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# Characterizing NFT Markets through a Multilayer Network Approach

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**Abstract**

The rapid growth of Non-Fungible Tokens (NFTs) and the extensive trading activities associated with such an intriguing domain led to the emergence of large-scale and interconnected transaction networks involving the most prominent NFT markets. Despite such interdependencies representing an inestimable source of information for the proper understanding of the NFT landscape, previous studies treated each market separately, overlooking relevant phenomena.

In this study, we explore a multilayer network modeling approach to analyze transactions in multiple NFT markets. We reveal previously unnoticed macroscopic and mesoscopic traits by investigating indicators that discern whether markets are independent or linked: users trading NFTs are organized in cross-market communities where multi-market users act as bridges across marketplaces, adapting to the diverse nature of the markets they operate in. We also conduct an in-depth examination of such multi-market users, studying their specific activity patterns that leave a distinctive mark on the system: the majority of multi-market users well differentiate their earnings and expenses among the markets, while a fraction of them is directed toward a more polarized money allocation based on the typology of the markets.

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By offering a fresh perspective on this intricate financial system and emphasizing the importance of perceiving the NFT markets as a unique and interconnected world, our study paves the way for further contributions aimed at unraveling the complexity of cryptosystems and understanding the latent phenomena across NFT markets.

*Keywords:*
Blockchain-based Systems, Web3, NFT, Cryptocurrencies, Transaction Networks, Multilayer Networks



## 1. Introduction

Non-Fungible Tokens (NFTs) emerged as one of the most captivating applications of blockchain technology in recent years. With their unique ability to tokenize digital assets using the so-called *smart-contracts*, i.e., self-executing code-based policies, NFTs attracted numerous digital creators and investors, interested in certifying the uniqueness of assets through innovative approaches and finding profitable markets for their activities. As a result, NFTs gained noteworthy attention, becoming the de-facto pioneers of the Web3 advent. The remarkable expansion of NFTs is vividly evidenced by the astonishing trading volume exceeding $2 billion in the first quarter of 2021,[1] making the NFT technology pervasive in the digital realm, to the point of being the subject of extraordinary events, such as record-breaking auctions for the digital world[2], the sale of the screenshot of the first-ever tweet for more than $2.9 million[3] or the congestion of the Ethereum network caused by users rushing to purchase digital copies of cartooned cats.[4]

Such fervor, however, is not limited to the realm of tokens and cryptocurrencies. Indeed, it generates a wealth of data, offering an invaluable opportunity to analyze the crypto economy through the myriad of transactions stored on the blockchain. All of this translates into an increasingly complex and intriguing domain, capable of concealing more and more in-

[1]https://nonfungible.com/reports/2021/en/q1-quarterly-nft-market-report
[2]https://www.christies.com/about-us/press-archive/details?PressRelease ID=9970
[3]https://www.cnbc.com/2021/03/22/jack-dorsey-sells-his-first-tweet-ever-as-an-nft-for-over-2point9-million.html
[4]https://qz.com/1145833/cryptokitties-is-causing-ethereum-network-congestion

sights — as transactions increase — for the proper understanding of a new paradigm, with its pitfalls and opportunities.

It is therefore demanding to fulfill the challenge of developing appropriate and robust analytical frameworks that are capable of best modeling the large-scale and complex networks of NFT transactions (generated by the major trading markets, i.e. online platforms or digital marketplaces where users can buy, sell, trade, and often mint (create) non-fungible tokens (NFTs) and unveiling their main patterns. Given the networked nature of NFT transactions, some studies in the literature have proposed approaches based on graph analysis. These approaches either examine individual markets or consider the entire ecosystem of many markets as a unique trading system. Although these graph-based approaches have provided interesting insights into the NFT landscape, they consider the relationships between actors in different marketplaces as belonging to a single and flat network structure. However, such platforms are characterized by an independence/cross-linkage dichotomy that must be taken into account. While each platform has its own rules that drive its internal dynamics, seemingly isolating NFT platforms from one another, in reality, these platforms are interconnected through multimarket users—individuals who perform operations across multiple markets.

In light of the above considerations, in this work, we aim to fill a gap in the literature by proposing the first multilayer network modeling of transactions within and across the most relevant NFT markets to date. In our multilayer modeling, the layers (markets) are linked through pillar nodes. A pillar node is a unique entity that exists across multiple layers of a multilayer network, serving as a point of interconnection between these layers. Unlike nodes confined to a single layer, pillar nodes maintain a presence in two or more layers simultaneously, creating vertical links. In our case, these pillar nodes represent multi-market users that operate across multiple NFT platforms. By participating in multiple markets, these users create inter-layer connections that allow capturing the complex interdependencies within the broader NFT marketplace.

To the best of our knowledge, this work represents the first attempt to study an NFT transaction network from a multilayer perspective. By adopting this novel approach, we aim to reveal patterns and insights that otherwise would remain unobservable, overcoming the need to treat such a domain as a collection of distinct and physically separated markets. Moreover, we aim to provide a characterization of users engaging in different markets, by observing their activity patterns [1], unveiling their main spending habits, strategic roles, and trading dynamics, adding one more piece toward understanding the role of agents bridging different trading networks.

Through the proposed network modeling and analysis approach, we aim to answer the following research questions:

**(Q1)** Does a multilayer-network perspective over the transactions in the main NFT markets reveal hidden traits of the ecosystem, particularly concerning multi-market users and multi-market communities, that remain undiscovered when market transactions are modeled separately or flattened together?

**(Q2)** What are the patterns of activity of multi-market users, i.e., those engaging in trading operations across multiple markets, and how are these patterns reflected in their financial preferences?

While answering the above research questions, this study explores various aspects of multi-market trading in the context of financial transactions within the considered NFT markets. From this perspective, the key findings can be summarized as follows:

- **Relevance of a multilayer network approach:** Our findings highlight that the presence of a substantial fraction of multi-market users reinforces the usage of multilayer networks to model intertwined markets. This modeling approach provides a more comprehensive understanding of the interconnected nature of markets. The significance of this approach is further underscored by the large number of multi-market users we discovered, particularly between the two largest markets in our study, which emphasizes the interconnectedness of the NFT ecosystem and justifies the need for a multilayer network model

- **Multilayer community structure in NFT markets:** Our findings indicate the need for adopting multilayer modeling for the most relevant NFT markets to gain deeper insights into their modular structure. This study reveals the existence of communities spanning different markets. For instance, a generalist market such as OpenSea plays a unifying role across different layers, acting as a cohesive element and promoter of market cooperation. On the other side, we also observe cases of "market independence", i.e. communities with limited connectivity outside their reference market, especially when it is specialized in a particular type of tradable items

- **Multi-market users:** Our results highlight the significance of multi-market users in the NFT ecosystem, not only due to their substantial numbers and role in connecting different markets but also because of their distinct activity patterns. Compared to their single-market counterparts, these users demonstrate higher levels of activity and a greater propensity to act as investors. While most multi-market users tend to diversify their activities homogeneously across various NFT marketplaces, we observed an intriguing asymmetry in their trading behavior. Specifically, their patterns of expenses and earnings differ, influenced by factors such as the NFT category and the unique characteristics of each marketplace.

