation network G_T at a given time T, to predict the network configuration at a future time. We consider two time points: 2022 and 2023, corresponding to T_4 and T_5. The *node2vec* algorithm is applied to the 2022 network (G_{T4}) to generate node embeddings, in order to infer a predicted network $\hat{G}_{T5}$, representing the expected structure for 2023.

The predicted network $\hat{G}_{T5}$ is compared with the observed one G_{T5}, by analyzing the overlap in asset relationships. The same process is repeated using G_{T5} to forecast the 2024 network, denoted $\hat{G}_{T6}$.

To tune the embedding process, several combinations of the *node2vec* hyperparameters p and q were tested. The best configuration was selected heuristically, based on the similarity between predicted and observed links.

In the case of predicting $\hat{G}_{T5}$, the following parameters gave the best performance:

$$r = 10 \text{ (walks per node)}, \quad l = 80 \text{ (walk length)}, \quad p = 1, \quad q = 0.5$$

The same embedding architecture and hyperparameter configuration were employed to construct $\hat{G}_{T6}$ using G_{T5} as input.

The architecture can be summarized as follows, aiming to produce a predicted network $\hat{G}_{T5}$ most similar to the actual G_{T5}, where:

- G_{T4}: observed network at time T_4;
- G_{T5}: observed network at time T_5;
- $\hat{G}_{T5}$: predicted network at time T_5;
- NE: node embedding method;
- S: network similarity function;
- C: comparison and selection method.

Algorithm node embedding on correlation networks

1: **Generate node embeddings:**

$$E_{T4} = NE(G_{T4})$$

2: **Predict future network:**

$$\hat{G}_{T5} = \text{Predict}(E_{T4})$$

3: **Evaluate similarity with ground truth:**

$$similarity = S(\hat{G}_{T5}, G_{T5})$$

4: **Select best prediction:**

$$\hat{G}_{T5}^{best} = C(\{\hat{G}_{T5}^{(1)}, \hat{G}_{T5}^{(2)}, \ldots\}, G_{T5})$$

5: **Output:**

$$\hat{G}_{T5}^{best}$$

Node2vec relies on the skip-gram model, originally developed for word embedding in natural language processing, which optimizes embeddings by maximizing the likelihood of observing a node's neighborhood given its embedding. For each node, skip-gram treats its neighboring nodes—defined by biased random walks on the graph—as the "context," and learns embeddings by maximizing the conditional probability of these context nodes given the target node's embedding. This objective is formalized as the maximization of the overall log-likelihood function across all nodes and their contexts. During training, the log-likelihood quantifies how well the current embeddings explain the observed network neighborhood structure. Monitoring the log-likelihood progression provides an internal metric of convergence and embedding quality: increases in log-likelihood indicate that the embeddings better capture local graph topology, while stabilization suggests training has reached a satisfactory representation. This log-likelihood metric is an intrinsic measure of model fit during the embedding learning process. Therefore, it should be interpreted as an internal goodness-of-fit metric rather than a definitive performance evaluation. While useful for tracking training dynamics and ensuring embedding stability, additional validation methods are necessary to evaluate the effectiveness of the embeddings for the specific application at hand. In fact, we employed dimensionality reduction techniques and clustering such as t-Distributed Stochastic Neighbor Embedding (t-SNE) and Uniform Manifold Approximation and Projection (UMAP) to facilitate the qualitative assessment of the learned latent space. These methods enable the projection of high-dimensional node embeddings into a two-dimensional space where structural relationships can be visually inspected. The underlying assumption is that nodes exhibiting similar topological and relational properties within the original network should be mapped to proximate locations in the embedding space. To clarify, UMAP served a dual purpose in our analysis. Primarily, it was utilized to reduce the high-dimensional node2vec embeddings into a two-dimensional latent space, facilitating visualization and interpretability of the complex relational structures captured by the embeddings. Additionally, this reduced representation was instrumental for the manual identification of clusters, as the spatial proximities in the UMAP projection reflect underlying topological similarities among assets. Unlike purely algorithmic clustering methods, the visual coherence of asset groupings within the UMAP space provided an intuitive and robust basis for cluster delineation. Therefore, UMAP functioned not only as a preprocessing step for dimensionality reduction but also as an interpretative tool to guide cluster assignment, enhancing the understanding of emergent network structures. This approach ensures that the clusters correspond to meaningful latent patterns rather than arbitrary partitions, thereby reinforcing the validity of the predictive embeddings and their subsequent economic interpretation.

Analyzing the spatial clustering of nodes in the low-dimensional projection allows us to assess how well the embedding preserves both local and global similarity structures of the original network. In particular, a strong correspondence between clusters identified in the predicted embeddings and those in the actual network indicates that the embedding successfully captures meaningful asset groupings and underlying market structure. This qualitative validation of clustering serves as a complementary approach to quantitative evaluation methods, such as log-likelihood monitoring. It provides additional evidence that the embedding encodes relevant structural information, even in the absence of explicit supervised performance metrics. Moreover, this technique was employed as an exploratory and visual tool to investigate how nodes aggregate into clusters and to examine the extent to which the predicted structure (i.e., embedding combined with predicted links) reflects the observed network. This interpretative evaluation allowed us to qualitatively assess which assets (nodes) fall into which clusters or categories, as presented in the Results section (Table 3).

4 Data

4.1 Data collection

Data were collected from the Coinbase Data Marketplace (Coinbase, nd) and consist of daily closing prices for a range of assets between February 21$^{\text{st}}$, 2019, and December 31$^{\text{st}}$, 2023.

Asset selection followed inclusive and deterministic criteria based on classifications from the Bloomberg Database. Specifically, firms were included if they met at least one of the following conditions: (i) more than 10% of their revenue was derived from metaverse-related business activities; (ii) an estimated growth of over 10% in the metaverse sector by 2025; (iii) over 10% of their capital expenditure was allocated to metaverse-related developments; or (iv) they acted as suppliers or solution providers for the metaverse industry.

The final dataset includes five cryptocurrencies, four metaverse investment indices, two treasury assets, two volatility indices, and 34 publicly traded companies. Among the selected indices, particular attention is given to the MVI, a product launched in 2021 by Index Coop to track trends in virtual entertainment, business, social activity, and gaming. As a result, MVI data are unavailable prior to 2021. In total, 47 metaverse-related assets were categorized into 13 thematic areas.

Table 1 provides a detailed overview of the data sources and classification.

