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Impact of copyright sharing on the success of non-fungible token collections

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ABSTRACT

The decision to share the copyright of non-fungible token (NFT)-associated artworks has sparked considerable debate. Copyright sharing benefits NFT collections by fostering broader public engagement in remixing and unlocking network effects, but it also undermines the exclusive rights of NFT creators. This study explores the impact of copyright sharing on the social and financial success of NFT collections. The findings show that copyright sharing increases the use of NFTs as social media profile pictures significantly and affects average sale prices positively, indicating social success and financial success, respectively. These benefits are further amplified when the artworks of the NFT collection are more likely to be remixed.

1. Introduction

Non-fungible tokens (NFTs) are unique digital assets recorded on blockchains, which enable verifiable ownership and proof of authenticity. Unlike a typical digital image (e.g., JPEG) file that can be copied endlessly, an NFT carries a unique identifier and metadata recorded in a blockchain, effectively serving as a digital certificate of authenticity and ownership for digital artwork. The blockchain ledger immutably records every token transaction, creating a transparent history of who has owned the artwork over time. Such public, tamper-proof records make it easy to authenticate the source and ownership of digital artworks, solving the longstanding problem of establishing authenticity for digital art. Moreover, traditional digital assets suffered from opaque valuation and scarce resale opportunities. In contrast, NFTs have unlocked liquidity and community participation for various stakeholders, such as creators (artists) and buyers, on a scale previously unseen for digital artworks. In February 2022, the NFT market saw weekly trading volume reach $1.68 billion, with the number of active traders per week climbing to 542,040.[1]

The copyright sharing approach, in which copyright owners voluntarily waive copyrights and contribute their work to the public domain, typically through the Creative Commons Zero (CC0) license, represents a controversial yet increasingly popular model within NFT communities. On one hand, copyright sharing enables the unrestricted reuse, modification, and building upon of the original NFT artworks. This openness significantly increases public engagement with NFT artworks, creating network effects and attracting a broader audience of buyers and creators. On the other hand, this approach also has several negative effects, including the loss of exclusive profit rights, the loss of control over the artworks, and vulnerability to replication. Given this debate, it is therefore essential to study empirically whether copyright sharing is a beneficial strategy for the success of NFT collections.

Existing research on NFT success mainly focuses on the financial perspective, largely overlooking critical social dimensions. Specifically, prior studies have concentrated primarily on financial valuation, investigating how NFT prices correlate with other financial assets, such as stocks, bonds, gold, and cryptocurrencies, or utilizing machine learning methods to predict future NFT price movements [1–5]. However, NFT collections are not merely financial assets; they hold significant social value by acting as representations of communities and signals of identity. In the context of NFTs, social value refers to the intangible benefits that arise from interpersonal interactions, community engagement, identity expression, cultural affiliation, and the shared symbolic meanings embedded in these digital assets [2,6]. The social value inherent in NFT collections contributes to the development of stronger, more engaged communities, which, in turn, can enhance both the performance of the collections and broader societal well-being. In this regard, we study the social success of NFT collections by measuring their social influence, specifically operationalized as the proportion of NFTs from a given collection used as profile pictures on prominent social

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[1] https://www.okx.com/web3/marketplace/nft/stats/overview.

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media platforms. By integrating analyses of financial and social dimensions, our study aims to provide a more comprehensive framework to understand the dual nature—the market appeal and social impact of NFT collections. Thus, our first research question is

RQ1. What are the impacts of copyright sharing on the social and financial success of NFT collections?

Beyond assessing the direct effects of copyright sharing, we consider whether its impact varies across NFT collections. Copyright sharing enables community members to engage in remixing (i.e., modifying and recombining original artworks into derivative works), but their actual willingness to do so depends on the art's intrinsic propensity to be remixed. The high remixability of an NFT collection's artwork amplifies network effects, boosting the NFT collection's visibility and ecosystem growth and ultimately driving its success. Furthermore, the psychological benefits of remixing, such as a sense of creative empowerment and stronger community connections, can also drive an NFT collection's success. The critical role of remixing, therefore, leads to our second research question:

RQ2. How does remixing amplify the social and financial success of NFT collections adopting a copyright-sharing strategy?

To address these questions, we examine empirically the impact of copyright sharing on NFT success and the role of remixing by analyzing panel data from 2677 NFT collections over 81 weeks, spanning from the 31st week of 2021 to the 7th week of 2023. The data are sourced from multiple platforms, including NFTGO, Flipside, X (formerly known as Twitter), and the Inspect website. We employ propensity score matching (PSM) for each period to create comparable groups of CC0 and non-CC0 NFT collections, followed by random effects regressions. The findings indicate that copyright sharing significantly increases both the proportion of NFTs used as social media profile pictures and the average sale price within collections. These effects are more pronounced when the artworks of NFT collections are designed in ways that encourage remixing. Additionally, this study includes a heterogeneity analysis to examine the impact of copyright sharing across different NFT categories. Finally, to ensure the robustness of our results, we conduct rigorous robustness checks to validate the reliability and consistency of findings.

This study makes several contributions. First, by examining the impacts of copyright sharing in NFT ecosystems empirically, we expand both the NFT and intellectual property (IP) sharing literature. Previous studies on IP rights sharing for digital resources [7–10] have produced mixed and inconclusive findings [27–29]. To the best of our knowledge, this research is the first to investigate copyright-sharing strategies in the context of NFTs. Our work provides contextual explanations for the benefits of copyright sharing by emphasizing the unique characteristics of NFTs and the Web3 ecosystems. Second, we extend existing NFT research by highlighting that NFT collections represent financial assets and communities with significant social value. We posit that social success is a critical dimension for evaluating NFT collection outcomes. Moreover, we propose that the propensity for remixing is a crucial moderating factor, significantly enhancing the effectiveness of copyright sharing. Finally, our study provides practical insights for NFT stakeholders by emphasizing that copyright sharing can be strategically beneficial, though their effectiveness depends critically on fostering and sustaining active remixing behavior among community participants.

The remainder of this paper is structured as follows. Section 2 reviews relevant literature and develops hypotheses based on network effect theory, social identity theory, and open innovation theory. Section 3 describes the data utilized for this research and outlines the specific methodologies employed for hypothesis testing. Section 4 presents the main empirical findings, supplemented by heterogeneity analyses and robustness checks. Finally, Section 5 summarizes the fundamental discoveries and discusses the contributions and limitations of this study.

2. Literature review and hypothesis development

This section develops hypotheses by drawing upon relevant literature and theories. Specifically, we build mainly upon network effect theory, supplemented by social identity theory and open innovation theory, to construct a theoretical framework. Section 2.1 proposes hypotheses regarding the impact of copyright sharing on the success of NFT collections, from both social and financial perspectives. The social success of an NFT collection can be represented by the extent to which its images are adopted as profile pictures on social media platforms. This adoption serves as a form of identity signaling, similar to how individuals use purchases and knowledge expressions to convey their interests, status, or group affiliations [11–19]. The larger the proportion of NFTs used as profile pictures within an NFT collection, the more broadly recognized and socially valuable the collection is perceived. Additionally, the average price of NFTs in an NFT collection indicates its financial success. Subsequently, Section 2.2 develops hypotheses regarding how remixing can amplify the social and financial success of NFT collections that have adopted a copyright-sharing strategy.

2.1. The impact of copyright sharing on the success of NFTs

2.1.1. The role of network effects in NFT ecosystems

The theory of network effects (or network externalities) describes the phenomenon in which the value a user derives from a product or service increases as more people use it [20,21]. This value can be generated directly, where each new user enhances the utility for all others (e.g., a social network), or indirectly, where growth in a user base attracts complementary goods, which in turn benefit the users (e.g., operating systems) [22–24].

Like software [25–28], entertainment [29–31], and other digital platforms [32,33], NFT collections function as network goods whose value is intrinsically linked to user participation and interaction. This is because an NFT collection often represents a community, with its artwork as a shared symbol and its growth dependent on member co-creation. Consequently, its success is driven by network effects, where value escalates with user usage and ecosystem engagement. Copyright sharing acts as a powerful catalyst for this process; by removing copyright restrictions, it lowers the barrier for community members to utilize, modify, and build upon the collection's artwork. Therefore, network effect theory provides a suitable theoretical lens for explaining how copyright sharing influences an NFT collection's success. We will integrate this theory with social identity theory and open innovation theory to explain the social and financial benefits arising from copyright sharing.