In conclusion, the research provides valuable insights into the dynamics of multi-market trading in NFT domains, emphasizing the relevance of multi-layer network modeling in understanding the intricate relationships within and across the considered NFT marketplaces. These findings, though based on our specific dataset, are significant given its size and representativeness.

## 2. Related Work

The media and economic echo caused by Non-Fungible Tokens has drawn the attention of many research groups interested in studying novel opportunities and challenges in such an intriguing domain [2, 3, 4, 5, 6, 7, 8, 9, 10, 11], widely recognized as the trailblazer for the Web3.

Among the first contributions, the work from Wang *et al.* [12] emerges as a detailed overview of the state-of-the-art NFT solutions, in terms of technical components, protocols, standards, and desired properties.

From a network and computational social science perspective, the seminal work by Nadini *et al.* [13] is to date recognized as the pivotal contribution to the study of the NFT landscape, as the authors collected and analyzed about 6M transactions involving nearly 5M NFTs between 2017 and 2021 from the Ethereum and WAX blockchains; they unveiled high specialization towards specific collections from traders, visual homogeneity in NFT collections, and higher informativeness of the visual features in NFT price predictability compared to just looking at transaction histories.

In a recent work, Guidi *et al.* [14] explored the development of the so-called NFTs 2.0, i.e., the expansion of their original concept to unprecedented capabilities and opportunities.

Price forecasting represents the most-addressed topic in the NFT research landscape because of the rise and expansion of the crypto-economy. Dowling [15] observed a lack of correlation between the pricing of NFTs and how cryptocurrencies perform, albeit the latter aspect might still provide some useful insights into the pricing dynamics of NFTs [15, 16, 17, 18, 19]. Intrinsic influence factors on the price of NFTs were studied by Mekacher *et al.* [20] through about 4M transactions collected between 2018 and 2022. Specifically, the authors studied how the rarity of visual attributes of more than 1M NFTs spanning 400 collections might impact their financial performances, unveiling that rarer tokens achieve higher selling prices. Similarly, Ho *et al.* [21] investigated the *Axies* play-to-earn gaming NFTs showing how utility-based intrinsic features, such as attack/defense card-specific scores, might improve the predictive power of the NFT pricing w.r.t. uniquely relying on rarity traits. Costa *et al.* [22] proposed a multimodal deep learning framework that exploits NFT images and descriptions as the unique source for predicting their selling prices, showing the effectiveness of intrinsic traits in addressing such a compelling challenge. Besides, He *et al.* [23] investigated the task of generating profitable NFT images from user-input texts. Kapoor *et al.* [24] provided one of the first investigations of external influence factors in NFT pricing, with a particular focus on social influence. Indeed, by creating and analyzing a dataset linking OpenSea NFTs and their corresponding Twitter data, the authors carried out an NFT performance prediction task exploiting both sources of information, showing how integrating social features led to an improvement of 6% in accuracy compared to the case solely based on intrinsic ones. Further confirmations of the influence of social media on NFT pricing were recently found by Ziemke *et al.* [25]. Another emerging field of investigation within the NFT ecosystem concerns spotting vulnerabilities [26, 27], as well as fraudulent [28] and anomalous activities [29, 30, 31], which can easily develop due to the decentralized nature and lack of regulation of such a technology.

Graph-based modeling was exploited as a very promising approach for studying the NFT landscape. In this regard, Vasan *et al.* [32] leveraged network analysis to delve into more than 48k NFTs listed by over 15k artists, unveiling that earning, resp. spending, possibilities are influenced by the order of arrival into the platforms for artists, resp. investors. Besides, the authors spotted that the linkage between artists and collectors is paramount for developing close-knit and enduring investment networks. Furthermore, Colavizza [33] inferred and analyzed the seller-buyer networks of about 40k

NFT sales, showing how the NFT landscape is actually driven by a small set of sellers and buyers, and that the growth of the market is characterized by buyer-seller ties, which also persist during dips. Recently, the potential of network modeling in the Web3 domain was also exploited by La Cava *et al.* [34] to shape inspiration flows in the NFT ecosystem, spotting that the pervasiveness of inspiration might have led to a temporary saturation of the visual features space, and to allow for a multimodal exploration of NFT inspiration networks [35]. Moreover, Galdeman *et al.* [36] studied the network growth of two markets (Cryptokitties and OpenSea), highlighting how markets with different purposes present different evolution rules.

It is worth noting that all the approaches discussed so far have focused on NFT price forecasting or analyzing NFT dynamics by only considering individual markets or single transaction networks, thus limiting the scope. In contrast, our work aims to exploit multilayer-network modeling to examine the main NFT markets as (i) it allows a more comprehensive and expressive analysis of the NFT landscape by considering multiple markets simultaneously, and (ii) it enables unveiling cross-market traits and activity behavioral patterns that have previously been overlooked.

## 3. Methodology

In this section, we describe the data we used and the network models we devised to analyze the transactions in the NFT markets from both single-layer and multilayer perspectives.

### *3.1. Data*

To properly model transactions related to NFTs buying and selling, it is desirable to have data with high market representativeness, good temporal coverage, and extended inclusiveness of the many platforms into which the NFT world is fragmented. To this aim, we resorted to the dataset collected and analyzed by Nadini *et al.* [13], as it meets all the mentioned criteria, having a multi-market coverage that is absent in newer datasets. In particular, it contains more than 6M transactions shaping NFT sales between more than 500k different users, comprising five among the most-known markets, namely:

- *Cryptokitties*: one of the first gaming projects within the NFT ecosystem;

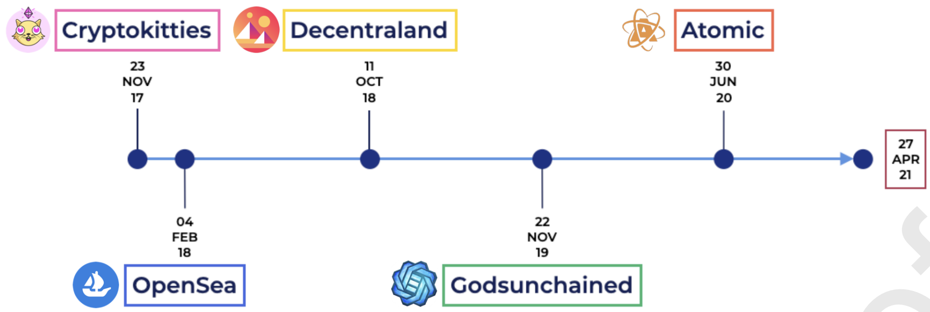


Figure 1: **Timeline of NFT markets.** Markets are shown on a timeline ordered by the time of their first transactions. The dataset covers the period from the introduction of *Cryptokitties* on November 23, 2017, up to almost a year after the first transaction in the *Atomic* market.