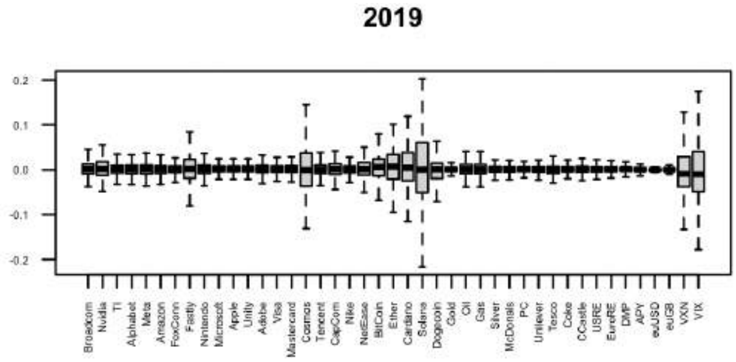
Table 1: Data collection

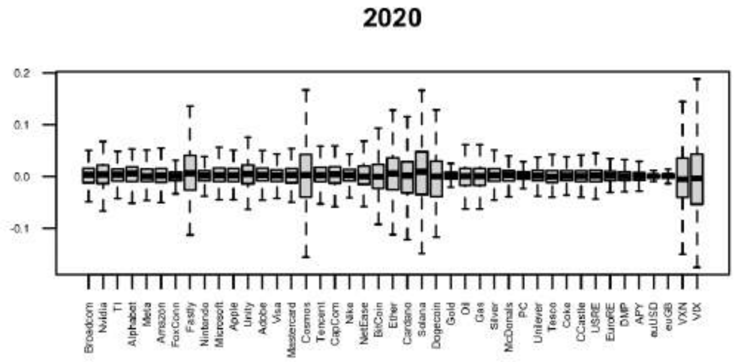
Area	Assets
Processing & IT / Operating Systems	Broadcom; Nvidia; Alphabet; Meta;
	Texas Instruments (hereinafter TI)
Networks & fixed connection	Amazon; FoxConn; Fastly
Platforms & platforms development	Nintendo; Microsoft; Unity; Apple
Interchange	Adobe
Payments	Mastercard; Visa
Contents	Cosmos; Tencent; CapCom; Nike; NetEase
Cryptos	BitCoin; Ether; Cardano; Solana; Dogecoin
Safe Havens	Gold; Crude Oil (hereinafter COil);
	Natural Gas (hereinafter NGas); Silver
Consumer Staples	McDonalds; P&C; Unilever; Tesco; Coke
Real Estate	Crown Castle (CCastle); US RE; Euro RE;
	Developed Markets Property (DMP)
Treasuries	US Dollar (USD); German Bund (GB)
Volatility Index	VIX; VNX

4.2 Data description

In the descriptive analysis, box plots were employed to visualize the evolution of log returns over time (Figure 2).

The 2019 box plots do not yet include the MVI, which was launched in 2021 by Index Coop—a decentralized, community-driven organization offering crypto index solutions. While an exact launch date is not always consistently reported in public sources, multiple reliable references confirm that MVI was introduced in 2021. In the first time window analyzed—preceding the emergence of the metaverse narrative—market variability is observed particularly in cryptocurrencies such as Solana, which stands out for its high volatility, as well as in the fixed connectivity sector (e.g., Fastly) and among content-related assets (e.g., Cosmos). Notable fluctuations are also evident in the volatility indices (VIX and VXN), which serve as indicators of investor sentiment and broader market uncertainty. In 2019, the behavior of the VIX and VXN reflected a landscape marked more by episodic uncertainty than systemic instability. Events such as the U.S.–China trade tensions and the Federal Reserve's monetary policy reversal led to brief volatility spikes. The VXN, tied to the tech-heavy Nasdaq-100, naturally displays higher volatility due to the inherent instability of technology stocks. In contrast, the VIX—tracking 30-day expected volatility on the S&P 500 via option prices—responds more to short-term shocks associated with sector rotation and technology exposure. Nevertheless, the absence of structural disruptions kept both indices within a moderate range, resulting in a year of contained, yet reactive, volatility driven by macroeconomic and geopolitical developments.





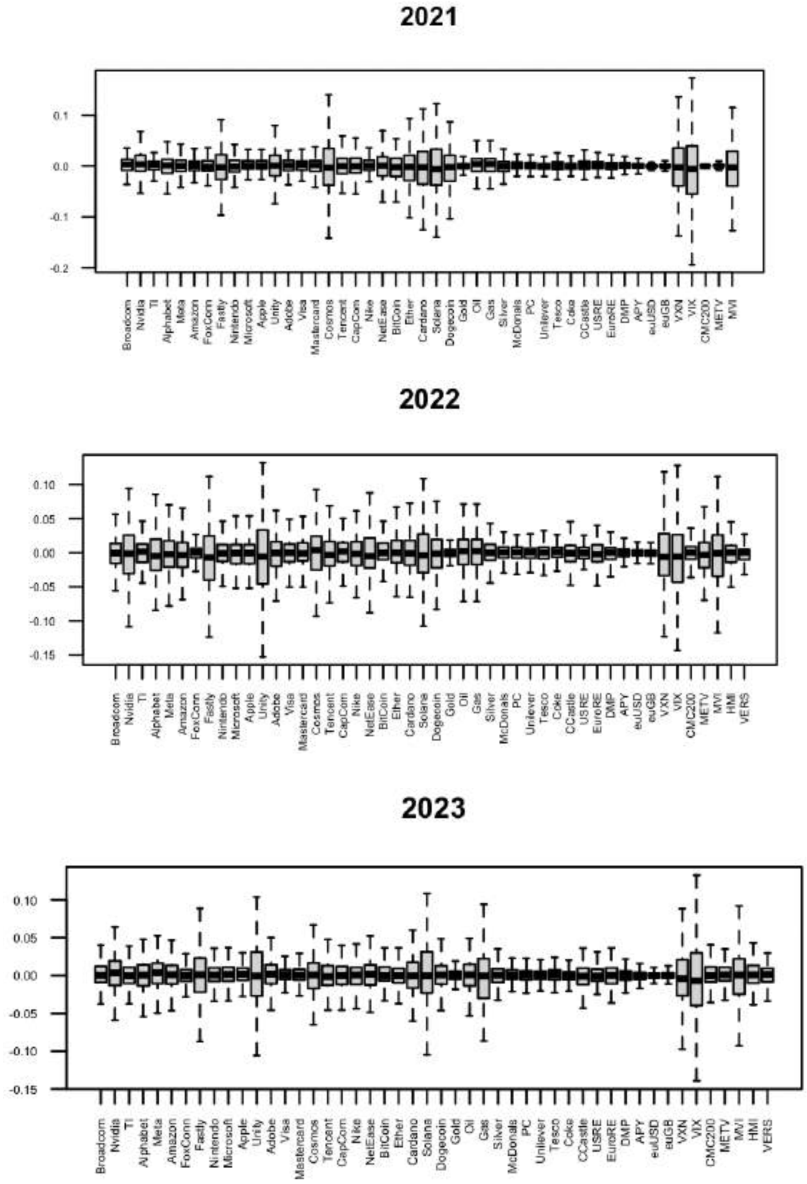


Figure 2: 2019–2023: Box plot of assets' log returns

In 2020, the pattern of market variability persists, with pronounced fluctuations in cryptocurrencies—extending to Bitcoin, Ether, Cardano—and continued volatility in the fear indices (VIX and VXN). Dispersion remains elevated and even intensifies in content-related assets (e.g., Cosmos) and the fixed connectivity sector (e.g., Fastly), while assets associated with IT infrastructure and operating systems begin to show growing variability in their log returns. This trend reflects the early signals of structural transformations in the digital ecosystem, likely amplified by the pandemic-induced acceleration of technological adoption and market digitization.