2.1.2. The impact of copyright sharing on social success

The hypothesized impact of copyright sharing on the social success of an NFT collection is grounded in network effect theory, with social identity theory providing the psychosocial underpinnings. A copyright-sharing strategy, by granting the public the right to use NFT artworks freely, encourages the creation of numerous memes and derivative works [34–37]. These community-driven activities significantly enhance the NFT collection's public visibility [30,33] and cultural penetration [10,38–40], augmenting its value as a community symbol [41]. Social identity theory explains why this enhanced symbolic value drives the adoption of the collection's NFTs as profile pictures. In the NFT context, each NFT collection is perceived as a distinct social group (a process of social categorization). As an NFT collection's identity becomes more prominent and appealing, the motivation for signal affiliation intensifies. Consequently, individuals are more inclined to use the NFT artwork as a profile picture to express group membership and display a shared cultural identity (a process of social identification) [42,43].

This entire process manifests a network effect: as more users engage with the NFT artwork, the NFT collection's value as a community symbol strengthens. This, in turn, increases the utility for individuals to adopt the NFT artwork as a profile picture, prompting wider profile picture adoption driven by the need for social identification. Therefore, we propose the following hypothesis:

H1a. Copyright sharing positively influences the proportion of NFTs within a collection utilized as profile pictures on social media platforms.

2.1.3. The impact of copyright sharing on financial success

The hypothesized impact of copyright sharing on the financial success of an NFT collection is based on the interplay of network effect theory and open innovation theory. A copyright-sharing strategy transforms the NFT artwork copyright from a closed asset into an open resource for external creators. This approach aligns with open innovation, a theory positing that organizations can benefit from leveraging external creativity, thereby overcoming the inherent limitations of their internal resources [34,35,37,44–51]. By incentivizing diverse creations based on the original NFT artwork (such as derivative NFT collections, games, and merchandise), copyright sharing facilitates an external innovation process. This significantly increases the quantity and variety of complementary goods and services surrounding the original NFT collection. Successful complementary offerings enhance the collection's brand value and elevate the perceived scarcity of the original NFTs as "genesis" pieces [52,53]. Furthermore, these complementary goods enrich the entire ecosystem [54,55], and a richer ecosystem, in turn, increases the attractiveness of and demand for the original NFTs. Given their typically fixed supply, this heightened demand naturally drives prices upward.

This entire process manifests a network effect: open innovation by a broader base of creators leads to more and better complementary goods. This enhances the brand and enriches the ecosystem, which increases the utility and attractiveness of owning the original NFTs, ultimately resulting in a higher average price.

Despite the advantages of copyright sharing, previous studies have discussed several drawbacks. NFT creators and owners may not profit exclusively from their IP if they share it freely [56]. Copyright sharing can also lead to a loss of control [57], increasing the risk of malicious use [58] and the emergence of copycats [8,59]. These can potentially devalue the original NFT collections.

However, we argue that the benefits of copyright sharing outweigh its drawbacks for two main reasons: the unique feature of NFTs (tokenization) and the industry environment of NFTs (the openness and permissionless nature of the Web3 ecosystem). First, unlike traditional digital resources, an NFT not only corresponds to the resource itself (e.g., the NFT-associated artwork) but also introduces a token, a verified digital record stored on the blockchain. Because tokens can be traded, NFTs add tradability to the resource. When the copyright of a resource is shared, it reduces control over the original resource and limits the ability to generate exclusive profits, potentially diminishing its financial value. However, despite the sharing of copyright, the token retains its scarcity, tradability, and the potential to generate revenue. Therefore, tokenization allows for preserving certain exclusivity and profitability while still benefiting from broader network effects through copyright sharing.

Second, in the Web3 ecosystem, openness and permissionlessness are widely accepted as social norms [60,61]. Successful organizations in this space often adopt open strategies to promote interoperability, allowing different platforms and technologies to connect and collaborate seamlessly, like how LEGO blocks can be combined in endless ways [62]. In contrast, organizations that maintain closed strategies tend to experience weaker network effects, making them more susceptible to disruption. Therefore, we argue that the collaborative and open nature of copyright sharing aligns with the core principles of Web3 and enables more substantial network effects, which overcome the above drawbacks and drive the financial success of NFT collections:

H1b. Copyright sharing results in a higher average price of an NFT collection.

2.2. The role of remixing

2.2.1. Remixing as a catalyst for network effects

Remixing (i.e., reworking and recombining existing creative elements) is an essential form of community engagement [63,64]. Community members reuse, alter, and build upon the foundational artwork of NFTs, thereby facilitating the generation of novel ideas and products [7]. The concept of remixing originated in the media industry, where it describes the process of modifying music by altering its constituent tracks, or editing and reassembling animation or gaming videos, based on remixers' interests and interpretations [39,63]. Scholars have also adopted the term *remixing* to characterize the processes of knowledge reuse and recombination [7,9,65,66].

While the copyright-sharing strategy provides a foundation for community members to engage in remixing, their actual willingness to do so varies across NFT collections, as each collection is associated with different artworks. We hypothesize that the positive effects of copyright sharing are more pronounced for NFT collections whose artworks exhibit a greater propensity to be remixed. This assumption is grounded in the idea that remixing—a form of community engagement and complementary-good creation—is a crucial mechanism for activating network effects, social identification, and open innovation. The following will demonstrate how the propensity to remix amplifies the impact of copyright sharing on both the social and financial success of an NFT collection.

2.2.2. The amplifying role of remix propensity on social success

A high propensity for an NFT collection's art to be remixed amplifies the network effects that drive social success. When an NFT collection's artwork is more amenable to remixing, it naturally generates a higher volume and diversity of derivative, user-generated content. This proliferation of content significantly boosts the collection's public visibility and cultural penetration, strengthening its value as a community symbol and enhancing the social identification process: As the NFT collection becomes a more vibrant and visible cultural force, individuals find it more compelling to align with the group, leading to increased profile picture adoption to signal their affiliation.

Moreover, highly remixable art facilitates active community participation in co-creating the NFT collection's culture, which yields significant psychological benefits that deepen social identification. First, when individuals can access and innovate with core IP freely, they perceive themselves as culture producers rather than mere recipients [67,68]. Second, the collaborative process of remixing strengthens interpersonal connections within the community [55]. Finally, empowering community members to utilize the artwork and participate in decision-making processes freely reduces their uncertainty regarding the collection's future [69]. This reduction in uncertainty is critical, as it is a proven motivator for identity formation [68,70]. Together, these psychological advantages deepen an individual's social identification with the NFT collection and intensify their motivation to express this affiliation through profile picture usage publicly. This leads to our hypothesis:

H2a. The impact of copyright sharing on the adoption of associated images as profile pictures is more pronounced when these images are more likely to be remixed.

2.2.3. The amplifying role of remix propensity on financial success

By amplifying network effects, a higher propensity for an NFT collection's art to be remixed can also foster greater financial success. When NFT collections feature artworks with characteristics that encourage public engagement in remixing, they fuel more vigorous open innovation and motivate external creators to build upon the original NFT artwork. This results in more abundant and diverse complementary goods, which create a stronger brand and a more thriving ecosystem. These enhancements increase the attractiveness of and demand for the original NFTs, exerting upward pressure on the average price. Therefore, a high propensity to remix artwork within an NFT collection is a critical condition allowing copyright sharing to translate more effectively into financial success. Thus, we propose the following hypothesis:

H2b. The impact of copyright sharing on the average price of an NFT collection is more pronounced when the associated images are more likely to be remixed.

Based on these hypotheses, we propose an integrated research framework that captures the relationships among the key constructs discussed above. This framework, illustrated in Fig. 1, summarizes our theorized links between copyright sharing, remixing propensity, and the success of NFT collections, which serves as the foundation for the following empirical analysis.