- *OpenSea*: the first and most-known NFT market, which covers tokens from various categories (e.g., Collectibles, Art, Utility) and is hence defined as *generalistic*;
- *Decentraland*: the leading platform in the Metaverse,
- *Godsunchained*: hosting cards for the homonymous trading card game; and
- *Atomic*: another well-known multi-categorical NFT market.

The temporal coverage of the dataset is about three years, from November 23, 2017 (the date when the first Cryptokitty token was sold) to April 27, 2021 (the date of the last captured transaction), as reported in Figure 1. This period corresponds to a steady-state and 'ordinary' phase of the NFT ecosystem, preceding the extreme speculative spikes of later years. Focusing on this time window enables the analysis of structural and behavioral patterns under stable market conditions, capturing a diverse range of user activities, trading strategies, and market interactions. Crucially, our choice of dataset and markets was driven by both methodological and representational needs: *(i)* all considered markets rank among the most widely adopted in the early NFT ecosystem, and *(ii)* all—except for Atomic—operate on the Ethereum blockchain, which ensures the feasibility and consistency of multi-layer modeling. For this reason, we omitted Atomic from our analysis, as it is based on a different blockchain (WAX), making it unlikely to match its traders with those of Ethereum-based markets.

Our proposed methodology relies on the most studied publicly available dataset to date, which encompasses a substantial portion of the recent NFT transaction history, thus ensuring that our findings are highly representative and robust. Besides, considering the evolving nature of the NFT domain and the daily influx of new transactions, we conceived our methodology to be highly generalizable to fresh data as soon as they become available, thus enabling a continuous and flexible analysis of the NFT ecosystem. Other more recent and larger datasets, such as [37], which covers over 70 million NFT transactions on OpenSea, or [38], were not taken into consideration. Even though they are valuable, we excluded them from this investigation because they are limited to a single market and/or cover different periods. To the best of our knowledge, the selected dataset [13] represents the only publicly available resource to study multi-market user activities in a shared temporal window.

### *3.2. Multilayer network modeling*

**Single-layer transaction network model.** We denote with $\mathcal{V}$ and $\mathcal{L}$ the set of users and markets, respectively, available in our dataset. For each market $i \in \mathcal{L}$, we model the set of transactions occurring within $i$ as a directed and weighted network $G_i = \langle V_i, E_i, c_i \rangle$, where the set $V_i \subseteq \mathcal{V}$ contains users that performed at least one transaction in $i$, and the edge set $E_i \subset V_i \times V_i$ is the set of transactions, such that any $(x, y) \in E_i$ indicates that user $x \in V_i$ completed at least one transaction towards (i.e., bought an NFT from) user $y \in V_i$. Moreover, $c_i : E_i \to \mathbb{N}$ is an edge-weighing function such that, for each $(x, y) \in E_i$, $c_i((x, y))$ returns the number of transactions from user $x$ to user $y$ in the market $i$.

**Multilayer transaction network model.** We model the set of transactions occurring within and across the markets as a directed weighted multilayer network $\mathcal{G} = \langle V_{\mathcal{L}}^M, E_{\mathcal{L}}^M, \mathcal{V}, \mathcal{L}, c \rangle$. Inspired by the notation proposed in [39], $\mathcal{V}$ and $\mathcal{L}$ are the set of users and markets defined in the single-layer modeling. Nodes in the multilayer network are entity-layer pairings defined as $(v, l) \in V_{\mathcal{L}}^M \subseteq \mathcal{V} \times \mathcal{L}$, where $l$ specifies the layer in which user $v$ is acting ($M$ stands for multilayer). Note that we will refer to users in general as *entities*, while we will use the term *node* referring to the pair $(entity, layer)$. Moreover, $E_{\mathcal{L}}^M \subseteq V_{\mathcal{L}}^M \times V_{\mathcal{L}}^M$ is the set of directed edges between user-layer pairings, so that it could include an edge between nodes of the same layer or across layers. Specifically, in our case, the edges are the union of the within-market links and edges connecting multi-market nodes. The latter are called *pillar nodes* and correspond to users who exist in different layers. Formally, a node $(v, l_i)$ is defined as a pillar node if $\exists(v, l_j) \in V_{\mathcal{L}}^M$ with $\{l_i, l_j\} \subseteq \mathcal{L}$. Having formally defined pillar nodes in our network, we focus on the edges. The edge set is defined as $E_{\mathcal{L}}^M = L \cup P$, where $L$ is the set of within-market edges, i.e., the ones in each single-layer network $G_i$, defined as

$$L = \bigcup_{i \in \mathcal{L}} \{((x, i), (y, i)) \ s.t. \ (x, y) \in E_i\},$$

and $P$ is the set containing the edges connecting pillar nodes, i.e., users that are present in different layers, and it is defined as

$$P = \{((x, l_1), (x, l_2)) \ s.t. \ \{l_1, l_2\} \subseteq \mathcal{L}, x \in V_{l_1} \cap V_{l_2}\}.$$

Therefore, if a node $v$ is acting on two markets $l_1$ and $l_2$, than $P$ will include the edges $((v, l_1), (v, l_2))$ and $((v, l_2), (v, l_1))$ . Finally, the weighting function $c : E_M \rightarrow \mathbb{R}$ assigns each edge a weight expressing the number of transactions that occurred between the corresponding entity-layer pairs. Figure 2 depicts an example of a multilayer network representation with two layers ($\mathcal{L} = \{l_1, l_2\}$). $\mathcal{V}$ is composed of the users ($v_i$) in all the layers (union), while the nodes of the multilayer network are the pairings node-layer, as in the case of the pink entity $v_1$. Since the pink node appears in both layers, the nodes related to the entity $v_1$ are $(v_1, l_1)$ and $(v_1, l_2)$. The set of edges $E_{\mathcal{L}}^M$ is the union of the edges on the single layers (dotted blue and red lines, such as the edge $((v_3, l_1), (v_4, l_1)))$ and the intra-layer edges (grey lines, for instance, the edge $((v_2, l_1), (v_2, l_2))$ between entity $v_2$ ).