In 2021, variability remains stable in the domains of cryptocurrencies, content-related assets (e.g., Cosmos), and fixed connectivity (e.g., Fastly). A notable increase in dispersion emerges among platform-related assets (e.g., Unity), accompanied by intensified fluctuations in both the VXN and VIX indices. The Metaverse Index (MVI) enters the scene, reflecting the growing relevance of metaverse-linked assets and the volatility trend driven by their strong impact on the tech sector. This shift suggests a deepening connection between digital innovation and market sensitivity to emerging technological narratives.

The 2022 box plots show the emergence of new metaverse-linked assets such as METV and HMI. However, the MVI captures greater market variability, while dispersion in the VXN and VIX further intensifies. The trend in network connections (e.g., Fastly) remains stable, whereas platform-related assets (e.g., Unity) display increasing dispersion. Compared to previous years, the variability within the crypto domain contracts, while dispersion rises in IT operating systems (e.g., Nvidia, Alphabet, Meta) and in more traditional assets such as crude oil and natural gas. This shift suggests a broadening of market sensitivity beyond digital-native sectors, reflecting cross-domain uncertainty in a post-pandemic economic context

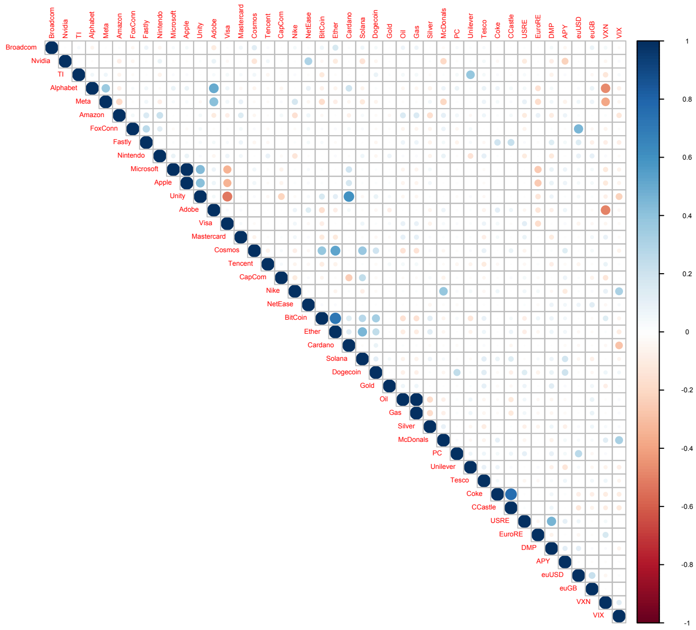
In the final series analyzed (2023 box plots), a contraction in market variability is observed for IT systems (e.g., Alphabet, Nvidia) and fixed network assets (e.g., Fastly), while platforms (e.g., Unity) show increased dispersion. Among safe-haven assets, crude oil becomes less volatile, whereas natural gas shows a reinforced variability pattern. MVI, VIX, and VXN remain unstable and highly speculative markets. This suggests a selective rebalancing of volatility, with market speculation increasingly concentrated in tech-related and perception-driven assets.

5 Results

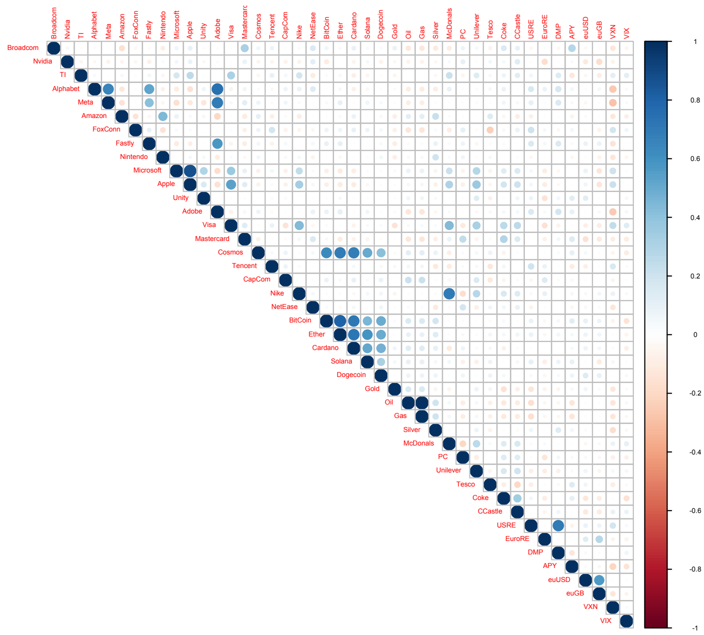
5.1 Correlation analysis

In this section, annual linear correlation analyses were proposed to examine the relationships among the financial returns of the assets.

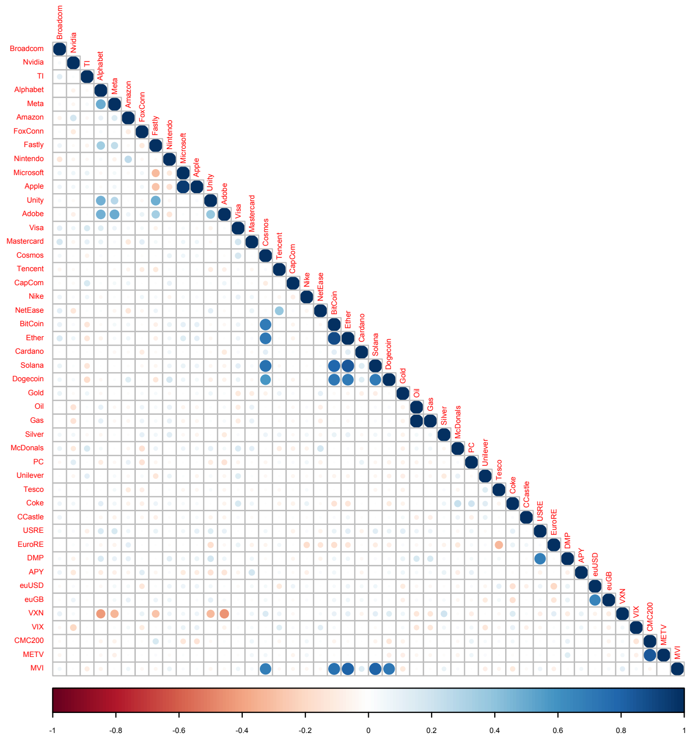
The results are based on the annual correlation matrix $C_T \in \mathbb{R}^{n \times n}$, where n is the number of assets and T denotes the year, which serves as the foundation for subsequent network modeling, as described in the methodology. Each element $C_T(i, j)$ of the matrix represents the Pearson correlation coefficient between the log returns of assets i and j.