3. Data, measurements, and regression models

3.1. Data

To investigate the impact of copyright sharing and the crucial role of community remixing within the NFT ecosystem, we select a sample of 4186 Ethereum ERC721[2] NFT collections from NFTGO, a leading data analysis platform for NFTs. Based on the listing requirements of NFTGO,[3] the selected NFT collection sample meets specific requirements. These collections achieve sufficient trading volume and number of sales, while excluding those involved in malicious activities such as NFT spamming, data manipulation, or the inclusion of backdoors in contract code. This ensures that the sample we are working with has a certain market scale and consists of legitimate and trustworthy data.

We collect fundamental information about each NFT collection from this data source, including collection names, contracts, categories, textual introductions, links (i.e., official websites and social media), and NFT images. Moreover, we extract textual descriptions of these NFT collections from their official websites using web crawlers, and from their official X accounts via the X API. Separately, we collect data on the number of NFTs used as profile pictures on X from the third-party analytics platform Inspect.xyz. We also gather search volume data for each NFT collection from Google Trends. Finally, we retrieve on-chain data from Flipside, a blockchain data analytics provider, including average sale prices, mint prices, trading numbers, and token supply quantities for each collection. The data cover the period from the 31st week of 2021 to the 7th week of 2023. The starting time point of our study is based on the launch of the Nouns NFT collection in August 2021, a significant event that heightened attention toward the CC0 license and influenced subsequent NFT collections to adopt this license. It is important to note that the data regarding the adoption of NFTs as X profile pictures extends from October 2022 onward due to limitations in data availability.[4]

3.2. Measurements

An NFT collection's adoption of copyright sharing is determined by its use of the CC0 license. However, accurately identifying collections implementing the CC0 license presents a significant challenge. In this study, we leverage the requirement that NFT creators who dedicate their works to the public domain must officially declare their adoption of the CC0 license. To identify such cases, we conduct a keyword search using the terms "CC0," "Creative Commons Zero," "public domain," "feel free to use any way you want," and "no rights reserved" across collection briefs on NFT marketplaces, official websites, and X profiles. Our analysis identifies 177 NFT collections using CC0 to share copyright.

The financial success of an NFT collection is assessed by its average sale price. To ascertain the collection's authentic value, we analyze transaction prices recorded on the blockchain, a method preferred over relying on the floor price, which is susceptible to artificial manipulation. It is important to note that average sale price, mint price, and volume are logarithmically transformed to control for their skewness [71,72]. In addition, they are denominated in Ether (ETH). In our robustness checks, these values will also be analyzed in United States dollars (USD) to ensure the stability and consistency of our findings.

The social success of an NFT collection is gauged by the adoption of NFT artworks as profile pictures on social media. Specifically, a collection is considered more socially successful if a higher proportion of its NFTs are used as profile pictures on platform X. Using an NFT image as a profile picture is a common way to express support for and affiliation with an NFT collection. For example, many X users have adopted Mfer NFTs as profile pictures (see Fig. 2).

3.2.1. Measuring the propensity of an NFT image to be remixed

Another challenge in this research is measuring the propensity of an NFT-associated image to be remixed. To address this, we employ image complexity as a proxy to assess this propensity. Existing research demonstrates a correlation between moderate image complexity and an increased likelihood of individuals generating derivative works. This can be attributed to the fact that highly complex visual works are often too intricate to understand or use easily, potentially deterring creators [73,74]. Moreover, complex works typically offer limited scope for re-creation, while simpler works provide more opportunities for innovation [63]. On the other hand, excessively simple works are not conducive to remixing either. Creative remixing often involves adding, removing, or altering elements of the original artwork, and overly simple works lack sufficient complexity to serve as a foundation for community-driven reuse [63]. In conclusion, NFT images with moderate complexity are most conducive to remixing by community members, as opposed to those with either minimal or excessive complexity.

Previous studies have primarily utilized two methods to calculate image complexity. The first method uses edge detection technology, which identifies the edges of an image. These edges are areas where there are significant changes in image intensity. We use the Canny algorithm from the OpenCV library. Unlike other edge detection algorithms, the Canny algorithm employs two thresholds to detect both strong and weak edges, including weak edges in the output if they are connected to strong ones [75,76]. We employ thresholds of 50 and 150 in our analysis. Values below 50 are considered non-edges, effectively minimizing noise from factors such as shading and shadows, whereas values above 150 are identified as strong edges. For values between 50 and 150, the classification as edges depends on whether they are connected to adjacent strong edges; only those linked to strong edges are considered genuine, enhancing the detection of subtle yet significant edges. Following the application of the Canny algorithm, the output is the detected edges of an image. Images that contain more edges are considered more complex [77].

The second widely used method for assessing image complexity is JPEG compression [77–80]. This approach measures image complexity by evaluating the compressed file size, drawing on the concept of Kolmogorov complexity. According to this concept, the complexity of an object is correlated with the length of the shortest algorithm required to describe it. Thus, a more complex image necessitates a longer algorithm for description, which is reflected in a larger compressed file size. In our analysis, we set the JPEG compression quality parameter to 95.

Given the high similarity among images within a collection and the vast number of images in some collections, we opt for a random sampling approach. For each NFT collection, we randomly select 50 images

[2] NFT contracts usually follow two main standards: ERC721 and ERC1155. This study focuses on ERC721 because only a few NFT collections in our sample adopt the CC0 license with ERC1155.

[3] https://docs.nftgo.io/docs/listing-criteria.

[4] Data regarding the use of NFTs as X profile pictures, provided by Inspect.xyz, is only available starting from October 2022. As a result, regressions utilizing this data possess a slightly shorter time span compared to others. The wider time span for other regressions, ranging from the 31st week of 2021 to the 7th week of 2023, is intended to enhance result precision by including a larger dataset.

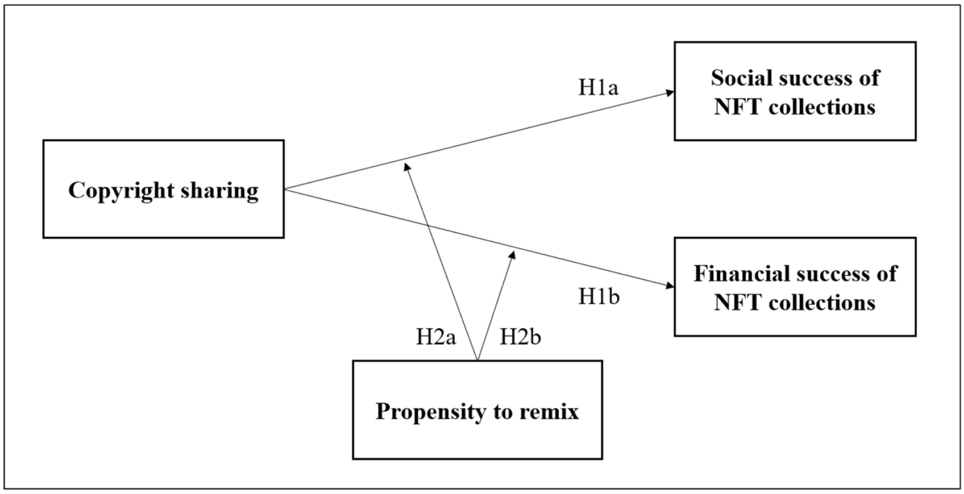

Fig. 1. Research framework.

Fig. 2. Mfer NFT owners using the associated images as profile pictures on the platform X.

(or the entire collection if it contains fewer than 50 images). To ensure comparability of the calculated image complexity, we standardized the images by resizing them to 1000 pixels in width and height. We then employ both the Canny and JPEG compression methods to compute the complexity of each image. It is important to note that each algorithm's results can be sensitive to specific parameters. Therefore, we set different parameters for robustness checks in Section 4.4.3. Finally, we average the image complexity scores within each collection to derive a collection-level image complexity metric. A higher score indicates greater complexity. Detailed descriptions of the variables used in our empirical models are illustrated in Table 1.

Table 1
Variable descriptions.