## 4. Results

In this section, we present the main results of our study, which stem from the idea of gaining a comprehensive overview of the main NFT markets to provide novel insights into such an intricate ecosystem. The timeframe considered (2017–2021) represents a steady-state and 'ordinary' period of the NFT ecosystem, deliberately chosen to avoid the disruptive spikes of later years and to allow the observation of diverse trading patterns and user behaviors across markets. Led by the two research questions on the capability of the multilayer network approach of finding patterns not easily discoverable by single-layer modeling approaches, and on the specific traits of multi-market accounts, here, we encompass two pivotal aspects: an in-depth exploration

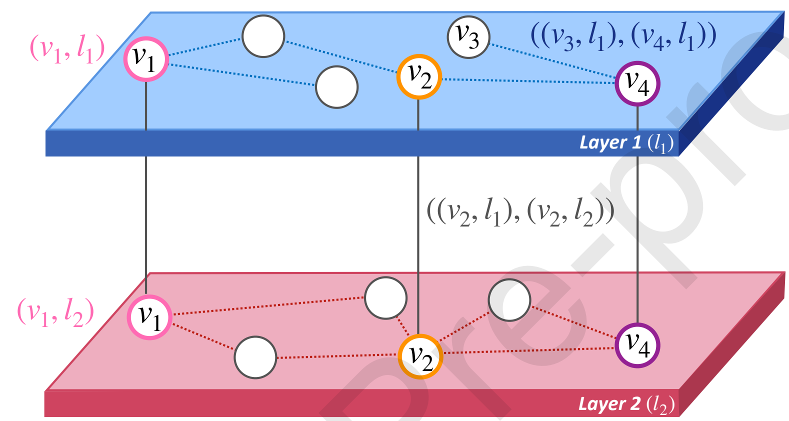


Figure 2: **Multilayer modeling.** This illustrative multilayer network exemplifies our modeling approach. Comprising two layers, denoted as $l_1$ and $l_2$, the nodes within each layer represent entity-layer pairings, such as the node $(v_1, l_1)$. An "entity" refers to a node appearing across multiple layers, resulting in distinct nodes like $(v_1, l_1)$ and $(v_1, l_2)$ for the entity $v_1$. Internal layer edges, like $((v_3, l_1), (v_4, l_1))$, connect nodes sharing the same layer information, denoted as $l_1$. Pillar nodes, representing entities, can also be connected, as illustrated by the edge $((v_2, l_1), (v_2, l_2))$ linking the orange entity $v_2$; in this case, the connected nodes share the same entity rather than the same layer. It is essential to note that for the sake of visualization simplicity, the depicted graph is undirected, while our modeling provides a directed graph.

Table 1: Number of users and transactions for each market

| | Cryptokitties | OpenSea | Decentraland | Godsunchained |
|---|---|---|---|---|
| #Users | 99 984 | 214 238 | 4747 | 2535 |
| #Transactions | 481 522 | 962 460 | 11 757 | 4085 |

| Market | Market's nodes |
|---|---|
| *Cryptokitties* | 47.12% |
| *OpenSea* | 23.72% |
| *Decentraland* | 54.06% |
| *Godsunchained* | 94.2% |

(*a*)

| | Cryptokitties | OpenSea | Decentraland | Godsunchained |
|---|---|---|---|---|
| Cryptokitties | **99 984** | 47 059 | 584 | 552 |
| OpenSea | 47 059 | **214 238** | 2 521 | 2 381 |
| Decentraland | 584 | 2 521 | **4 747** | 115 |
| Godsunchained | 552 | 2 381 | 115 | **2 535** |

(*b*)

Figure 3: **Pillar distribution.** (a) The percentage of nodes on each market that are also engaged in other platforms (defined as pillars); (b) for each market pairing, the number of users involved in transactions on both platforms.

of community structures within the multilayer network - to address the first goal - and the identification and examination of pillar nodes - to answer the second question.

Initially, we employ the multilayer modeling approach to identify pillar nodes, recognizing their fundamental role in shaping the dynamics of the NFT landscape. Subsequently, we delve into the community structure of the multilayer network, aiming to uncover latent features pertaining to interoperability and interconnectivity. Further, we investigate how pillar nodes are distributed among these communities, offering nuanced insights into their role in the network structure. Lastly, a comprehensive analysis is conducted on the pillars' activity patterns within the two largest markets, OpenSea and Cryptokitties. This examination encompasses their preferences, spending, and earning patterns across various platforms, and a discerning exploration of their roles as buyers or sellers within these dominant markets.

In accordance with the modeling outlined in Section 3.2, we constructed a multilayer network, establishing a comprehensive framework for analyzing various NFT markets. Table 1 presents an overview of the number of users (traders) and transactions within each platform, offering insights into the scale of the respective markets. While OpenSea's prominence matches its large-scale adoption and scope, the high volumes in Cryptokitties represent an intriguing aspect, especially considering its nature as a gaming-focused platform. Conversely, we spotted that the Decentraland and Godsunchained platforms remain particularly contained in terms of user base and transactions, due to their stronger niche scope.

### *4.1. Multi-market nodes through pillar analysis*

Our first effort towards multilayer network modeling is the investigation of the significance of multi-market nodes, elements required to connect layers - markets - in the multilayer network representation. Identifying and studying such strategic users is important due to the manifold contributions they offer to the evolution of the NFT domain. First, they serve as crucial bridges connecting multiple and potentially heterogeneous markets, thereby enhancing the accessibility and connectivity of the entire NFT ecosystem. Secondly, these users might actively promote market interoperability, addressing the potential shortcomings due to their decentralized nature. Finally, their engagement with users from other markets draws attention to niche markets, favoring small markets' expansion and fostering organic growth of the entire NFT landscape.

In terms of multilayer network representation multi-market nodes embody the definition of pillar. For this reason, we quantify how pillars are frequent and whether there are markets more coupled than others. Figure 3 (a) illustrates the percentage of nodes on each market that concurrently operate on other platforms. Specifically, the percentage $p(m)$ relative to market $m$ corresponds to the ratio of nodes that also performed transactions in markets different from $m$ over the total number of nodes in layer/market $m$. The data reveals that OpenSea stands out as the market with the lowest percentage of such users, likely due to its significantly higher number of users compared to other markets. Surprisingly, in the case of CryptoKitties, which is a market primarily oriented towards gaming, a substantial proportion of users engage in multiple markets. It is noteworthy that almost all Godsunchained users are also acting on other markets, while Decentraland demonstrates a non-negligible proportion, further highlighting the varying degrees of market interconnection. A finer-grained perspective on this phenomenon is reported in Figure 3 (b), where we show the number of users involved in the interactions of each market pairing. Cryptokitties and OpenSea exhibit the highest number of shared pillars, with OpenSea notably standing out due to its broad, generalistic appeal that results in a higher node overlap with other markets. Conversely, the least intersection occurs between Decentraland and Godsunchained, possibly attributable to distinct platform goals and a smaller user base, as evident from the diagonal of the table. In brief, the multi-market trait is primarily associated with a trade-off involving participation in both specialized and generalist/investment markets. However, restricting activity solely to specialized markets constrains the potential for engaging in multi-market trading. In general, the above findings highlight that the presence of a substantial component of multi-market users reinforces the usage of multilayer networks to model intertwined markets.