Broadcom
Nvidia
TI
Alphabet
Meta
Amazon
FoxConn
Fastly
Nintendo
Microsoft
Apple
Unity
Adobe
Visa
Mastercard
Cosmos
Tencent
CapCom
Nike
NetEase
BitCoin
Ether
Cardano
Solana
Dogecoin
Gold
Oil
Gas
Silver
McDonals
PC
Unilever
Tesco
Coke
CCastle
USRE
EuroRE
DMP
APY
euUSD
euGB
VXN
VIX
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1

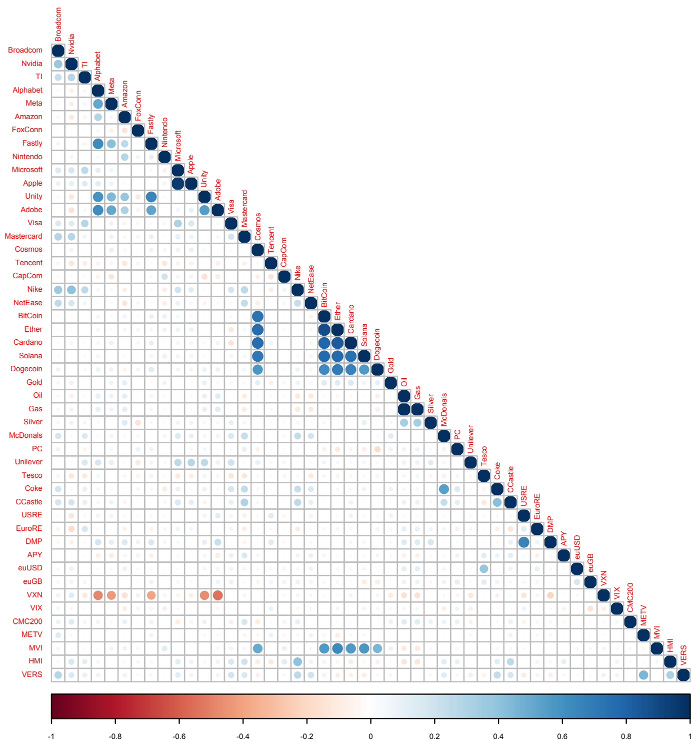
(a) 2019


Broadcom
Nvidia
TI
Alphabet
Meta
Amazon
FoxConn
Fastly
Nintendo
Microsoft
Apple
Unity
Adobe
Visa
Mastercard
Cosmos
Tencent
CapCom
Nike
NetEase
BitCoin
Ether
Cardano
Solana
Dogecoin
Gold
Oil
Gas
Silver
McDonals
PC
Unilever
Tesco
Coke
CCastle
USRE
EuroRE
DMP
APY
euUSD
euGB
VXN
VIX
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1

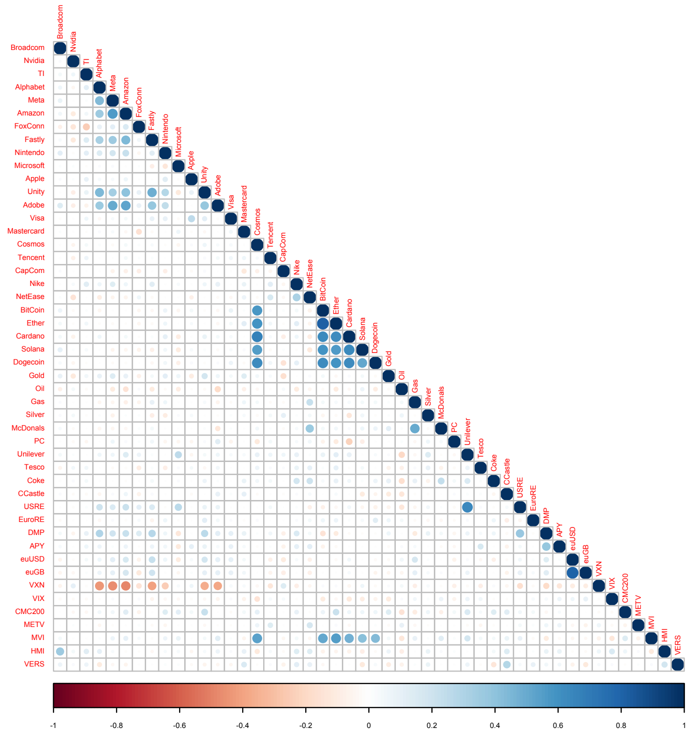
(b) 2020


Broadcom
Nvidia
TI
Alphabet
Meta
Amazon
FoxConn
Fastly
Nintendo
Microsoft
Apple
Unity
Adobe
Visa
Mastercard
Cosmos
Tencent
CapCom
Nike
NetEase
BitCoin
Ether
Cardano
Solana
Dogecoin
Gold
Oil
Gas
Silver
McDonals
PC
Unilever
Tesco
Coke
CCastle
USRE
EuroRE
DMP
APY
euUSD
euGB
VXN
VIX
CMC200
METV
MVI
-1
-0.8
-0.6
-0.4
-0.2
0
0.2
0.4
0.6
0.8
1

(c) 2021


Broadcom
Nvidia
TI
Alphabet
Meta
Amazon
FoxConn
Fastly
Nintendo
Microsoft
Apple
Unity
Adobe
Visa
Mastercard
Cosmos
Tencent
CapCom
Nike
NetEase
BitCoin
Ether
Cardano
Solana
Dogecoin
Gold
Oil
Gas
Silver
McDonals
PC
Unilever
Tesco
Coke
CCastle
USRE
EuroRE
DMP
APY
euUSD
euGB
VXN
VIX
CMC200
METV
MVI
HMI
VERS
-1
-0.8
-0.6
-0.4
-0.2
0
0.2
0.4
0.6
0.8
1

(d) 2022



(e) 2023

Figure 3: 2019 - 2023: Heatmaps on Pearson correlation

For each yearly matrix, linear correlations were explored visually through heatmaps (Figure 3) and quantitatively summarized using the Pearson correlation coefficient (r), providing insights into the strength and direction of asset return relationships.

In Figure 3, all positive correlations are marked in blue, with increasingly strong shades as the correlation coefficient approaches 1, while negative correlations are shown in red, with shades intensifying as r approaches -1, within the canonical range $[-1, 1]$.