Variable	Notation	Description
Profile picture ratio	$ProfilePictureRatio_{it}$	The proportion of NFTs within a collection utilized as X profile pictures
Average sale price	$lnAvgPrice_{it}$	The average sale price of NFTs in a collection
CC0	$CC0_i$	A binary variable indicating the use of a CC0 license in an NFT collection (1 for usage, 0 otherwise)
Complexity		The mean complexity score of NFTs in a collection, calculated by algorithms including Canny and JPEG compression
Average mint price	$lnAvgMintPrice_{it}$	The average mint price of NFTs in a collection
Supply	$Supply_{it}$	The cumulative number of NFTs minted for a collection (in thousands)
Transaction number	$Transaction_{it}$	The transaction number of NFTs in a collection
Awareness	$Awareness_{it}$	Public awareness of an NFT collection, as measured by Google Trends
Category		The types of NFT collections include profile pictures, collectibles, art, photography, music, land, metaverse, games, utility, intellectual property, social, sports, decentralized finance, and domain names

3.3. Regression models

To analyze the success differences between NFT collections that have adopted CC0 and those that have not,[5] we employ panel data using collection–week units (the collection is denoted by i and the week by t). A weekly timeframe is chosen because NFTs typically have lower liquidity. A daily analysis period could lead to many variables being zero, while a monthly period might overlook critical short-term fluctuations. The weekly aggregation strikes a balance by smoothing out short-term volatility, while still capturing relevant temporal trends without wasting resources.

Concerned that inherent disparities between CC0 and non-CC0 NFT collections could potentially confound our study, we implement PSM for each period, aiming to enhance the comparability of the two groups. Following previous literature using dynamic matching [81–83], our matching procedure involves several steps. Initially, we calculate the propensity score for each NFT collection using logistic regression. Subsequently, for each CC0 collection, we identify and weigh non-CC0 collections using a kernel function that considers the distance between their propensity scores. Given that our panel consists of NFT collections observed over time, we implement matching on a week-by-week basis (i.e., 81 times in total) to avoid temporal mismatches that could arise from matching collections across non-aligned time periods [81–83]. Specifically, matching across the entire panel history could lead to situations where a CC0 collection in Week t was matched with a non-CC0 collection whose covariates came from Week $t + k$, introducing bias. Our approach ensures that matched collections exhibit similar covariates within the same period but differ in CC0 adoption status. This dynamic matching strategy, however, results in an unbalanced panel, as NFT collections may appear in different numbers of weeks depending on their matching status. To address this issue, we estimate regression models that account for heterogeneity across NFT categories and time periods. This approach helps mitigate potential bias from the unbalanced panel structure induced by week-by-week matching, ensuring comparability across matched observations over time. We also conduct robustness checks using a different matching method, and results remain consistent (see Section 4.4.4).

Finally, to check the validity of the matching, we test for covariate balance. The results consistently show that, after matching, the mean differences in covariates between CC0 and non-CC0 NFT collections are significantly reduced and are no longer statistically significant (see Appendix A). The initial sample of 4186 NFT collections is refined to 2677 after matching.

To test H1a and H1b, we use regression models that include NFT category dummies (θ_j) and week dummies (τ_t) to account for potential influences from NFT category characteristics and temporal trends. Additionally, we include NFT collection random effects (μ_i), which is supported by the Breusch–Pagan Lagrange multiplier test (Prob $> \chi^2 = 0.000$). It is important to note that as our independent variable ($CC0_i$) operates at the NFT collection level, including NFT collection fixed effects would absorb the variation attributable to this variable. Furthermore, we incorporate five time-variant, collection-specific control variables that may influence the outcome variables. Supply, the number of NFTs minted in a collection, impacts the sale price through supply-demand dynamics and affects the proportion of NFTs used as profile pictures by influencing the total number of available NFTs. The average mint price, as the initial price, sets expectations for subsequent secondary sale prices. The number of transactions reflects market liquidity and demand, driving up both the sale price and the profile picture usage. Public awareness, measured by Google Trends, indicates a collection's public interest level. More popular NFT collections are more likely to be used as profile pictures and to see higher demand, thereby increasing their sale price.[6] Finally, we also control for the lagged sale price to account for the potential impact of past prices on current outcome variables. β is the coefficient of our interest:

$$\begin{aligned} ProfilePictureRatio_{it} = {} & \alpha + \beta CC0_i + \gamma_1 lnAvgPrice_{i,t-1} + \gamma_2 Supply_{it} \\ & + \gamma_3 lnAvgMintPrice_{it} + \gamma_4 Transaction_{it} \\ & + \gamma_5 Awareness_{it} + \theta_j + \tau_t + \mu_i + \varepsilon_{it} \end{aligned} \tag{1}$$

$$\begin{aligned} lnAvgPrice_{it} = {} & \alpha + \beta CC0_i + \gamma_1 lnAvgPrice_{i,t-1} + \gamma_2 Supply_{it} \\ & + \gamma_3 lnAvgMintPrice_{it} + \gamma_4 Transaction_{it} + \gamma_5 Awareness_{it} + \theta_j \\ & + \tau_t + \mu_i + \varepsilon_{it} \end{aligned} \tag{2}$$

To test H2, we first divide our sample into low-, medium-, and high-complexity groups. Each group contains an approximately equal number of NFT collections. This categorization is informed by the discussion in Section 3.2.1, which demonstrates that the complexity of the work exhibits a nonlinear relationship with the propensity for remixing. Specifically, works of moderate complexity are more likely to be remixed than those of low or high complexity. We then conduct group-specific regressions using Eqs. (1) and (2) to determine if β reaches its highest value at a medium complexity level.

4. Results and additional analysis

4.1. Descriptive summary statistics and correlations

Table 2 provides descriptive summary statistics after the matching process. The primary analytical sample comprises 113,914 collection–week observations. However, the number of observations available for specific variables varies due to data limitations. $ProfilePictureRatio_{it}$ is only obtainable from October 2022 onward, resulting in a sample of 16,294 observations. Furthermore, image complexity variables are computed for 105,568 observations, as image data is not retrievable for some NFT collections. The distribution of image complexity within these NFT collections is detailed in Appendix B. Table 3 displays the correlation matrix for the variables. Multicollinearity can pose a significant challenge in regression because it results in unstable estimates and ambiguous interpretations of coefficients. To assess the potential presence of multicollinearity, we compute the variance inflation factor (VIF) for the variables used in Eqs. (1) and (2), following the approach outlined by Chatterjee and Hadi [84]. As shown in Appendix C, the VIF values for all variables are 1.25 or below, within the accepted threshold of 5, indicating that multicollinearity is not a concern in our analysis.

4.2. Main regression results

4.2.1. The impact of copyright sharing on the social success of NFT collections

The results of Eq. (1), presented in column (1) of Tables 4 and 5, demonstrate that NFT collections employing the CC0 license experience an increase in the proportion of NFTs used as social media profile

[5] The majority of NFT projects adopt the CC0 license to share the copyrights of artworks, placing these artworks in the public domain. Almost no NFT projects select other CC licenses. A small subset use customized licenses, such as those implemented by Bored Ape Yacht Club (https://boredapeyachtclub.com/licenses/bayc) and CryptoPunks (https://licenseterms.cryptopunks.app), which differ significantly from one another. These specialized licenses grant only limited rights to current NFT holders and offer less openness than the CC0 license. Consequently, we believe that comparing CC0 and non-CC0 NFT projects is a reasonable approach to investigating the impacts of sharing copyrights.

[6] To address potential scale issues among control variables, Appendix D conducts a robustness check using log-transformed versions of *Transaction* and *Awareness*.

Table 2
Descriptive summary statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
$ProfilePictureRatio_{it}$	16,294	0.025	0.063	0.000	0.786
$AvgPrice_{it}$	113,914	2.135	65.510	0.000	8572.040
$CC0_i$	113,914	0.039	0.194	0.000	1.000
$CannyComplexity_i$	105,568	245,467.360	156,340.670	12,051.000	1132,240.800
$JpegComplexity_i$	105,568	201,080.740	107,951.970	6237.000	792,397.200
$Supply_{it}$	113,914	6.546	4.864	0.014	100.000
$AvgMintPrice_{it}$	113,914	0.125	0.420	0.000	30.000
$Transaction_{it}$	113,914	130.023	565.494	1.000	27,409.000
$Awareness_{it}$	113,914	1.663	14.209	0.000	1659.574

Table 3
Correlation matrix.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$ProfilePictureRatio_{it}$	1.000								
$AvgPrice_{it}$	0.016	1.000							
$CC0_i$	−0.007	−0.001	1.000						
$CannyComplexity_i$	−0.083	−0.018	−0.080	1.000					
$JpegComplexity_i$	−0.094	−0.015	−0.095	0.902	1.000				
$Supply_{it}$	0.064	0.017	−0.026	−0.041	−0.035	1.000			
$AvgMintPrice_{it}$	0.069	0.039	−0.027	0.018	0.020	−0.078	1.000		
$Transaction_{it}$	0.248	−0.002	−0.003	−0.052	−0.054	0.176	0.010	1.000	
$Awareness_{it}$	0.206	0.024	−0.014	−0.025	−0.025	0.076	−0.002	0.088	1.000

Table 4
Impact of copyright sharing on social success: Grouped regression results based on Canny complexity.