### *4.2. Community structure of the multilayer transaction network*

A well-known and universal trait of networks capturing complex systems such as biological, social, transportation, and financial networks, is their mesoscopic organization into cohesive modules of tight-knit elements, namely communities [40]. In the context of financial and transaction networks, communities are very relevant since they may indicate spontaneous submarkets, coordinated economic agents, or even organizations of fraudulent users. These phenomena are even more evident and complex in multilayer financial networks where users or agents belonging to a common group act across different economic systems or markets, determining the formation of multilayer communities, which extend across various layers and frequently unveil significant properties of the encoded complex system.

To cope with the identification of communities spanning different markets, we employ the Infomap [41] community detection algorithm, renowned for its efficacy in analyzing transaction networks [42]. Leveraging its random-walk-based nature, the Infomap algorithm proves instrumental in uncovering meaningful communities even within the multilayer network, allowing us to discern and interpret patterns of user connectivity and interaction across NFT markets. We applied such a method on our multilayer directed weighted network $\mathcal{G}$ outlined in Section 3.2. The Infomap algorithm identifies non-overlapping communities at the node level, where each node represents a unique user-layer combination. This distinction is important: while a user

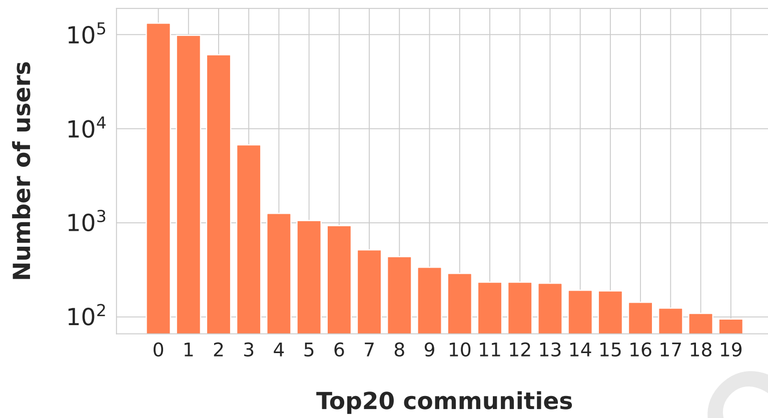


Figure 4: Number of users for each of the top 20 communities found by the InfoMap algorithm.

is restricted to one community within a single layer, they can belong to different communities across layers. For example, the same user might belong to community A in Layer 1 and community B in Layer 2. All results presented in this analysis were obtained using Infomap's default parameters. To validate the robustness of these findings, we conducted a stability analysis by running the algorithm 10 times with different random seeds. Comparing these results with our default configuration yielded a median Normalized Mutual Information (NMI) score of 0.87, with a standard deviation of 0.014. These metrics demonstrate that our community detection results are stable.

Figure 4 displays the user-community distribution of the 20 largest communities obtained via Infomap. The height of the $i$-th bar of the plot indicates the number of nodes included in the $i$-th community. Communities are ordered by the number of nodes. The results unveil a highly skewed partitioning, with the largest community encompassing 42.62% of all wallets (or users) and the 10 biggest communities together accounting for 95.47%; the remainder is distributed across very small modules or subgraphs.

We now analyze how users from different layers (markets) are distributed across the most populated communities using two coverage metrics: *layer coverage* and *community coverage*, defined as follows:

- The layer coverage $cov_L$ measures what fraction of a layer's users belong

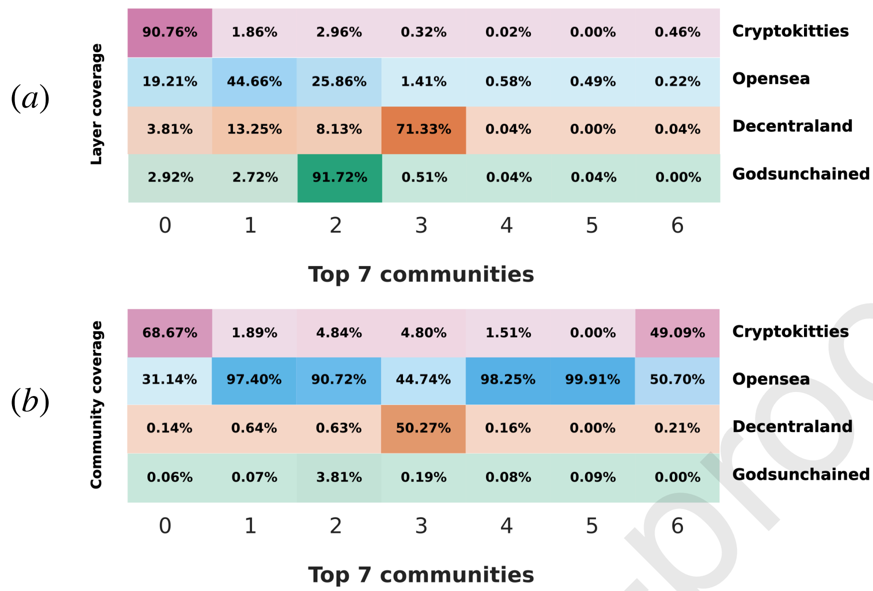


Figure 5: **Layer and community coverage in Infomap communities.** The charts illustrate the seven largest communities as columns of the matrix, and the different layers as rows. In (a), the values report the percentage of layer's users that belong to a specific community; while in (b), the percentages refer to the ratio of users of the community that belong to a specific community. In (a) rows sum to 1 while in (b) columns sum to 1.

to a specific community:

$$cov_L(i, c) = \frac{|V_i \cap V_c|}{|V_i|}$$

where $V_i$ represents the set of nodes in layer (market) $i \in \mathcal{L}$ and $V_c$ represents the set of nodes assigned to community $c$.

- Conversely, the community coverage $cov_C$ measures what fraction of a community's users participate in a specific layer:

$$cov_C(i, c) = \frac{|V_i \cap V_c|}{|V_c|}$$

These complementary metrics help us understand both how communities span across different markets and how markets are segmented into communities.

Figure 5 includes two matrices, the first one (Figure 5a) describes the layer coverage for the top 7 communities, while the second matrix (Figure 5b) shows how users of a community are divided into the different layers (community coverage). For instance, the third community (`id`=2) includes 61061 users. Among these, 55393 nodes are affiliated with OpenSea, 2957 nodes with Cryptokitties, 2325 nodes with Godsunchained, and the remaining 386 nodes are associated with Decentraland, and these sizes are reflected in the percentages of Figure 5b. While the percentage of a layer's nodes included in each community determines a different ranking, the nodes of the third community represent around 26% of OpenSea's nodes, then 3%, 92% and 8% of Cryptokitties, Godsunchained and Decentraland's nodes respectively (values reported in Figure 5a).