The correlation analysis for the year 2019 highlights positive linear correlations between assets of IT companies such as Alphabet and interchange sector firms like Adobe, which often operate in interconnected technological fields or share similar market dynamics. Shared macroeconomic factors characterize these market segments, as well as interdependencies between IT and tech, reflecting common investor behavior toward these assets. Strong positive links, with $r \approx 0.67$, are observed between the platform Unity and the cryptocurrency Solana, indicating early signs of growing interdependence between emerging metaverse technologies and digital assets, suggesting potential areas of market influence and risk transmission even before mainstream adoption. Stronger positive linear correlations emerge between content assets (Cosmos) and cryptocurrencies (Bitcoin), with $r \approx 0.76$, as well as among assets within the same domain of virtual economies (Ether, Bitcoin, Cardano). On the negative side, correlations of approximately $r \approx -0.56$ are observed between payments (Visa) and platforms (Unity), and similarly between market volatility (VXN) and interchange (Adobe) and IT (Alphabet). These patterns suggest that virtual economy assets were already closely linked in 2019, highlighting an early integration of content and crypto markets. Meanwhile, the negative correlations between payment systems and platforms, as well as between volatility indices and core tech/interchange sectors, may reflect differing investor responses to risk and sector-specific shocks, indicating a complex risk transmission structure even before the widespread adoption of metaverse technologies.

In 2020, positive linear correlations with progressively increasing intensity emerged among cryptocurrencies, expanding to include assets from other domains such as Dogecoin, with coefficients in the range $0.75 \leq r \leq 0.84$. Similarly, the positive relationship between IT (Alphabet) and interchange (Adobe) strengthened. Direct linear relationships were also reinforced between cryptocurrencies and content assets, with correlation coefficients ranging from $0.6 \leq r \leq 0.8$.

The results from 2020 and 2021 confirm strong positive linear correlations among assets within the same domain, particularly among cryptocurrencies (Ether, Cardano, Solana) with coefficient values $0.56 \leq r \leq 0.75$. In 2020, direct relationships were observed between IT operating systems (Alphabet and Meta) and interchange (Adobe), with correlations ranging from $0.67 \leq r \leq 0.85$. However, in 2021, the IT and interchange markets began to diverge, showing no clear linear correlations. Conversely, the bonds among cryptocurrencies strengthened, as did the relationship between content (entertainment and gaming) and cryptocurrencies. This shift suggests an increasing decoupling of traditional tech sectors from emerging digital asset clusters, emphasizing the growing centrality of metaverse-related and crypto assets in shaping market behavior. The MVI made its debut in 2021, exhibiting strong positive correlations with both content (entertainment and gaming) and cryptocurrencies, with coefficients exceeding 0.83. This highlights the rapid emergence of metaverse-oriented assets as a distinct and influential market segment, further reinforcing the integration between digital entertainment platforms and crypto economies in shaping investor behavior.

In 2022, the cryptocurrency sector remained tightly clustered, exhibiting strong positive linear correlations with coefficients greater than 0.88. Similarly, cryptocurrencies and content assets moved in a direct positive relationship, with correlation coefficients exceeding 0.83. However, MVI showed weaker linear correlations compared to its peak year, with the link between content and cryptocurrencies ranging between $0.6 \leq r \leq 0.7$. Negative correlations were observed between the VXN and IT assets (e.g., Texas Instruments) as well as payment systems (e.g., VISA), with coefficients ranging from $-0.46 \leq r \leq -0.65$. In 2023, many trends from 2022 were confirmed, such as strong positive linear relationships among cryptocurrencies, between content and cryptocurrencies, and between interchange and IT assets. The weaker correlations between the MVI and gaming or virtual economies also persisted. However, a new finding emerged: a negative linear correlation between the VXN and various tech sectors (e.g., Alphabet, Texas

Instruments) as well as fixed connections (e.g., Amazon). This suggests increasing divergence in market behavior within the technology space, possibly reflecting differentiated investor sentiment or sector-specific risks impacting volatility dynamics.

Short-term correlation analyses over the years reveal increasingly stronger ties within sectors, especially among cryptos and content assets, with the MVI reinforcing these connections. This suggests the metaverse is a dynamic and multifaceted ecosystem, characterized by evolving sector-specific trends and intermittent speculative phases rather than a uniform market movement.

5.2 Correlation network analysis

The correlation analysis underpinning the network-based study illustrates a maturing metaverse ecosystem and a progressive transformation of its associated assets, which increasingly influence financial markets over the long term. Consistent with the correlation analysis, the correlation network was constructed and analyzed annually from 2019 to 2023.

This methodological approach reveals a typical acceptance and consolidation trajectory within the metaverse, where assets evolve into an interconnected mosaic of sectors. Notably, shifts in the structure of ties are observed: volatility linked to IT companies remains relatively stable and less fragmented over time, whereas cryptocurrencies initially tied to payment systems expand their connections toward content and consumer staples within two years of the metaverse's introduction.

The MVI captures this evolving landscape by emphasizing assets related to volatility, consumption, content, and operating systems, highlighting its role as a barometer of this emerging digital economy. Network analyses were performed on the annual correlation networks, computing descriptive metrics as detailed in Table 2 and introduced in the methodology. These include structural elements such as network density—the proportion of existing edges out of all possible pairs —and average path length, which measures the mean geodesic distance between nodes, alongside their standard deviations.

The descriptive statistics show exceptionally cohesive networks, with density values exceeding 98%, indicating nearly complete interconnectivity among assets. Low standard deviations (values between 0.234–0.242) reflect uniform connectivity, while mean distances between 1.235 and 1.404 suggest efficient communication pathways within the networks.

Importantly, following the MVI's market introduction in 2021, the number of ties among assets has grown substantially, a trend sustained in subsequent years. This increase in connectivity signals an intensifying integration of metaverse-related assets into the broader financial ecosystem. Conversely, the count of isolated nodes prior to 2021 underscores a less connected market landscape before the metaverse's financial emergence. These findings imply that the metaverse is driving a structural convergence across previously distinct asset classes, fostering greater interdependence and potential contagion channels within financial markets. The increasing cohesion and shrinking average distances suggest enhanced market efficiency but may also point to heightened systemic risk due to tighter coupling of asset dynamics. This evolving network topology aligns with the notion that technological innovation catalyzes new patterns of financial integration and complexity.

Table 2: 2019 - 2023: Correlation networks descriptives

	2019	2020	2021	2022	2023
N. nodes	43	43	46	48	48
N. Ties	902	902	1,034	1,127	1,128
Density	0.988	0.988	0.998	1.000	1.000
Mean distance	1.404	1.391	1.396	1.235	1.235
Standard deviation	0.234	0.242	0.237	0.235	0.235

5.3 Graph embedding for link predictions

To anticipate future socio-technological trends, the node2vec algorithm was trained on the 2023 financial correlation network (G_{T5}) to generate predictive embeddings for 2024 ($\hat{G}_{T6}$). As detailed in methodological section, the algorithm was first validated on the 2022–2023 transition by embedding G_{T4} and predicting G_{T5}, demonstrating its heuristic effectiveness in capturing the network's temporal evolution.