	Dependent variable: $ProfilePictureRatio_{it}$			
	(1) Full sample	(2) Low complexity	(3) Medium complexity	(4) High complexity
$CC0_i$	0.009***	−0.002	0.066***	0.002
	(0.003)	(0.009)	(0.003)	(0.003)
$lnAvgPrice_{i,t-1}$	0.001***	0.002***	0.000***	0.000*
	(0.000)	(0.001)	(0.000)	(0.000)
$Supply_{it}$	0.001**	0.002***	0.001***	0.000
	(0.000)	(0.001)	(0.000)	(0.000)
$lnAvgMintPrice_{it}$	0.004***	0.004*	0.002	0.003***
	(0.001)	(0.002)	(0.001)	(0.001)
$Transaction_{it}$	−0.000	−0.000	−0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
$Awareness_{it}$	0.000***	0.000***	0.000**	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.035***	0.031***	−0.012*	0.034***
	(0.001)	(0.002)	(0.007)	(0.013)
Category dummies	Yes	Yes	Yes	Yes
Week dummies	Yes	Yes	Yes	Yes
Collection RE	Yes	Yes	Yes	Yes
R^2	0.245	0.165	0.179	0.712
Observations	14,853	4746	5132	4396

Note: Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5
Impact of copyright sharing on social success: Grouped regression results based on JPEG compression complexity.

	Dependent variable: $ProfilePictureRatio_{it}$			
	(1) Full sample	(2) Low complexity	(3) Medium complexity	(4) High complexity
$CC0_i$	0.009***	−0.002	0.057***	0.001
	(0.003)	(0.010)	(0.005)	(0.004)
$lnAvgPrice_{i,t-1}$	0.001***	0.002***	0.002***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
$Supply_{it}$	0.001**	0.002*	0.002***	−0.000*
	(0.000)	(0.001)	(0.001)	(0.000)
$lnAvgMintPrice_{it}$	0.004***	0.005**	0.005***	0.002***
	(0.001)	(0.002)	(0.001)	(0.001)
$Transaction_{it}$	−0.000	−0.000**	0.000***	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
$Awareness_{it}$	0.000***	0.000***	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.035***	0.032***	0.019***	0.020***
	(0.001)	(0.004)	(0.001)	(0.007)
Category dummies	Yes	Yes	Yes	Yes
Week dummies	Yes	Yes	Yes	Yes
Collection RE	Yes	Yes	Yes	Yes
R^2	0.245	0.096	0.264	0.887
Observations	14,853	5048	4911	4315

Note: Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

pictures compared with those that do not. The regression analysis reveals a significant average increase of 0.009 in this proportion. This indicates that waiving copyright protection enhances public recognition and support for NFTs on social networks, supporting the viewpoint proposed in H1a that copyright sharing benefits NFT success from a social perspective.

Furthermore, NFT collections are categorized into three groups of equal size—low, medium, and high—based on two distinct complexity metrics: Canny complexity and JPEG compression complexity, as shown in columns (2)–(4) of Tables 4 and 5. The subgroup regression results show that the coefficient of $CC0_i$ is both the highest and statistically significant only for NFT collections with medium image complexity. Specifically, the values are 0.066 and 0.057 in column (3) of Tables 4 and 5, respectively. Conversely, this coefficient is lower and statistically nonsignificant for collections with low or high complexity levels. These findings suggest that copyright sharing significantly enhances NFT collections' social success primarily when the NFT collections exhibit medium image complexity. At this level, community members will more likely remix images. This highlights the essential role of remixing in enhancing the effectiveness of copyright-sharing strategies, thereby supporting H2a.

4.2.2. The impact of copyright sharing on the financial success of NFT collections

The result of Eq. (2) is presented in column (1) of Tables 6 and 7, which indicates that NFT collections employing the CC0 license experience an average increase of 12.8 % ($= e^{0.121} - 1$) in their sale price compared with non-CC0 collections. This significant result supports H1b; relinquishing copyright protection in NFT collections is associated with higher market prices.

Similarly, NFT collections are categorized into three groups with different complexity levels, presented in columns (2)–(4) of Tables 6 and 7. The results of grouped regression reveal that for NFT collections with low and high levels of image complexity, the impact of copyright sharing on average sale price is not significantly different from zero, while for NFT collections with a medium level of image complexity, the coefficient of $CC0_i$ is the highest and most significant. Specifically, a 14.4 % ($= e^{0.135} - 1$) and a 12.3 % ($= e^{0.117} - 1$) price increase are observed for the medium-complexity group in Tables 6 and 7, respectively. This supports H2b, suggesting that the advantages of waiving copyright protection are visible primarily at a medium level of complexity, an environment where the propensity for the NFT collections to be remixed is higher than for those of low and high complexity. This shows the crucial role of community remixing in the positive effect of copyright sharing on the sale price of NFTs. We also conduct *Z*-tests for both social and financial outcomes in Appendix E to assess whether the coefficients of $CC0_i$ are significantly different across complexity subgroups.

4.3. Heterogeneity analysis

In this section, we examine the varying impact of copyright sharing across different types of NFTs. NFTs are commonly categorized based on their application, their theme, or the nature of the digital asset they represent. A comprehensive list of NFT categories is provided in Table 1. Our data show that CC0 adoption is most prevalent in four categories: profile pictures, collectibles, art, and the metaverse. This aligns with the nature of these categories, where value is driven by cultural adoption and community expansion rather than exclusivity and direct monetization, making CC0 a natural fit. In contrast, categories such as utility, photography, music, and IP prioritize ownership and monetization, leading to minimal CC0 adoption. Accordingly, this section focuses on the four categories where CC0 is most common. Profile picture NFTs are used as profile pictures online (e.g., CryptoPunks); collectible NFTs, similar to stamps or cards, are themed, like NBA Top Shot; art NFTs represent digital art, including paintings, animations, and generated art, like those in Art Blocks; metaverse NFTs are for virtual world use, covering things such as virtual land and buildings (e.g., Decentraland).

The grouped regression results in Tables 8 and 9 demonstrate that the effectiveness of copyright sharing varies across different NFT categories. Implementing a copyright-sharing approach enhances social success, particularly for profile picture NFTs, followed by art NFTs and then collectible NFTs. This enhancement is attributed to the fact that by opening access to artistic resources and allowing the public to use and

Table 6
Impact of copyright sharing on financial success: Grouped regression results based on Canny complexity.

	Dependent variable: $lnAvgPrice_{it}$			
	(1) Full sample	(2) Low complexity	(3) Medium complexity	(4) High complexity
$CC0_i$	0.121***	0.106	0.135**	0.069
	(0.023)	(0.104)	(0.058)	(0.058)
$lnAvgPrice_{i,t-1}$	0.563***	0.762***	0.618***	0.688***
	(0.016)	(0.018)	(0.020)	(0.042)
$Supply_{it}$	0.001	−0.002	−0.003	−0.000
	(0.003)	(0.003)	(0.002)	(0.003)
$lnAvgMintPrice_{it}$	0.151***	0.088***	0.137***	0.114***
	(0.008)	(0.010)	(0.019)	(0.018)
$Transaction_{it}$	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
$Awareness_{it}$	0.002***	0.003**	0.003***	0.001
	(0.001)	(0.001)	(0.000)	(0.001)
Constant	−0.073	0.449***	−0.444**	−0.175*
	(0.078)	(0.161)	(0.209)	(0.097)
Category dummies	Yes	Yes	Yes	Yes
Week dummies	Yes	Yes	Yes	Yes
Collection RE	Yes	Yes	Yes	Yes
R^2	0.680	0.736	0.659	0.716
Observations	102,494	31,361	31,922	31,774

Note: Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7
Impact of copyright sharing on financial success: Grouped regression results based on JPEG compression complexity.