Despite the tendency for most markets to cluster within distinct communities (for instance, the Cryptokitties' users are almost entirely included in the first community), we spotted a non-negligible fraction of users from different markets participating in the same communities, particularly notable among OpenSea users. For instance, community 2 includes almost all the Godsunchained users ( 91.72% ) but also a good fraction of OpenSea's users. Through this analysis, it becomes evident that the inherent nature of the platforms exerts a significant influence on the multilayer structure. Users trading within markets with specific purposes, such as gaming in Cryptokitties or engagement in the metaverse in Decentraland, tend to form cohesive clusters, exemplified by the first and fifth communities. In contrast, the more versatile OpenSea market emerges as a unifying force across layers, acting as a cohesive element as its users are distributed widely across multiple communities.

To stress the expressiveness of the multilayer network approach and catch all nuances of multilayer communities, we also explore community detection from an alternative perspective: by flattening our network by $\mathcal{G}$, where each entity (user) $v \in \mathcal{V}$ represents the users in all the markets they participated in. Each link in the flattened network represents the trading of an NFT between two users, irrespective of the specific marketplace where the purchase was made, thus obtaining a single-layer network. Subsequently, we performed community detection again through Infomap and computed the Normalized Mutual Information (NMI) score between the corresponding partitionings, which yielded a relatively low value of 0.186. Since NMI computation requires comparing partitions with the same number of nodes, we need to address a mismatch in our case: the multilayer partition contains $\sum_{i \in \mathcal{L}} |V_i^M|$ nodes (counting duplicates of users across layers), while the flattened partition has only $|\bigcup_{i \in \mathcal{L}} V_i^M|$ unique users. To align these partitions, we expand the flattened partition by duplicating each user's community assignment based on their presence in the multilayer network. For example, if a user operates across three different layers in the multilayer network (thus appearing three times, potentially with different community assignments), we replicate their flattened network community assignment three times. This ensures both partitions have the same number of nodes for a valid NMI calculation. In the literature, NMI represents one of the widely adopted quantities to assess the similarity of the partitioning returned by community detection methods. An NMI close to 0 indicates a poor overlap between partitioning, while perfect overlapping has an NMI score equal to 1. In our case, the low NMI score serves as further evidence in favor of adopting a multilayer perspective over these markets, as it allows for capturing the complexity of users engaging in trading operations across multiple markets.

In general, our findings on the community structure of financial transactions in multi-NFT markets have strongly indicated the need for adopting multilayer modeling for the most relevant NFT markets to gain deeper insights into their modular structure, revealing patterns that were previously hidden, as prompted in our research question **(Q1)**.

### *4.3. Multi-market nodes in communities*

In the previous section, we showed a non-negligible presence of communities spanning different markets. Consequently, it is natural to ask whether multi-market nodes influence this outcome since they act as *trait-d'union* (connecting links) among markets. So, we proceed with our investigation from a mesoscopic perspective on the structural traits of pillar nodes, analyzing how pillar nodes are distributed among the most populated communities. Figure 6 shows both the composition of each layer in terms of pillar and non-pillar nodes (single market) and the pillar percentage that each community covers. Pillars play a notable role in communities 0 and 3, accounting for around 41% and 31% of nodes in the community, respectively. Community 6 stands out with the highest concentration of pillars, where they represent 95% of all community nodes. Multi-market nodes are also present in community 2, even if in a negligible percentage ( 8.2%), while being practically absent (percentage below 0.1% ) in communities 1, 4, and 5. The red line in the plot tracks the pillar coverage, meaning the percentage of pillars that the multi-market node in a community covers. The key aspect of this plot

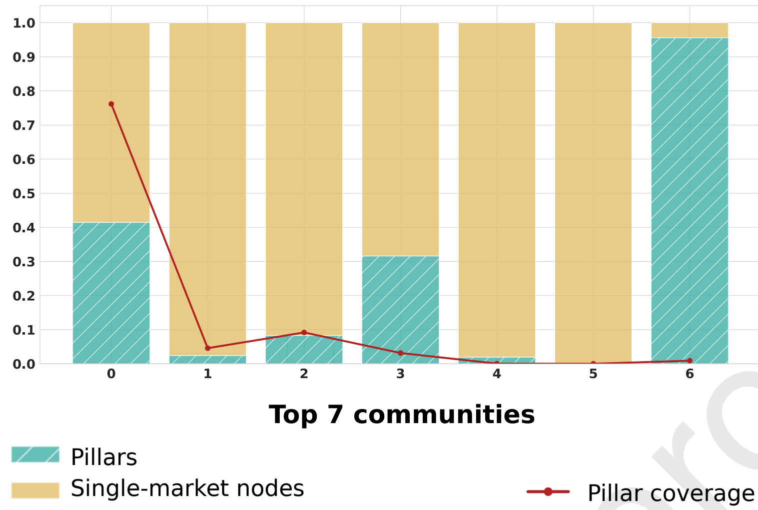


Figure 6: **Pillars in the top seven communities.** The bars (with green and blue segments) show the composition of each community respectively in terms of pillar and non-pillar nodes. The red line highlights the percentage of pillars that are covered by the multi-market nodes in each of the 7 largest communities.

is that the majority of pillars are included in the first community, which, according to Figure 5, is mainly composed ( 76.2% of pillars) by Cryptokitties and OpenSea users. Summing up, it is evident that a concentration of multi-market accounts in a single multilayer community (`id`=0), but even in the cases where multi-market nodes are much more infrequent, they play a relevant role in the formation of across-market communities. Given the above findings on the coverage of multi-market users by communities **(Q1)**, from now on, we narrow our focus on Cryptokitties and OpenSea, which are the two largest and most interconnected markets, to gain deeper insights into the dynamics behind such multi-market users.

### *4.4. Multi-market user activity patterns*

To answer **Q2**, we started the analysis of multi-market nodes' activity patterns by investigating whether and to what extent they exhibit different trading patterns compared to the single-market nodes. From a preliminary analysis, it emerges that multi-market users exhibit higher activity levels, as they tend to engage in more transactions than single-market nodes. However, delving into the outcome of these transactions reveals an intriguing trend:

the expenses of multi-market users exceed their earnings, indicating that they tend to invest in the platform(s) more than single-market users. Notably, OpenSea stands out as particularly prominent in this regard, with higher absolute values for both directions (incoming and outgoing).

The emergence of such an intriguing spending behavior prompted us to delve deeper into the investigation of user activity within the OpenSea and CryptoKitties markets. As part of this analysis, we seek to understand whether users exhibit a preference for a specific market when conducting operations, including both transactions initiated and received. To explore this dynamic, we focus on computing the maximum per-layer activity level, a metric that captures the intensity of user engagement by highlighting the maximum activity level in each market layer. This approach provides a clear snapshot of whether users prefer specific markets for their transactions, simplifying the interpretation of nuanced behaviors and trends in the cryptocurrency and NFT ecosystem. The maximum per-layer activity level is calculated independently for outgoing and ingoing operations. Here we formally outline the computation process for the outgoing case. For the ingoing case, simply reversing the graph (changing the direction of each edge) enables us to apply the same computational process.