To ensure sufficient embedding quality prior to dimensionality reduction, we adopted an empirical threshold on the Skip-Gram log-likelihood. This threshold was determined by identifying the point at which the likelihood curve began to plateau across multiple training runs, typically accompanied by stable and interpretable cluster patterns in the UMAP projection. More importantly, this selection criterion was also guided by the degree of topological alignment between the predicted network configuration $\hat{G}_{T5}$ and the observed structure G_{T5}.

Although this threshold does not constitute a formal convergence criterion, it served as a practical heuristic to ensure that the learned embeddings captured meaningful topological information before proceeding with the cluster interpretation. Following the dimensionality reduction step described in the methodology, we analyzed the two-dimensional latent space produced by the UMAP projection of the node2vec embeddings. Within this space, assets with similar structural roles in the predicted network tended to be mapped to proximate locations, forming visually coherent groupings.

While no formal clustering algorithm was applied, six distinct clusters were identified based on visual inspection of node proximity and spatial continuity in the embedded space. This manual cluster assignment reflects emergent structures that align with the latent relational patterns captured by the embedding model. The resulting clusters were found to be stable across multiple model initializations, consistently grouping key assets and reinforcing the robustness of the observed configuration.

Applying the same log-likelihood threshold and UMAP-based inspection to the prediction of $\hat{G}_{T6}$ from G_{T5}, we generated the cluster assignments presented in Table 3, which lists the assets grouped within each of the six identified communities. These groupings are interpreted as representations of asset clusters sharing similar structural properties or market behaviors, as inferred from their positions in the latent space. Although the clustering process was not derived from a supervised or algorithmic classification procedure, it provides a valuable qualitative validation of the embedding model's ability to encode economically and topologically meaningful patterns in the asset network.

Table 3: Forecasted 2024 clusters or categories based on 2023 embeddings

Categories	Nodes
Category 1	Amazon, Broadcom, P& C,Tencent, TI, VIX
Category r 2	Adobe, Apple, VXN, CMC200, HMI, DMP, Nintendo, Nvidia, Visa, COil
Category 3	CCastle, Nike, Ether, Solana, Gold, US RE, Microsoft, Tesco, €GB, FoxConn
Category 4	Fastly, Silver, Coke, Cosmos, NetEase, Unilever, METV, MVI, Bitcoin
Category 5	McDonalds, Dogecoin, Meta, CapCom, NGas, VERS, Mastercard, Cardano
Category 6	APY, Unity, EURO RE, Alphabet, €USD

Note: Cluster and node assignments are obtained based on the embedding quality, as measured by the skip-gram model's likelihood, and the structural groupings resulting from UMAP projection.

The projected network structure for 2024 (Table 3), predicts structural realignments driven by accelerating technological transformation, particularly within metaverse-related sectors. These clusters reflect emerging dynamics in digital consumption, virtual social interaction, and decentralized ownership models, underscoring the increasing relevance of cryptocurrencies and platform-based ecosystems. Notably, assets linked to consumer staples, operating systems, and interchange platforms exhibit strong co-movement with the volatility index (VIX), suggesting shared exposure to macroeconomic uncertainty and systemic technological shifts. This alignment may stem from: (a) shared sensitivity to broad market sentiment; (b) overlapping investment narratives tied to innovation and transformation; and (c) the inherently uncertain nature of technological evolution as a risk amplifier. Further, the observed proximity between digital payment systems, real estate platforms, and infrastructure-related assets reflects a growing convergence in the digitalization of economic value, especially in the context of the virtual property economy. Finally, the juxtaposition of traditional safe-haven instruments (e.g., treasuries) with high-volatility assets (e.g., cryptocurrencies) illustrates a bifurcated investment landscape shaped by risk diversification and emerging market narratives.

Table 3 summarizes these findings by reporting the asset composition of each cluster derived from the 2023 network correlation, offering a scenario-based interpretation of financial network topology in 2024.

The scenario outlined for 2024 Table 3 an interesting evolution of the transformative power of new environments such as metaverse.

The MVI, which aggregates metaverse-related assets, offers meaningful insight into the evolving structure of financial markets—particularly in relation to volatility indices and traditional safe-haven instruments. In the 2024 forecast, a trend toward market hybridization is confirmed through the emerging connections between interchange platforms, content-based sectors (such as entertainment and gaming), and consumer staples. These components increasingly represent foundational pillars of the expanding metaverse ecosystem. A noticeable structural decoupling is also observed between the MVI and traditional volatility indicators, suggesting a diversification of risk dynamics. This decoupling may be attributed to the integration of metaverse technologies into more conventional sectors, such as real estate and financial services. As digital assets and fintech solutions become embedded in traditional asset classes, a new cross-domain financial architecture begins to take shape. Consequently, in a more mature and stabilized market context—characterized by reduced systemic volatility—the VIX and VXN indices appear less sensitive to fluctuations within the metaverse asset space. This indicates that, over the long term, these indices may no longer serve as reliable proxies for monitoring the dynamics of emerging digital ecosystems. To further investigate the evolution of the metaverse asset network over time, Figure 4 presents a Sankey diagram that visualizes the temporal transformation of structural linkages. The graphical visualization (Figure 4) illustrates the evolution of cluster membership for each asset, highlighting transitions in relational structure from the current 2023 financial network scenario to the projected 2024 configuration. This representation emphasizes how changes in topological connections drive shifts in asset positioning within the latent embedding space. While Sankey diagrams are not conventionally employed in stock market forecasting due to the complexity of interacting variables such as macroeconomic shocks and volatility, in this context they provide a compelling visual representation of the shifting interdependencies among asset groups. This qualitative analysis complements the embedding-based forecasts and reinforces the observed in short-term structural realignments. Figure 4 shows the consolidation of the hybridization of metaverse-oriented companies, highlighting cryptocurrencies as strongly connected to interchange platforms, real estate, treasury assets, and content and payment systems. The shifts produced through the embedding underscore a dynamic and fluid market environment where traditionally distinct industries are converging under the influence of digital transformation. This convergence implies a growing interdependence among technological, financial, and consumer sectors, suggesting that strategic decisions within one domain may increasingly affect and be affected by developments in adjacent domains. Consequently, companies operating in these sectors must develop the capacity to respond to both technological disruptions and cross-sector opportunities. The strong ties observed in the 2023 correlation network between emerging technologies and gaming (content sector) are evolving in the 2024 projection, increasingly aligning with a "play-to-earn" paradigm, where user participation is economically incentivized. Fintech is emerging as a central node within this structure, functioning as a key enabler of content monetization and distribution. Furthermore, while financial instruments were primarily associated with cryptocurrencies in 2023, the 2024 embedding reveals a diversification trend toward a broader range of investment classes, indicating a shift from speculative digital assets to more structured, globally oriented financial strategies. This transition points to the maturation of the metaverse economy and reflects investor interest in more stable, long-term digital infrastructure.