	Dependent variable: $lnAvgPrice_{it}$			
	(1) Full sample	(2) Low complexity	(3) Medium complexity	(4) High complexity
$CC0_i$	0.121***	0.094	0.117***	0.091
	(0.023)	(0.087)	(0.029)	(0.091)
$lnAvgPrice_{i,t-1}$	0.563***	0.720***	0.733***	0.738***
	(0.016)	(0.016)	(0.021)	(0.026)
$Supply_{it}$	0.001	−0.002	−0.003	−0.003
	(0.003)	(0.003)	(0.003)	(0.002)
$lnAvgMintPrice_{it}$	0.151***	0.107***	0.101***	0.094***
	(0.008)	(0.009)	(0.018)	(0.009)
$Transaction_{it}$	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
$Awareness_{it}$	0.002***	0.003***	0.003***	0.002
	(0.001)	(0.001)	(0.000)	(0.001)
Constant	−0.073	0.343***	−0.368***	0.059
	(0.078)	(0.110)	(0.091)	(0.167)
Category dummies	Yes	Yes	Yes	Yes
Week dummies	Yes	Yes	Yes	Yes
Collection RE	Yes	Yes	Yes	Yes
R^2	0.680	0.726	0.716	0.677
Observations	102,494	31,359	31,938	31,760

Note: Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8
Impact of copyright sharing on social success: Grouped regression results based on NFT categories.

	Dependent variable: $ProfilePictureRatio_{it}$			
	(1) Profile pictures	(2) Collectibles	(3) Art	(4) Metaverse
$CC0_i$	0.012**	0.008***	0.010***	−0.028
	(0.006)	(0.001)	(0.000)	(0.017)
$lnAvgPrice_{i,t-1}$	0.001***	0.000***	0.000*	0.006
	(0.000)	(0.000)	(0.000)	(0.004)
$Supply_{it}$	0.001*	0.001***	0.000	−0.002
	(0.001)	(0.000)	(0.000)	(0.003)
$lnAvgMintPrice_{it}$	0.005**	0.002***	0.004	−0.008
	(0.002)	(0.000)	(0.003)	(0.011)
$Transaction_{it}$	−0.000**	0.000***	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
$Awareness_{it}$	0.000***	0.000**	−0.000	−0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.033***	0.001***	0.040***	0.021
	(0.003)	(0.000)	(0.002)	(0.022)
Category dummies	Yes	Yes	Yes	Yes
Week dummies	Yes	Yes	Yes	Yes
Collection RE	Yes	Yes	Yes	Yes
R^2	0.228	0.087	0.277	0.301
Observations	10,985	1668	800	356

Note: Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9
Impact of copyright sharing on financial success: Grouped regression results based on NFT categories.

	Dependent variable: *lnAvgPrice*$_{it}$			
	(1) Profile pictures	(2) Collectibles	(3) Art	(4) Metaverse
$CC0_i$	0.107***	0.174***	0.037*	0.499*
	(0.010)	(0.024)	(0.019)	(0.290)
$lnAvgPrice_{i,t-1}$	0.596***	0.645***	0.866***	0.715***
	(0.004)	(0.009)	(0.024)	(0.054)
$Supply_{it}$	−0.002***	−0.000	−0.003**	0.002
	(0.001)	(0.000)	(0.002)	(0.009)
$lnAvgMintPrice_{it}$	0.131***	0.132***	0.053***	0.157*
	(0.005)	(0.002)	(0.008)	(0.082)
$Transaction_{it}$	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
$Awareness_{it}$	0.003***	−0.000***	0.003***	−0.004
	(0.000)	(0.000)	(0.001)	(0.002)
Constant	−0.118***	−0.146***	0.438***	0.724
	(0.029)	(0.004)	(0.023)	(0.762)
Category dummies	Yes	Yes	Yes	Yes
Week dummies	Yes	Yes	Yes	Yes
Collection RE	Yes	Yes	Yes	Yes
R^2	0.669	0.658	0.747	0.690
Observations	62,794	16,021	7148	3584

Note: Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

build upon them freely, a sense of inclusion, connection, and empowerment is fostered within the community. Consequently, this encourages greater willingness among individuals to utilize NFT images as profile pictures, improving the NFT's social success. However, this effect is not observed for metaverse NFTs, which may be attributed to the fact that metaverse NFTs are generally not used as social media avatars, or it may result from the limited precision of estimates in the metaverse category due to the small sample size.

Interestingly, for metaverse NFTs, while the proportion used as social media profile pictures remains unaffected by copyright sharing, their financial success, as indicated by the average sale price, shows the largest positive impact among the four NFT categories. This may be due to the high interoperability of metaverse NFTs. By allowing unlimited external contributions, copyright sharing can spur more ecological evolution and development in NFTs with stronger interoperability, increasing their intrinsic value and enhancing their average price. In contrast, art NFTs exhibit the lowest financial success through copyright sharing, likely because their financial value relies predominantly on their artistic value, which is less influenced by licensing.

4.4. Robustness checks

4.4.1. Changing price unit from ETH to USD

In the main analysis, we use ETH as the unit of measurement for pricing, grounded in the assumption that individuals in the blockchain realm evaluate the worth of NFTs primarily in terms of ETH. However, considering the off-chain perspective, the USD value of ETH fluctuates over time. Some evaluators of NFT prices take this exchange rate into account. To examine whether the impact of copyright sharing on NFT success and the role of remixing holds in a USD perspective, we reanalyze the data with prices in USD, including both the average sale price and the average mint price in Eqs. (1) and (2). The findings presented in Tables 10 and 11 provide similar conclusions, thereby confirming the robustness of our results.

4.4.2. Changing financial success from price to volume traded

In the main test, we utilize an NFT collection's weekly average sale price as the outcome variable to gauge the financial success of NFT collections. This measure reflects individuals' evaluations of the collection, indicating their willingness to pay to join the NFT community and their expectations of its potential appreciation. In this section, we use the logarithm of the weekly volume traded as an alternative measure. This measure not only captures transaction prices but also reflects the market liquidity of the collection, another essential aspect of NFT's financial success. Results presented in column (1) of Table 12 demonstrate that sharing copyright increases the volume traded compared to implementing copyright restrictions. When grouped regression analyses are conducted, as shown in columns (2)–(4), the results maintain consistency with the main test findings: At a medium complexity level, the CC0 coefficient is both statistically significant and exhibits the highest value.

Table 10
Impact of copyright sharing on social success (in USD): Grouped regression results based on Canny complexity.

	Dependent variable: *ProfilePictureRatio*$_{it}$			
	(1) Full sample	(2) Low complexity	(3) Medium complexity	(4) High complexity
$CC0_i$	0.008***	−0.004	0.065***	0.002
	(0.003)	(0.008)	(0.002)	(0.002)
$lnAvgPriceUSD_{i,t-1}$	0.001***	0.003***	0.000***	0.000
	(0.000)	(0.001)	(0.000)	(0.000)
$Supply_{it}$	0.001**	0.002***	0.001***	0.000
	(0.000)	(0.001)	(0.000)	(0.000)
$lnAvgMintPriceUSD_{it}$	0.004***	0.003*	0.002*	0.003***
	(0.001)	(0.002)	(0.001)	(0.001)
$Transaction_{it}$	−0.000	−0.000	−0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
$Awareness_{it}$	0.000***	0.000***	0.000**	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.003	−0.014	−0.000	−0.023**
	(0.009)	(0.016)	(0.008)	(0.009)
Category dummies	Yes	Yes	Yes	Yes
Week dummies	Yes	Yes	Yes	Yes
Collection RE	Yes	Yes	Yes	Yes
R^2	0.245	0.178	0.179	0.713
Observations	14,853	4746	5132	4396

Note: Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 11
Impact of copyright sharing on financial success (in USD): Grouped regression results based on Canny complexity.