For each pillar $u$, we compute the activity level on the OpenSea market (with the value for the Cryptokitties market representing its complement) as:

$$p(u)_O = c(u)_O / c(u)_{\mathcal{L}}$$

where:

$$c(u)_O = out\_degree(u, G_O)$$

and:

$$c(u)_{\mathcal{L}} = \sum_{m \in \mathcal{L}} out\_degree(u, G_m)$$

In short, the activity level $p(u)_O$ for a pillar $u$ indicates the fraction of transactions (outgoing) made on Opensea ($c(u)_O$) relative to the total transactions across both markets ($c(u)_{\mathcal{L}}$). A value of $p(u)_O$ closer to 0 indicates a preference for Cryptokitties, while values closer to 1 indicate a preference for OpenSea (as shown in the bottom part of Figure 7. We visualize these market preferences in the heatmap shown in Figure 7. The heatmap consists of two rows: the top row represents incoming transactions (received), while the bottom row represents outgoing transactions (active actions). Each row is divided into 13 columns representing different value intervals, with each cell displaying the percentage of users whose $p(u)_O$ falls within that interval. The intervals are structured as follows: three special intervals correspond to exact values - 0 (exclusive Cryptokitties activity), 1 (exclusive OpenSea activity), and 0.5 (perfectly balanced activity between platforms). As indicated by the symbols above the $x$-axis ticks, intervals before 0.5 are left-inclusive, while intervals after 0.5 are right-inclusive, creating symmetry around the central value.

In general, we observe contrasting patterns in activity between the two platforms and between incoming and outgoing operations. For incoming transactions, the most common behavior isbalancing the activities across platforms, as shown by the higher numbers in the three central intervals. However, we notice an overall skew towards the Cryptokitties market (0), with 15% of users receiving all their transactions on this platform. This skew towards Cryptokitties becomes more pronounced in outgoing operations, as shown in the second row of Figure 7. In fact, the most common pattern for outgoing transactions is for pillar users to perform transactions exclusively on Cryptokitties (62.3% with $p(u)_O = 0$). At the same time, the perfectly balanced interval also shows a notable percentage. While some users primarily operate on Cryptokitties but maintain some activity on OpenSea, the opposite scenario shows a single distinct pattern: complete preference for OpenSea (5.8%). This observation can be attributed to platform characteristics: on Cryptokitties, users driven by gaming tendencies are more inclined to initiate operations. Conversely, OpenSea, being a general-purpose market, is even more likely to attract incoming transactions.

In order to obtain a more detailed understanding of such trends and delve further into addressing our **(Q2)**, we now turn our attention to the financial aspect of user interactions, to verify whether the polarized patterns remain consistent at a more granular level. In this context, we investigate expenses and earnings by utilizing the $p(u)_O$ metric. This approach enables us to discern whether users demonstrate a favored platform when it comes to spending or earning financial returns within the cryptocurrency and NFT ecosystem.

Figure 8 uses the same visualization method as Figure 7, with $c(u)_O$ computed on the amount earned (or spent) by each user instead of the number of operations. The most common pattern remains to balance the financial flow between the two markets. However, an interesting result emerges from polarized users: while Cryptokitties maintains its dominance, the number of users exhibiting polarized behavior on OpenSea increases when considering

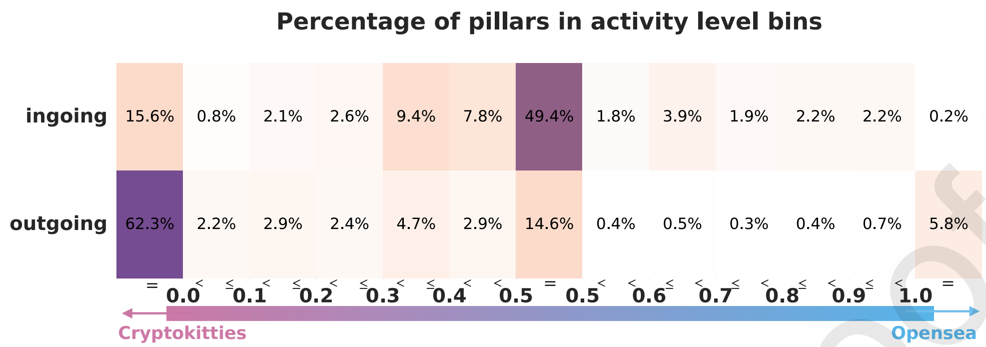


Figure 7: **Distribution of market preferences** between OpenSea and Cryptokitties for pillar users, measured as the proportion of transactions on each platform. The heatmap shows incoming (top row) and outgoing (bottom row) transactions, with cells indicating the percentage of users in each activity interval. Activity-level intervals range from 0 (exclusive Cryptokitties use) to 1 (exclusive OpenSea use), with 0.5 representing balanced activity. Intervals are distributed symmetrically around 0.5, with left-inclusive ranges before 0.5 and right-inclusive ranges after (as indicated by ticks on the $x$-axis).

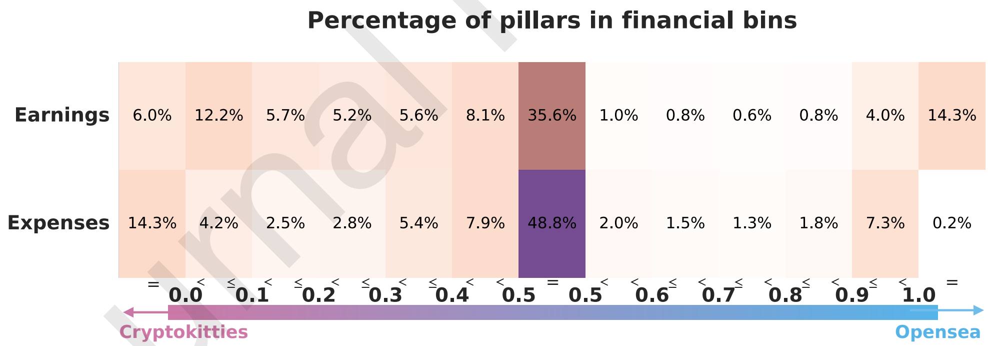


Figure 8: **Earnings and Expenses preferences** between OpenSea and Cryptokitties for pillar users, measured as the proportion of earnings and spending on each platform. The heatmap shows earnings (top row) and expenses (bottom row), with cells indicating the percentage of users in each financial interval. Activity level intervals range from 0 (exclusive Cryptokitties use) to 1 (exclusive OpenSea use), with 0.5 representing balanced activity. Intervals are distributed symmetrically around 0.5, with left-inclusive ranges before 0.5 and right-inclusive ranges after (as indicated by ticks on the $x$-axis).