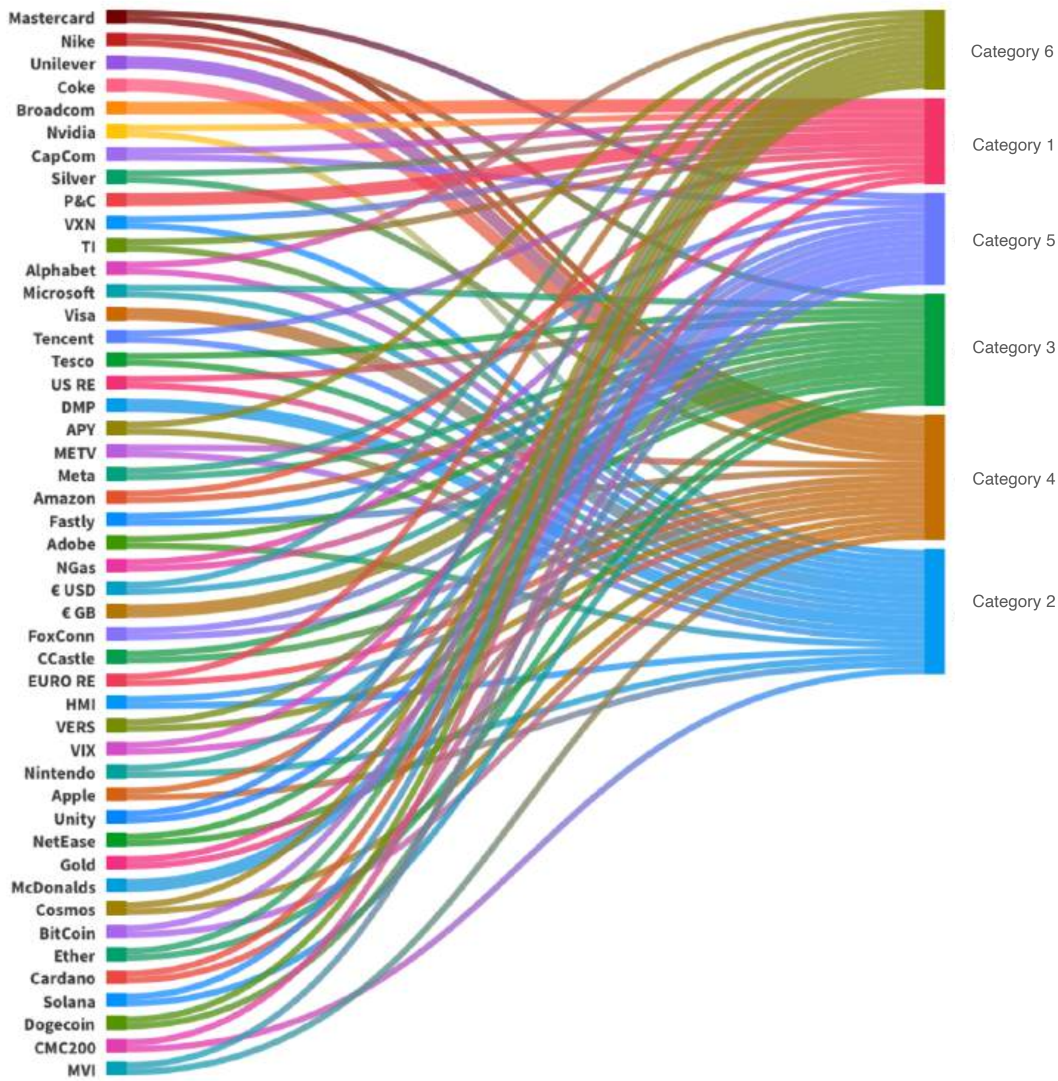


Figure 4: Sankey diagram of future scenario from 2023 to 2024

6 Discussion and conclusion

This study aimed to analyze the metaverse as a growing intersectoral landscape by examining the relationships between the Metaverse Index (MVI) and the returns of metaverse-oriented companies over time. The objective was to evaluate the potential of linear correlation networks as tools for financial prediction and to detect emerging socio-technological trends.

To this end, we collected and processed daily closing prices for the period 2019–2023 from the Coinbase Data Marketplace, including the MVI and 47 metaverse-oriented assets categorized into 13 thematic areas: (1) processing and IT/operating systems; (2) network and fixed connection; (3) platforms and platform development; (4) interchange; (5) payments; (6) contents; (7) cryptocurrencies; (8) safe havens; (9) consumer staples; (10) real estate; (11) treasuries; (12) volatility indices; and (13) NFT index.

After normalizing the time series through logarithmic return transformations, we conducted a correlation analysis. The data revealed no significant relationships with the MVI until 2021, the year of its launch. From that point, the analysis indicated strong linear associations among assets within the same domain but limited synergy between different domains. These findings are consistent with prior research (Vidal-Tomás, 2021; Momtaz, 2022), which points to the speculative and compartmentalized nature of the metaverse financial ecosystem.

Network correlation analysis was then employed to track the structural evolution of asset relationships across time. From 2019 to 2023, this analysis uncovered a gradual hybridization process, where initially isolated domains—such as cryptocurrencies and payment systems—began to converge with entertainment, consumer staples, and real estate. The MVI, though not central in the network, emerged as a key anchor point for metaverse-related assets, consolidating ties particularly in content creation and distribution. This convergence reflects the growing importance of interoperability and digital ownership, indicative of a maturing market driven by Web 3.0 technologies.

To explore predictive potential, we trained the node2vec algorithm on the 2022 correlation network to learn embeddings that reflect the structural features of the 2023 market. The empirical overlap between predicted and observed asset ties in 2023 demonstrated the model's reliability, providing a foundation to replicate the procedure for 2024 forecasts. Using the 2023 network, node2vec was applied with $p = 1$ and $q = 0.5$, parameters selected based on prior performance and the guidance of Grover and Leskovec (2016). The embedding for 2024 revealed six emergent asset categories or groupings, interpreted through dimensionality reduction and clustering via UMAP and validated internally using the skip-gram model's log-likelihood. The clusters highlighted the continued evolution of the metaverse economy, with significant implications for consumer behavior, digital asset integration, and cross-sectoral investment strategies. In particular, the scenario suggests an expansion of "play-to-earn" ecosystems and growing links between fintech, real estate, and digital infrastructure. Meanwhile, volatility indices (VIX and VXN) are increasingly decoupled from the metaverse, reflecting lower systemic risk in a more stable digital economy.