	Dependent variable: *lnAvgPriceUSD*$_{it}$			
	(1) Full sample	(2) Low complexity	(3) Medium complexity	(4) High complexity
$CC0_i$	0.064***	0.085	0.122**	0.063
	(0.022)	(0.090)	(0.057)	(0.062)
$lnAvgPriceUSD_{i,t-1}$	0.589***	0.730***	0.629***	0.690***
	(0.016)	(0.023)	(0.024)	(0.035)
$Supply_{it}$	−0.002	−0.005	−0.006**	−0.001
	(0.003)	(0.003)	(0.002)	(0.003)
$lnAvgMintPriceUSD_{it}$	0.130***	0.095***	0.121***	0.097***
	(0.006)	(0.012)	(0.013)	(0.014)
$Transaction_{it}$	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
$Awareness_{it}$	0.002***	0.002***	0.003***	0.001
	(0.000)	(0.001)	(0.000)	(0.001)
Constant	2.125***	1.767***	1.759***	1.461***
	(0.085)	(0.135)	(0.107)	(0.225)
Category dummies	Yes	Yes	Yes	Yes
Week dummies	Yes	Yes	Yes	Yes
Collection RE	Yes	Yes	Yes	Yes
R^2	0.768	0.812	0.746	0.819
Observations	102,275	31,279	31,888	31,765

Note: Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 12
Impact of copyright sharing on financial success (volume traded): Grouped regression results based on Canny complexity.

	Dependent variable: *lnVolume*$_{it}$			
	(1) Full sample	(2) Low complexity	(3) Medium complexity	(4) High complexity
$CC0_i$	0.305**	0.310	0.474**	0.031
	(0.113)	(0.189)	(0.148)	(0.098)
$lnAvgPrice_{i,t-1}$	0.671***	0.729***	0.718***	0.704***
	(0.021)	(0.033)	(0.025)	(0.082)
$Supply_{it}$	0.105***	0.133***	0.120***	0.086***
	(0.027)	(0.037)	(0.028)	(0.024)
$lnAvgMintPrice_{it}$	0.098***	0.101***	0.098***	0.054
	(0.019)	(0.019)	(0.029)	(0.038)
$Transaction_{it}$	0.002***	0.002***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
$Awareness_{it}$	−0.001	−0.002	0.000	−0.002
	(0.001)	(0.001)	(0.000)	(0.001)
Constant	4.811***	6.418***	4.059***	4.126***
	(0.093)	(0.274)	(0.125)	(0.229)
Category dummies	Yes	Yes	Yes	Yes
Week dummies	Yes	Yes	Yes	Yes
Collection RE	Yes	Yes	Yes	Yes
R^2	0.587	0.640	0.596	0.594
Observations	102,494	31,361	31,922	31,774

Note: Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.4.3. Using different parameters when calculating image complexity

The calculation of image complexity is sensitive to specific parameters in both the Canny algorithm and the JPEG compression approach. To demonstrate the robustness of our findings, we vary these parameters to observe if the results change. The Canny algorithm employs two thresholds to identify weak and strong edges. In the main test, these thresholds are set at 50 and 150. Intensity changes below 50 indicate gradual transitions, classifying regions as non-edges, while changes above 150 suggest sharp transitions, confirming them as edges. For intensity changes between these thresholds, the classification as edge or non-edge depends on whether they are adjacent to previously identified edges. For robustness checks, we adjust these values to 100 and 200. The quality parameter can take an integer value from 1 to 95 for the JPEG compression method. A higher quality-parameter value means less compression and higher image fidelity; a lower value means more compression and lower image fidelity. In the main test, we selected 95 for this parameter. In our robustness test, we set the parameter at another extreme: 1. The grouped regression results based on Canny complexity thresholds of 100 and 200 are shown in Tables 13 and 14, and the results based on JPEG compressions of 1 are displayed in Tables 15 and 16. All these results are consistent with our main findings, indicating that the positive effect of copyright sharing is most pronounced at a medium level of complexity, the ideal condition for remixing original NFT artworks.

4.4.4. Using a different matching method

In the main analysis, we perform regression after conducting a week-by-week kernel PSM with a bandwidth of 0.01. To test the robustness of our results, we use an alternative matching method—week-by-week nearest neighbor PSM. The balance test for control variables reveals that, for each time period, there are no significant differences in the covariates between the CC0 and non-CC0 NFT collections after matching. Due to space constraints, we do not provide the 81 *t*-test result tables. The post-matching regression results can be found in Tables 17 and 18, which are consistent with the main results. Overall, copyright sharing proves to be an effective strategy that enhances both the social and financial success of NFT collections. This strategy is more effective when the NFT collection is associated with images that the public has a higher propensity to remix. This suggests that remixing plays an essential role in maximizing the benefits of copyright sharing.

Table 13
Impact of copyright sharing on social success: Grouped regression results based on Canny complexity with alternative thresholds.

	Dependent variable: *ProfilePictureRatio*$_{it}$			
	(1) Full sample	(2) Low complexity	(3) Medium complexity	(4) High complexity
$CC0_i$	0.009***	−0.002	0.054***	0.004
	(0.003)	(0.010)	(0.004)	(0.003)
$lnAvgPrice_{i,t-1}$	0.001***	0.002***	0.000***	0.000**
	(0.000)	(0.001)	(0.000)	(0.000)
$Supply_{it}$	0.001**	0.002***	0.001***	0.000
	(0.000)	(0.001)	(0.000)	(0.000)
$lnAvgMintPrice_{it}$	0.004***	0.004*	0.002	0.004***
	(0.001)	(0.002)	(0.001)	(0.001)
$Transaction_{it}$	−0.000	−0.000*	0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
$Awareness_{it}$	0.000***	0.000***	0.000***	−0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.035***	0.029***	0.002	0.039***
	(0.001)	(0.003)	(0.005)	(0.012)
Category dummies	Yes	Yes	Yes	Yes
Week dummies	Yes	Yes	Yes	Yes
Collection RE	Yes	Yes	Yes	Yes
R^2	0.245	0.154	0.163	0.688
Observations	14,853	4634	5197	4443

Note: Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 14
Impact of copyright sharing on financial success: Grouped regression results based on Canny complexity with alternative thresholds.

	Dependent variable: *lnAvgPrice*$_{it}$			
	(1) Full sample	(2) Low complexity	(3) Medium complexity	(4) High complexity
$CC0_i$	0.121***	0.099	0.138**	0.106*
	(0.023)	(0.089)	(0.070)	(0.057)
$lnAvgPrice_{i,t-1}$	0.563***	0.806***	0.593***	0.659***
	(0.016)	(0.015)	(0.023)	(0.042)
$Supply_{it}$	0.001	−0.002	−0.001	−0.002
	(0.003)	(0.002)	(0.003)	(0.004)
$lnAvgMintPrice_{it}$	0.151***	0.073***	0.147***	0.122***
	(0.008)	(0.008)	(0.018)	(0.020)
$Transaction_{it}$	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
$Awareness_{it}$	0.002***	0.002**	0.003***	0.002**
	(0.001)	(0.001)	(0.000)	(0.001)
Constant	−0.073	0.369***	−0.345**	−0.267***
	(0.078)	(0.140)	(0.144)	(0.073)
Category dummies	Yes	Yes	Yes	Yes
Week dummies	Yes	Yes	Yes	Yes
Collection RE	Yes	Yes	Yes	Yes
R^2	0.680	0.739	0.654	0.716
Observations	102,494	31,417	31,982	31,658

Note: Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5. Conclusions

This study demonstrates that adopting a copyright-sharing strategy, particularly through the CC0 license, enhances both the social and financial success of NFT collections. Our empirical findings show that NFT collections under the CC0 license experience a higher proportion of NFT-associated images being used as social media profile pictures, as

Table 15
Impact of copyright sharing on social success: Grouped regression results based on JPEG compression complexity with an alternative parameter.