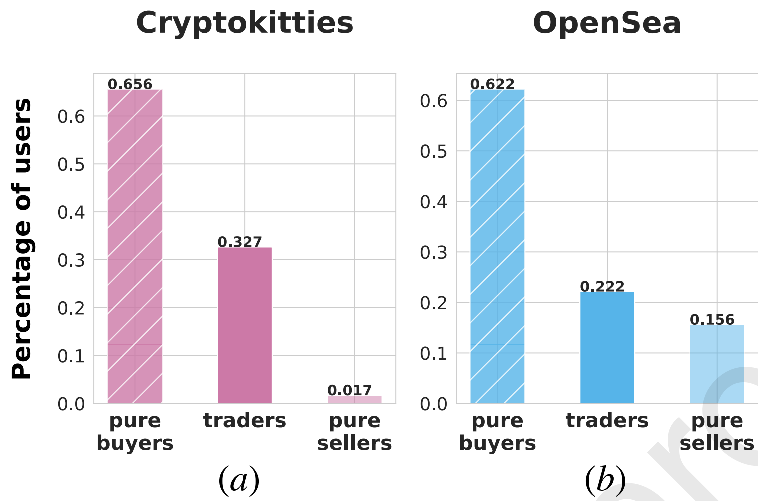


Figure 9: **Buyer and seller roles.** The plots show the distribution of user roles within Cryptokitties (a) and OpenSea (b) markets. Nodes are categorized into distinct roles: *pure buyers* engaging exclusively in outgoing transactions, *pure sellers* involved solely in ingoing operations, and *traders* participating in both performing and receiving transactions.

earnings instead of expenses. This pattern does not hold for Cryptokitties, where we observed a more balanced trend between polarized earnings and expenses. This asymmetry in expenses may be attributed to the nature of transactions on OpenSea, where the distinction between performing and receiving a transaction is more pronounced compared to Cryptokitties. In the latter, users, driven by affection, tend to engage in both activities simultaneously.

This hypothesis is supported by Figure 9 that shows the distribution of users' roles. We distinguish nodes as *pure buyers*, resp. *pure sellers*, if they perform exclusively outgoing, resp. ingoing, operations. Users are considered traders if they both perform and receive transactions. Figure 9 highlights the higher percentage of multi-market users acting as traders in Cryptokitties (Figure 9 (a), compared to the fraction exhibited by OpenSea (Figure 9 (b). Interestingly, these users tend to exhibit consistent patterns across markets, as 77.85% of them maintain the same role in the two markets.

To sum up, most multi-market users maintain their multi-market attitude as to the number of financial operations and the allocation of their expenses and earnings across the market. Differences between the two main markets, OpenSea and Cryptokitties, emerge in the case of polarized multi-market accounts and are due to the category of NFT market, i.e. generalistic or specialized, and to the type of multi-market accounts. Indeed, we observe a remarkable difference between expenses and earnings, whereas exclusively sellers are more frequent.

## 5. Conclusion

As the NFT landscape keeps evolving, the need to embrace its complexity to unravel the latent dynamics behind this unprecedented form of economy increases. In this work, we benefited from the availability of large-scale transactional information involving trading operations in the NFT ecosystem to develop and validate a multilayer network modeling aimed at providing valuable insights into the main NFT trading platforms.

Our findings underscore the necessity of adopting multilayer modeling for significant NFT markets, revealing both interconnected and independent community structures. This approach uncovers communities spanning different markets, with generalist platforms like OpenSea acting as unifying elements across layers. Conversely, we observed 'market independence' in specialized markets, highlighting the NFT ecosystem's diversity. Our preliminary investigations not only validated the multilayer approach but also shed light on the existence of latent across-market trading activities carried out by specific users acting as pillars in our model, i.e., the multi-market users.

We characterized these users operating in multiple markets to offer an unprecedented look at the dynamics of the NFT domain. Notably, these traders are found to exhibit higher activity levels compared to their single-market peers, typically engaging in a greater volume of transactions spanning multiple markets. Although most multi-market users homogeneously differentiate their activities and incomes among the different NFT marketplaces, surprisingly, their activities show a certain level of polarization, as a group of multi-market users has allocated their expenses mainly on assets traded in the OpenSea market. This behavior can be ascribed to the inherent investment-oriented and generalistic nature of OpenSea, which attracts users interested in placing long-term investments and anticipating future value growth of their tokens. Conversely, the more consumer-oriented and specialized nature of gaming platforms like Cryptokitties aligns better with the more balanced trade-off between earnings and expenses we spotted.

These peculiarities in user activity patterns also led to the discovery of polarized trading behavior (i.e., earnings or expenses) among the multi-market users who, despite being active across various markets, tend to prefer one of them for their trading operations. Furthermore, the multi-market users were found to be coherent in their roles (e.g., sellers, buyers, or traders), maintaining consistency across the different platforms. This trait suggests the emergence of specific behavioral strategies and discernible footprints, adding additional clues toward a proper understanding of such NFT landscape.

Our findings have many real-world implications for both NFT platform evolution and regulatory aspects.

Platforms can leverage this unprecedented multilayer view to identify and analyze multi-market users, gaining deeper insights into their behavior to enhance user engagement and retention strategies and foster more constructive cross-platform collaborations, ensuring the sustainability of the entire ecosystem despite market fluctuations.

From a regulatory standpoint, the ability to track multi-market users across platforms provides a more comprehensive approach to fraud detection and illicit activity monitoring. Indeed, by moving beyond single-platform analysis, we enable the detection of activities spanning multiple markets that would otherwise remain latent and undetected in isolated market perspectives.

We believe our findings represent a stepping point for future research, which should cover topological and organizational phenomena, such as trading clique formation and niche market development. Furthermore, a deeper exploration of the main socio-economic factors driving the emergence of strategic user behaviors [43] and user-market interactions could be an interesting future extension of this work. Another key point to explore is the temporal aspect of multi-market users' behavior, to assess, for instance, whether they engage consistently in time across multiple markets or they transit from one to the other.

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**Declaration of interests**

☒ 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.

☐ The author is an Editorial Board Member/Editor-in-Chief/Associate Editor/Guest Editor for *[Journal name]* and was not involved in the editorial review or the decision to publish this article.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

# Author statement

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**Author contributions:**

**Alessia Galdeman**: Conceptualization, Methodology, Software, Validation, Visualization, Writing - Original draft.

**Lucio La Cava**: Conceptualization, Methodology, Validation, Writing - Original draft.

**Matteo Zignani**: Conceptualization, Methodology, Writing - Original draft.

**Andrea Tagarelli**: Conceptualization, Methodology, Writing - Original draft.

**Sabrina Gaito**: Conceptualization, Methodology, Writing - Original draft.