7 Limitations and further developments

Several limitations of the current approach must be acknowledged. First, node2vec embeddings are sensitive to hyperparameters p and q, as well as the choice of embedding dimensionality. Although we followed standard heuristics from the literature, further tuning could enhance accuracy and generalizability. Scalability may also become a constraint in larger networks, though this was not a limitation in our asset set. Interpretability is another key issue: embeddings lie in abstract vector spaces and may not directly convey intuitive relationships with asset features. To address this, we applied dimensionality reduction and clustering techniques (UMAP and t-SNE) to make spatial structures more interpretable and visually accessible. Additionally, the likelihood metric from the skip-gram training process was used as an internal goodness-of-fit indicator to monitor embedding quality. While informative, this metric does not evaluate predictive accuracy. For greater robustness, future studies could incorporate distance-based validation metrics, such as correlating geodesic distances in the original network with Euclidean distances in the embedding space. Alternatively, embeddings could be used as input features for downstream supervised tasks (e.g., node classification or link prediction), and evaluated using empirical performance. Moreover, the use of Sankey diagrams—while unconventional in financial forecasting—proved useful in visualizing dynamic asset reconfigurations across time. However, this representation does not model causal or probabilistic dependencies and should be interpreted as a qualitative synthesis of evolving relational structures.

This study illustrates how network embedding techniques can help identify underlying market dynamics and anticipate structural transitions within an emerging meta-economy. The findings suggest that the metaverse is no longer confined to isolated speculative assets but is gradually integrating with traditional finance, consumer behavior, and real estate—paving the way for new forms of economic interaction. Looking ahead, firms aiming to operate in metaverse-related domains should focus on developing interoperable platforms and innovative digital services, potentially based on tailored intellectual properties. These assets could become significant components of future stock markets, necessitating the creation of new indices or virtual stock portfolios tailored to digital ecosystems. The gamification of finance, driven by virtual economies and user-centric models, may further reshape how investment decisions are made in this evolving digital landscape.

Author contributions

Emma Zavarrone: data curation, methodology, formal analysis, investigation, supervision. Alessia Forciniti: data curation, methodology, writing-original draft preparation; writing-review and editing. Emanuele Mario Parisi: conceptualization, data resources, investigation. Angelo Miglietta: conceptualization, investigation, supervision.

Declarations

The authors declare no conflicts of 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. This research received no external founding.

References

Aharon, D. Y., Ender, D., and Smadar, S. (2022). Real returns from unreal world? market reaction to metaverse disclosures. *Research in International Business and Finance*, 63.

Ball, M. (2022). *The metaverse: and how it will revolutionize everything.* Liveright Publishing.

Bushnell, M. (2022). Global capital markets and cryptocurrency: Exploring the international political economy of blockchain ecosystems and metaverse development. *Advance: Social Sciences & Humanities.*

Chen, Z. (2022). Metaverse and stock market—a study based on fama-french model. In *Proceedings of the 2022 3rd International Conference on E-commerce and Internet Technology (ECIT 2022).*

Citi (2022). Metaverse and money: Decrypting the future. global perspectives and solutions. Technical report, Citi GPS.

Coinbase (n.d.). Coinbase data marketplace. Retrieved from `https://www.coinbase.com/it/explore`.

Ergun, Z. C. and Karabiyik, B. K. (2023). The price determinants of nfts: The case of metaverse. In El Khoury, R. and Alareeni, B., editors, *How the Metaverse Will Reshape Business and Sustainability*, Contributions to Environmental Sciences & Innovative Business Technology. Springer, Singapore.

Giudici, P. and Spelta, A. (2016). Graphical network models for international financial flows. *Journal of Business & Economic Statistics*, 34(1):128–138.

Grover, A. and Leskovec, J. (2016). node2vec: Scalable feature learning for networks. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining 2016*, San Francisco, California.

Hiraoka, Y., Imoto, Y., Lacombe, T., Meehan, K., and Yachimura, T. (2024). Topological node2vec: Enhanced graph embedding via persistent homology. *Journal of Machine Learning Research*, 25:1–6.

Horky, F. (2023). The metaverse hype: Identifying bubbles and comovements of metaverse tokens. *Journal of Chinese Economic and Business Studies.* (Forthcoming).

Khashanah, K. and Alsulaiman, T. (2016). Network theory and behavioral finance in a heterogeneous market environment. *Complexity*, 21:530–554.

Mantegna, R. N. and Stanley, H. E. (2000). *An Introduction to Econophysics: Correlations and Complexity in Finance.* Cambridge University Press.

Mikolov, T., Chen, K., Corrado, G., and Dean, J. (2013). Efficient estimation of word representations in vector space. In *Proceedings of ICLR 2013*.

Momtaz, P. P. (2022). Some very simple economics of web3 and the metaverse. *FinTech*.

Mukherjee, S. and Hussaini, N. (2023). Linkage of non-fungible (nft) tokens to measures of uncertainty: Does fear bode well for nft holders? *Journal of Economics, Finance and Management Studies*, 36:3267–3290.

"Ozkal, I., "Ozkal, I. A., and Başçiftçi, F. (2024). Metaverse token price forecasting using artificial neural networks (anns) and adaptive neural fuzzy inference system (anfis). *Neural Comput & Applic.*, 36:3267–3290.

Pamucar, D. and Biswas, S. (2023). A novel hybrid decision making framework for comparing market performance of metaverse crypto assets. *Decision Making Advances*, 1(1):49–62.

Panchenko, V., Gerasymchuk, S., and Pavlov, O. V. (2013). Asset price dynamics with heterogeneous beliefs and local network interactions. *Journal of Economic Dynamics and Control*, 37(12):2623–2642.

Perozzi, B., Al-Rfou, R., and Skiena, S. (2014). Deepwalk: Online learning of social representations. In *Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, New York, USA. Association for Computing Machinery.

Schnoering, H. and Inzirillo, H. (2022). Constructing a nft price index and applications. *arXiv preprint arXiv:2202.0896*.

Tan, T. M., Makkonen, H., Kaur, P., and Salo, J. (2022). How do ethical consumers utilise sharing economy platforms as part of their sustainable resale behavior? the role of consumers' green consumption values. *Technological Forecasting and Social Change*, 176.

Tang, M., Qu, M., Wang, M., Zhang, J., et al. (2015). Line: Large-scale information network embedding. In *Proceedings of WWW 2015*.

Vidal-Tomás, D. (2021). The entry and exit dynamics of the cryptocurrency market. *Research in International Business and Finance*, 58.

Wasserman, S. and Faust, K. (1994). *Social Network Analysis: Methods and Applications*. Cambridge University Press.

Weinberger, M. (2022). What is metaverse?—a definition based on qualitative metasynthesis. *Future Internet*, 14(11).

Xu, Y., Liu, W., He, T., and Tsai, S. B. (2024). Buzzword or fuzzword: An event study of the metaverse in the chinese stock market. *Internet Research*, 34(1):74–194.

Yemenici, A. D. (2022). Entrepreneurship in the world of metaverse: Virtual or real? *Journal of Metaverse*, 2(2):71–82.