	Dependent variable: $ProfilePictureRatio_{it}$			
	(1) Full sample	(2) Low complexity	(3) Medium complexity	(4) High complexity
$CC0_i$	0.009***	−0.006	0.026***	0.002
	(0.003)	(0.008)	(0.006)	(0.005)
$lnAvgPrice_{i,t-1}$	0.001***	0.000***	0.002***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
$Supply_{it}$	0.001**	0.001***	0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
$lnAvgMintPrice_{it}$	0.004***	0.001*	0.005***	0.005***
	(0.001)	(0.001)	(0.002)	(0.002)
$Transaction_{it}$	−0.000	−0.000**	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
$Awareness_{it}$	0.000***	−0.000	0.000***	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.035***	0.002	0.036***	0.055***
	(0.001)	(0.002)	(0.001)	(0.016)
Category dummies	Yes	Yes	Yes	Yes
Week dummies	Yes	Yes	Yes	Yes
Collection RE	Yes	Yes	Yes	Yes
R^2	0.245	0.144	0.170	0.434
Observations	14,853	4253	5382	4639

Note: Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 16
Impact of copyright sharing on financial success: Grouped regression results based on JPEG compression complexity with an alternative parameter.

	Dependent variable: $lnAvgPrice_{it}$			
	(1) Full sample	(2) Low complexity	(3) Medium complexity	(4) High complexity
$CC0_i$	0.121***	0.121*	0.159**	−0.065
	(0.023)	(0.073)	(0.066)	(0.054)
$lnAvgPrice_{i,t-1}$	0.563***	0.789***	0.614***	0.595***
	(0.016)	(0.017)	(0.018)	(0.035)
$Supply_{it}$	0.001	−0.002	0.004	−0.008
	(0.003)	(0.002)	(0.003)	(0.007)
$lnAvgMintPrice_{it}$	0.151***	0.077***	0.148***	0.137***
	(0.008)	(0.010)	(0.013)	(0.027)
$Transaction_{it}$	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
$Awareness_{it}$	0.002***	0.002	0.002***	0.002***
	(0.001)	(0.002)	(0.000)	(0.001)
Constant	−0.073	0.664***	0.086	−0.300*
	(0.078)	(0.141)	(0.092)	(0.170)
Category dummies	Yes	Yes	Yes	Yes
Week dummies	Yes	Yes	Yes	Yes
Collection RE	Yes	Yes	Yes	Yes
R^2	0.680	0.708	0.716	0.673
Observations	102,494	31,700	31,683	31,674

Note: Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 17
Impact of copyright sharing on social success: Grouped regression results based on Canny complexity (week-by-week nearest neighbor PSM).

	Dependent variable: $ProfilePictureRatio_{it}$			
	(1) Full sample	(2) Low complexity	(3) Medium complexity	(4) High complexity
$CC0_i$	0.008***	−0.003	0.066***	0.002
	(0.003)	(0.008)	(0.002)	(0.003)
$lnAvgPrice_{i,t-1}$	0.001***	0.002***	0.000***	0.000*
	(0.000)	(0.001)	(0.000)	(0.000)
$Supply_{it}$	0.001**	0.002***	0.001***	0.000
	(0.000)	(0.001)	(0.001)	(0.000)
$lnAvgMintPrice_{it}$	0.004***	0.004*	0.002**	0.003***
	(0.001)	(0.002)	(0.001)	(0.001)
$Transaction_{it}$	−0.000	−0.000	−0.000*	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
$Awareness_{it}$	0.000***	0.000***	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.034***	0.030***	0.017***	0.004***
	(0.002)	(0.002)	(0.001)	(0.002)
Category dummies	Yes	Yes	Yes	Yes
Week dummies	Yes	Yes	Yes	Yes
Collection RE	Yes	Yes	Yes	Yes
R^2	0.239	0.131	0.169	0.752
Observations	13,926	4458	4836	4083

Note: Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 18
Impact of copyright sharing on financial success: Grouped regression results based on Canny complexity (week-by-week nearest neighbor PSM).

	Dependent variable: $lnAvgPrice_{it}$			
	(1) Full sample	(2) Low complexity	(3) Medium complexity	(4) High complexity
$CC0_i$	0.095***	0.076	0.105*	0.040
	(0.020)	(0.116)	(0.055)	(0.056)
$lnAvgPrice_{i,t-1}$	0.601***	0.710***	0.639***	0.772***
	(0.015)	(0.020)	(0.015)	(0.040)
$Supply_{it}$	−0.005**	−0.007*	−0.005	−0.007***
	(0.002)	(0.004)	(0.004)	(0.003)
$lnAvgMintPrice_{it}$	0.125***	0.085***	0.118***	0.077***
	(0.004)	(0.010)	(0.016)	(0.012)
$Transaction_{it}$	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
$Awareness_{it}$	0.002***	0.003**	0.004***	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	−0.103	0.497**	−0.332	−0.085
	(0.086)	(0.198)	(0.280)	(0.134)
Category dummies	Yes	Yes	Yes	Yes
Week dummies	Yes	Yes	Yes	Yes
Collection RE	Yes	Yes	Yes	Yes
R^2	0.675	0.721	0.649	0.707
Observations	95,501	29,343	29,707	29,463

Note: Standard errors in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

well as a higher average sale price compared to non-CC0 collections. Furthermore, a high propensity for remixing can amplify the benefits of copyright sharing. When community members actively engage in creating derivative works based on the original NFT artworks, network effects are strengthened, enhancing both the social impact and financial value of the NFT collection.

This study makes several contributions. First, it contributes to both the NFT and IP sharing literature by examining the impact of copyright sharing in the context of NFTs. The question of whether to waive the copyright protection of NFT artworks is a critical issue in practice, yet it has not been explored empirically in the academic literature. While previous studies on the impact of IP sharing in traditional digital resources have yielded inconsistent results, NFTs differ from them in key ways. Therefore, we propose a contextual explanation for why copyright sharing is more beneficial than detrimental for NFT collections: First, through tokenization, an NFT consists not only of the artwork but also of a token. Even if the artwork is used freely by the public, the token remains scarce and can capture the value generated through network effects. Additionally, within the Web3 ecosystem, openness and permissionless are established social norms. Successful projects usually embrace open innovation, increasing interoperability and allowing for mutual exploitation of resources to enhance the ecosystem collectively. In contrast, projects that adopt closed strategies tend to experience limited network effects and struggle to sustain themselves.

Second, this study contributes further to the NFT literature by illustrating that NFT collections are not merely financial assets but also communities with significant social value. Traditional NFT research has examined NFTs through a financial lens, focusing on topics such as portfolio optimization, market efficiency, the interconnectedness between NFTs and other financial markets, trading behavior such as herding, and price prediction. It has neglected the social dimension of NFT collections as communities. We innovatively evaluate the success of an NFT collection not only from a financial perspective, measured by the average collection price, but also from a social perspective, gauged by public endorsement and support. This dual metric provides a comprehensive evaluation of the collection's market appeal and its social influence. Furthermore, we examine the critical role of community members' engagement. The propensity for the NFT collection to be remixed by community members serves as a crucial moderating factor, significantly enhancing the effectiveness of copyright sharing.

Last, this study also provides practical insights for NFT stakeholders. NFT creators can open the copyright of associated artworks to allow diverse knowledge contributions, enhancing the success of their collections. The effectiveness of this approach is contingent upon cultivating a vibrant community characterized by a willingness to remix.

This study faces some limitations, due primarily to data availability issues. First, data on the adoption of NFTs as profile pictures on social media platforms are only accessible from October 2022 onward. This constraint narrows the analytical scope, especially regarding the social success of NFTs, since other datasets reach back to August 2021. For a more thorough exploration of how NFTs gain social traction over time, future research would benefit from a data set that covered a longer timeline, enhancing the reliability of findings on NFTs' social impact. Second, this study relies on complexity as a proxy measure to estimate the likelihood of an NFT collection being remixed, as remixing activities (e.g., derivative NFT collections, memes, merchandise) are not reliably recorded, making it challenging to measure them directly. In future research, with access to more comprehensive data sources that capture these activities across various forms, a more direct measure of remixing could be utilized to refine the analysis.

CRediT authorship contribution statement

Cheng Tao: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jin Hu:** Writing – review & editing, Project administration, Methodology. **Michael Chau:** Writing – review & editing, Supervision. **Peipei Li:** Writing – review & editing. **Daning Hu:** Writing – review & editing, Supervision, Project administration, Conceptualization.

Declaration of competing interest

The authors report there are no competing interests to declare.

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Supplementary materials

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